

**REAL-TIME MONITORING OF COMBINE HARVESTER GRAIN LOSS IN
GLUTINOUS RICE HARVESTING**

By

BOMOI MUHAMMAD ISA

**Thesis Submitted to the School of Graduate Studies, Universiti Putra
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Philosophy**

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DEDICATION

This thesis is dedicated to my late father, beloved mother, lovely wife, and daughter, and my entire family and friends.



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in
fulfilment of the requirement for the degree of Doctor of Philosophy

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July 2024

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The increasing demand for glutinous rice in Malaysia has prompted efforts to improve local production. One of the major challenges in achieving higher yields is significant grain loss during harvesting, largely due to improper management of combine harvester operational parameters. Conventional methods for measuring grain loss are labor-intensive and lack real-time monitoring capabilities. This study developed a real-time sensor-based system to detect and monitor grain loss during harvesting. The specific objectives include evaluating the performance of the combine harvester in glutinous rice fields, optimizing the operational parameters of the combine harvester to minimize grain loss, and developing a grain loss monitoring system. Field experiments, designed using Central Composite Design (CCD), focused on four key factors: forward speed (1.76–2.6 km/h), header height (150–350 mm), feed rate (2–6 kg/s), and cleaning fan speed (1100–1700 rpm). A total of 30 experimental runs were conducted to measure grain loss and evaluate the combine harvester's performance. Grain loss data were analyzed using

Response Surface Methodology (RSM) and Artificial Neural Networks (ANN), with model accuracy assessed using R^2 , mean absolute error (MAE), and root mean square error (RMSE). Statistical analysis of the two models showed strong model performance, with R^2 values of 0.9909 and 0.9892, MAE values of 1.25 and 1.73, and RMSE values of 1.69 and 3.68, respectively. The optimal operational settings of the combine harvester were determined using the RSM-DF model (2.26 km/h forward speed, 150 mm header height, 1100 rpm cleaning fan speed, and 3 kg/s feed rate) and the ANN-GA model (2.26 km/h forward speed, 252 mm header height, 1100 rpm cleaning fan speed, and 3 kg/s feed rate), resulting in minimum grain loss values of 23.58 kg/ha and 14.70 kg/ha, respectively. A real-time grain loss monitoring system was developed using PVDF piezoelectric sensors and a microcontroller-based circuit, achieving 88.45% accuracy at optimal settings (2.26 km/h forward speed, 350 mm header height, and 1500 rpm fan speed). Additionally, machine learning models were explored for predicting system performance, with the Decision Tree (DT) model outperforming the Random Forest (RF) model, achieving R^2 values of 0.9992 for training and 0.9987 for testing. The forward speed of the combine harvester was identified as the most critical factor affecting machine performance. Integrating a real-time grain loss monitoring system with machine learning predictions can significantly enhance combine harvester efficiency and reduce grain loss during glutinous rice harvesting.

Keywords: Combine Harvester Performance, Grain Loss Monitoring, Machinery, Optimization, Rice.

SDG: GOAL 2: Zero Hunger. GOAL 9: Industry, Innovation, and Infrastructure.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**PEMANTAUAN MASA NYATA KEHILANGAN BIJIRIN PENUAI
GABUNGAN DALAM PENUAIAN PADI PULUT**

Oleh

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Permintaan pulut yang semakin meningkat di Malaysia telah mendorong usaha untuk meningkatkan pengeluaran tempatan. Cabaran utama dalam mencapai hasil yang lebih tinggi ialah kehilangan bijirin yang ketara semasa penuaian, sebahagian besarnya disebabkan oleh pengurusan parameter penuai gabungan yang tidak betul. Kaedah konvensional untuk mengukur kehilangan bijirin adalah intensif buruh dan tidak menawarkan pemantauan masa nyata. Kajian ini bertujuan untuk membangunkan sistem berasaskan sensor untuk mengesan dan memantau kehilangan bijirin dalam masa nyata semasa penuaian. Objektifnya termasuk menilai prestasi penuai gabungan di sawah pulut, mengoptimumkan parameter operasi penuai gabungan untuk meminimumkan kehilangan bijirin, dan membangunkan sistem pemantauan kehilangan bijirin. Eksperimen lapangan telah dijalankan menggunakan Reka Bentuk Komposit Pusat (CCD) dengan empat faktor utama: kelajuan ke hadapan (1.76–2.6 km/j), ketinggian pengepala (150–350 mm), kadar suapan (2–6 kg/s), dan kelajuan kipas pembersihan (1100–1700 rpm). Sebanyak 30

larian telah dilakukan untuk mengukur kehilangan bijirin dan menilai parameter prestasi penuai gabungan. Data kehilangan bijirin telah dianalisis menggunakan Metodologi Permukaan Tindak Balas (RSM) dan Rangkaian Saraf Buatan (ANN). Ketepatan model ramalan telah dinilai menggunakan R^2 , ralat mutlak min (MAE), dan ralat kuasa dua min akar (RMSE). Keputusan menunjukkan bahawa RSM mengatasi ANN sedikit dalam meramalkan kehilangan bijirin, dengan nilai R^2 masing-masing 0.9909 dan 0.9892, dan ralat ramalan yang lebih kecil dalam MAE dan RMSE. Analisis statistik kedua-dua model menunjukkan prestasi model yang kukuh, dengan nilai R^2 0.9909 dan 0.9892, nilai MAE 1.25 dan 1.73, dan nilai RMSE masing-masing 1.69 dan 3.68. Tetapan operasi optimum penuai gabungan ditentukan menggunakan model RSM-DF (kelajuan hadapan 2.26 km/j, ketinggian pengepala 150 mm, kelajuan kipas pembersih 1100 rpm dan kadar suapan 3 kg/s) dan model ANN-GA (Kelajuan hadapan 2.26 km/j, ketinggian pengepala 252 mm, kelajuan kipas pembersih 1100 rpm, dan kadar suapan 3 kg/s), menghasilkan nilai kehilangan bijirin minimum masing-masing 23.58 kg/ha dan 14.70 kg/ha. Sistem pemantauan kehilangan bijirin masa nyata telah dibangunkan menggunakan penderia piezoelektrik PVDF dan litar berasaskan mikropengawal, mencapai ketepatan 88.45% pada tetapan optimum (kelajuan hadapan 2.26 km/j, ketinggian pengepala 350 mm dan kelajuan kipas 1500 rpm). Selain itu, model pembelajaran mesin telah diterokai untuk meramalkan prestasi sistem, dengan model Decision Tree (DT) mengatasi model Random Forest (RF), mencapai nilai R^2 0.9992 untuk latihan dan 0.9987 untuk ujian. Kelajuan hadapan penuai gabungan dikenal pasti sebagai faktor paling kritikal yang mempengaruhi prestasi mesin. Secara keseluruhannya, menyepadukan

sistem pemantauan kehilangan bijirin masa nyata dengan ramalan pembelajaran mesin boleh meningkatkan kecekapan penuai gabungan dengan ketara dan mengurangkan kehilangan bijirin semasa penuaian beras pulut.

Kata kunci: Beras, Jentera, Menggabungkan Prestasi Penuai, Pemantauan Kehilangan Bijirin, Pengoptimuman.

SDG: MATLAMAT 4: Sifar Kelaparan, MATLAMAT 9: Industri, Inovasi, dan Infrastruktur

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LIST OF ABBREVIATIONS

A/D	Analog Digital
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ANOVA	Analysis of variance
AP	Adequate Precision
BP	Back Propagation
CCD	Central Composite Design
CFS	Cleaning Fan Speed
CMOS	Complementary Metal Oxide Semi-conductors
CS	Chip Select
CV	Coefficient of Variance
DEM	Discrete Element Method
DR	Damping Ratio
DT	Decision Tree
EFC	Effective Field Capacity
EMA	Experimental Modal Analysis
EVA	Ethylene Vinyl Acetate
FAO	Food and Agricultural Organization
FC	Fuel Consumption
FE	Field Efficiency
Fe	Fuel Energy
FFT	Fast Fourier Transform
FMI	Field Machinery Index
FR	Feed rate

FS	Field Speed
GA	Genetic Algorithm
GLM	General Linear Model
GND	Ground
HE	Human Energy
HH	Header Height
IDE	Integrated Development Environment
KNN	K-Nearest Neighbors
LCD	Liquid Crystal Display
LED	Light Emitting Diode
LR	Linear Regression
MAE	Mean Absolute Error
MARDI	Malaysia Agricultural Research Development Institute
MCU	Microcontroller unit
ME	Machinery Energy
MI	Machinery Index
MISO	Master Input Slave Output
MLP	Multilayer Perception
MOG	Materials other than grain
MOSI	Master Output Slave Input
MR4	Malaysian Rice Variety 4
MSE	Mean Squared Error
N	Number of Impact
NB	Naïve Bayes
NF	Natural Frequency
NI	National Instrument
PC	Personal Computer

PCB	Printed Circuit Board
PET	Polyethylene Terephthalate
PVDF	Polyvinylidene Fluoride
RBF	Radial Basis Function
RF	Random Forest
RGB	Red Blue Green
RMSE	Root Mean Squared Error
rpm	Revolution per minute
RSM	Response Surface Method
RSM-DF	Response Surface Method Desirability Function
RX	Serial Data Receiver
SCK	Serial Clock Line
SCL	Clock Signal
SD	Standard Deviation
SDA	Serial Data Line
SS	Chip select
SSL	Self Sufficiency Level
SVR	Support Vector Regression
TE	Total Energy
TFC	Theoretical Field Capacity
TTL	Transistor-Transi
TX	Serial Data Transmitter
USB	Universal Serial Board
UV	Ultraviolet
VCC	Voltage Common Collector

CHAPTER 1

INTRODUCTION

1.1 Background of the research

Glutinous rice (*Oryza sativa* var. *glutinosa*), also known as sticky, sweet, or waxy rice, is a type of rice produced mostly in Southeast and East Asia as well as in the eastern regions of South Asia (Eakkanaluksamee & Anuntagool, 2020). It possesses unique functional and processing properties, mainly due to its distinct starch composition (Nawaz, 2018). This type of rice grain is different from normal white rice because it contains negligible amounts of amylose and high amounts of amylopectin, which makes the cultivar gluten-free (Sattaka et al., 2019; Shakri et al., 2021). It is in high demand because it is consumed during festivals in most Southeast Asian nations (Sattaka et al., 2020).

Glutinous rice and regular white rice share several similarities, as both are varieties of *Oryza sativa* and are widely consumed as staple foods in many cultures (Kathy, 2024). Nutritionally, both are primarily composed of carbohydrates, with similar protein levels and low-fat content, making them important energy sources (Qi et al., 2015). In appearance, both types of rice have polished grains that are white and opaque. They are also cultivated under similar conditions, requiring warm climates and water-intensive paddy fields (Shakri et al., 2021). The key difference between the two rice varieties is their starch composition, which affects their texture and usage.

In Malaysia, the production of glutinous rice is mainly concentrated in the northern part of the country, specifically in the states of Kedah and Perak, because of their favourable climate and soil conditions, which are suitable for growing high-quality glutinous rice throughout the year. The country produces two important local glutinous rice varieties, Susu and Siding, which are typically cultivated by small-scale farmers. Currently, the plantation area for these rice cultivars is limited to approximately 38.96 ha (Zainal & Shamsudin, 2021).

The utilization of combine harvesters is increasingly recognized as a means of minimizing production costs and increasing labor productivity due to labor shortages in rice cultivation (Alizadeh & Allameh, 2013). In the Malaysian paddy industry, mechanized harvesting using a combine harvester is one of the most successful mechanization practices, with approximately 100% of rice harvesting being mechanized (Ismail & El Pebrian, 2018). The use of combine harvesters significantly reduces the time, effort, and labour required for harvesting operations but contributes to grain loss (Alam et al., 2021).

Grain loss in paddy fields including glutinous rice and white rice typically occurs during the harvesting process, particularly when using combine harvesters. These losses significantly affect the total yield and farmers' profits. In Malaysia, farmers face the risk of reduced grain yield due to various factors, including the ineffective use of combine harvesters (Sharifuddin & Mustaffha, 2021).

A considerable loss of grain occurs during harvesting using a combine harvester due to inappropriate crop conditions and machine settings, leading to a decline in the quantity and quality of rice grains (Hou et al., 2021). Furthermore, the operation of the combine harvester is a matter of significant concern, because the operational decisions and adjustment of the machine settings are largely dependent on the discretion of the operators (Mahirah et al., 2017). Elsoragaby et al., (2019) highlighted the significance of combine harvesters in achieving efficient harvesting of rice crops, improving grain quality, minimizing loss, and reducing production costs. However, these machines encounter certain operational challenges such as machine bogging, improper settings, and high grain loss. Chaab et al., (2020) reported that the quantity of grain loss during harvesting is a critical measure of a combine harvester performance. The machine can only be considered efficient when it is properly adjusted and operated to minimize losses.

The performance factors that contribute to grain loss must be identified to effectively reduce these losses. However, it has been observed that the majority of combine harvester operators do not pay attention to the impact of these factors (Ahmad et al., 2020). Farmers often overlooked the importance of these variables. According to Al-sammarraie & Alhadithi, (2021), incorrect adjustment and calibration of the combine harvester operational parameters result in significant losses during operation. By improving the machine performance and field conditions, the utilization of combine harvesters in rice harvesting can effectively reduce post-harvest losses. This approach ensured that a greater quantity of rice grains was successfully harvested with minimal

loss. Therefore, achieving optimal combine harvester performance is crucial for establishing a sustainable and efficient system that maximizes yield during rice harvesting.

According to Yilmaz & Caner, (2015), grain loss is influenced by feeding rate and grain stalk ratio. Donnell Hunt, (2016) and Shahr et al., (2017) reported that improper combine harvester travel speed contributes to paddy harvesting losses. Paulsen et al., (2015) reported that separation loss reduces with the correct adjustment of the cleaning fan speed. Esgici et al., (2016) emphasized that the objective of proper harvesting is to maximize yield and minimize losses by improving combine harvester operational parameters. Mairghany et al., (2018) also highlighted the need to focus on reducing grain loss to achieve the highest quality and quantity of rice during combine harvester operations. Therefore, it is crucial to provide reliable measures to effectively minimize and address these losses.

To enhance glutinous rice yields and attain self-sufficiency, reducing grain loss during harvesting operations is a mechanization strategy aimed at increasing the production output. Harvesting has a significant impact on rice yield, quality, and production costs, making it the primary cause of postharvest losses (Ahmed et al., 2017). To mitigate this issue, Dutta et al., (2018) proposed that adopting appropriate technology could help operators minimize grain loss by facilitating proper machine handling. This is because the determination of grain loss is important for assessing the performance of a combine harvester, not only for economic benefit and total yield determination but also for global food

security concerns, as any amount of grain loss can affect the global food supply.

Improvements in productivity and harvest quality can be achieved by advancing grain loss monitoring systems during harvest. These systems are crucial for optimizing combine harvester performance and directly enhance productivity and harvest outcomes. This can increase farmers' incomes, provide accurate data and insights for yield optimization, minimize losses, and improve overall harvesting efficiency.

1.2 Significance of the research

Grain loss monitoring systems for combine harvesters can collect real-time data on grain loss and its associated parameters. The system provides a continuous collection of data that improves operator experience and access to performance monitoring, analysis, and control. The aim was to optimize and improve the performance of the combine harvester, predict future losses, and increase productivity and self-sufficiency in rice cultivation.

The effective use of the sensor monitoring system can save labor, reduce losses, and increase output and farmers' income. The application of the sensor monitoring system in Malaysia's paddy industry is relatively new, this study offers a prospective solution for the industry and its general aim of monitoring losses during combine harvester operations.

The findings of this study could be useful for improving the general performance of the operational parameters of combine harvesters. This research has the potential to be significant in Malaysia, as it proposes a novel approach to optimally guide operators in operating combine harvesters to minimize grain loss and enhance productivity, thereby contributing to the improvement of glutinous rice production and performance of the combine harvester.

1.3 Problem statement

Grain loss during rice harvesting in Malaysia significantly impacts production efficiency, with annual post-harvest losses reaching 557,000 metric tons, equivalent to RM 275 million, hindering production efficiency (Nodin et al., 2021). Despite addressing labor shortages by utilizing combine harvesters in rice harvesting, improper settings of the combine harvester operational parameters are a major cause of grain loss (Ahmad et al., 2020). This grain loss directly impacts farmers' incomes, with a reported 1.39% grain loss equivalent to an income loss of USD 29.26 (RM 120.55) per hectare (Sharifuddin & Mustaffha, 2021).

Addressing grain loss-related challenges requires a thorough evaluation to optimize the operational parameters of combine harvesters and reduce energy consumption. Improving energy efficiency in combine harvesters is essential for reducing costs, increasing productivity, and ensuring the sustainability of harvesting practices (Putri et al., 2020).

Conventional methods of measuring grain loss are labor-intensive, time-consuming, and lack accuracy, making real-time measurement impractical. This is evident in the manual collection and separation of harvesting residues both in the field and behind the combine harvester (Sumner & Williams, 2012; Esgici et al., 2016; Amponsah et al., 2017; Al-sammarraie & Alhadithi, 2021; Wang, et al., 2021). To address this, Johari et al., (2020) suggested further research using advanced technology to monitor various combine harvester performance characteristics such as machine capacity, field efficiency, grain loss, grain quality, and soil conditions.

Despite advancements in sensor-based technology, existing grain loss monitoring systems have certain limitations that require further improvement. These include interference from mechanical vibrations (Sun et al., 2017), difficulty in differentiating grains from non-grain materials (Xu et al., 2019), and the misidentification of grain as residue and vice versa due to overlapping signals from concurrent material collisions (Sun et al., 2019). Furthermore, most systems have only been tested in laboratories, limiting their practical field application. Lian et al. (2021) reported that relying on a single sensor detection method reduces sensor performance and accuracy.

To reduce grain loss during harvesting to acceptable levels (below 3% of total yield), there is a clear need for improved grain loss monitoring systems. These systems must address current limitations, particularly in signal processing, accurate material differentiation, and extensive field testing, to enhance the efficiency and profitability of rice production.

1.4 Research objectives

The main objective of this study is to develop a monitoring system for measuring real-time grain loss in a combine harvester. The following specific objectives were considered to achieve the main objective:

1. To study the field performance characteristics of the combine harvester and energy utilization in glutinous rice harvesting.
2. To evaluate the predictive performance of response surface methodology and artificial neural network models in optimizing the combine harvester to minimize grain loss.
3. To develop and evaluate a grain loss monitoring system with performance prediction using machine learning algorithms.

1.5 Scope of the research

- This study covers the development of a sensitive plate, the design of a monitoring circuit, experimental analysis for selecting the sensitive plate thickness, calibration, and field evaluation of the grain loss monitoring system.
- The sensitive plate was designed specifically for medium-sized combine harvesters.
- Experimental modal analysis was conducted to select an optimum plate thickness for the system.
- A stainless-steel plate with an optimum thickness of 1.5 mm was used to develop the sensitive plate.
- Three sensitive plates were utilized, each equipped with five sensors.
- The system adopted a PVDF piezoelectric thin-film sensor due to its superior properties. The sensor's length, width, and thickness are 170 mm, 22 mm, and 0.23 mm, respectively.
- An Arduino Mega with an ATmega2560 microcontroller board, featuring 16 analog inputs, was used to handle the 15 sensors in the system.

- Calibration tests were conducted using a variable-speed table-belt conveyor, with adjustments made to account for monitoring different rice varieties.
- Field studies were carried out over two harvest seasons, using the glutinous rice cultivar Pulut Siding.
- During the first season, the field performance, energy utilization, and grain loss measurements of the combine harvester were assessed in the first season.
- The second season focused on the field evaluation of the developed grain loss monitoring system.

1.6 Limitations and delimitations of the research

- The nature of the material effluents from the combine harvester affects the sensor's durability and long-term performance.
- The installation position of the sensing plates on the combine harvester is not adjustable due to the mechanical constraints of the machine, which affects the detection rate of grain loss.
- There were variations in sensitivity among the three sensing plates installed on the combine harvester, which may be attributed to the large material distribution from the machine. This could influence the uniformity of the grain loss measurements.
- The connection between the sensing plates and the monitoring circuit was damaged during the field evaluation of the system.
- The Arduino microcontroller was basically utilized for prototyping.
- The Arduino microcontroller utilized for the monitoring circuit does not have an in-built WiFi module or Ethernet unless an additional module is added.
- The performance accuracy of the system can be improved by considering other operational parameters of the combine harvester.
- This system can monitor other types of grain materials using the calibration procedure employed in this study.

1.7 Outline of the thesis

This thesis is organized into five chapters. A brief discussion of each chapter is provided below:

Chapter 1 presents the research background driving this study. It also defines the research objectives, significance of the research, and scope of the study.

Chapter 2 provides an overview of rice production in Malaysia with a focus on glutinous rice cultivation. Then, it discusses the types of losses that occur during paddy harvesting, an overview of combine harvesters, the impact of combine harvesters on paddy harvesting, types of losses in combine harvesters, factors affecting grain losses, and a review of grain losses in combine harvester operations. Conventional methods for measuring grain loss during harvest have also been described. This chapter presents the grain-loss sensing method, principle of grain loss monitoring, and types of sensors used in grain loss monitoring. It then reviews the existing studies on grain loss monitoring systems. Finally, this chapter reviews the techniques used in machine learning applications for grain loss monitoring.

Chapter 3 provides an overview of the study area, rice variety, combine harvester, and equipment used. It also describes the experimental design of the study, methods for measuring grain loss, operational factors and performance parameters of the combine harvester, and energy utilization in harvesting glutinous rice. This chapter also presents the methods used for

predicting grain loss using response surface methods and an artificial neural network. This chapter describes the selection of the sensor and sensitive plate material, structural design of the sensitive plate, experimental modal analysis of the sensitive plate, design of the monitoring system, and system setup for detecting real-time grain losses and data storage. It also describes the calibration experiment of the monitoring system, the installation of the grain loss monitoring system on the combine harvester, the method of monitoring grain losses, the experimental design of the field testing of the monitoring system, the method of separating grains from non-grain materials, and the method for determining the percentage accuracy of the monitoring system. The chapter concludes by describing the methods used to evaluate the performance of the monitoring system on a combine harvester, the procedure for predicting grain loss, and the accuracy of the monitoring system using machine learning algorithms.

Chapter 4 presents the results of this study and discusses the findings. The chapter begins by discussing the performance of the medium-sized combine harvester, including the time distribution and energy utilization in harvesting glutinous rice. The chapter then discusses the effects of combine harvester operational factors on grain loss and the evaluation of the response surface method and artificial neural network grain loss prediction models. Finally, the results of the plate modal analysis, calibration of the monitoring system, field performance of the grain loss monitoring system, and prediction of the performance parameters of the monitoring system using machine learning algorithms are presented.

Chapter 5 highlights the general conclusions, summarizes the key findings of the research, identifies the novelty of the study, and makes recommendations for further research.



CHAPTER 2

LITERATURE REVIEW

2.1 Overview of rice production in Malaysia

Rice is the third most widely produced crop in the world after sugarcane and maize. It is cultivated in over 100 countries, covering an area of approximately 162 million hectares with an annual production of 715 million mt of paddy rice (FAO and ITU, 2020). Asia is the leading rice producing country (Lanessa, 2017). Southeast Asia is one of the most important rice producing regions in the world, accounting for approximately 25% of the world's rice production (FAO, 2022). The average yield of rice in Southeast Asia is about 4.5 t/ha, which is lower than the average of 5.5 t/ha (FAO, 2022). The region is expected to increase its production and yield by approximately 10% by 2030 to meet growing demand for food.

In Malaysia, rice production is an important component of the country's agricultural industry, with rice being the most significant crop after palm oil. Rice cultivation in Malaysia is being dominated by local farmers. According to a study by Firdaus et al., (2020), Malaysia has a total rice cultivation area of approximately 689,298 ha, the smallest in Southeast Asia, with approximately 195,000 farmers involved in rice cultivation (Omar et al., 2019). From 2016 to 2020, the average rice yield in Malaysia was 4.65 mt/ha, as shown in Figure 2.1, with an annual production of approximately 2.00 million mt, as shown in Figure 2.2 (Dorairaj & Govender, 2023).

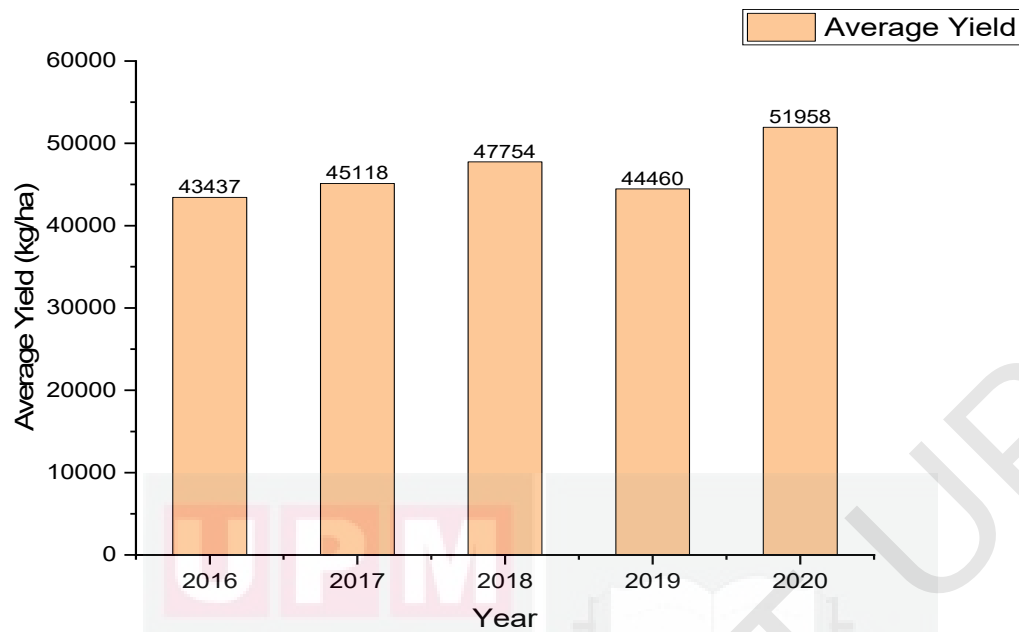


Figure 2.1: Average rice yield in Malaysia from 2016-2020
(Dorairaj & Govender, 2023)

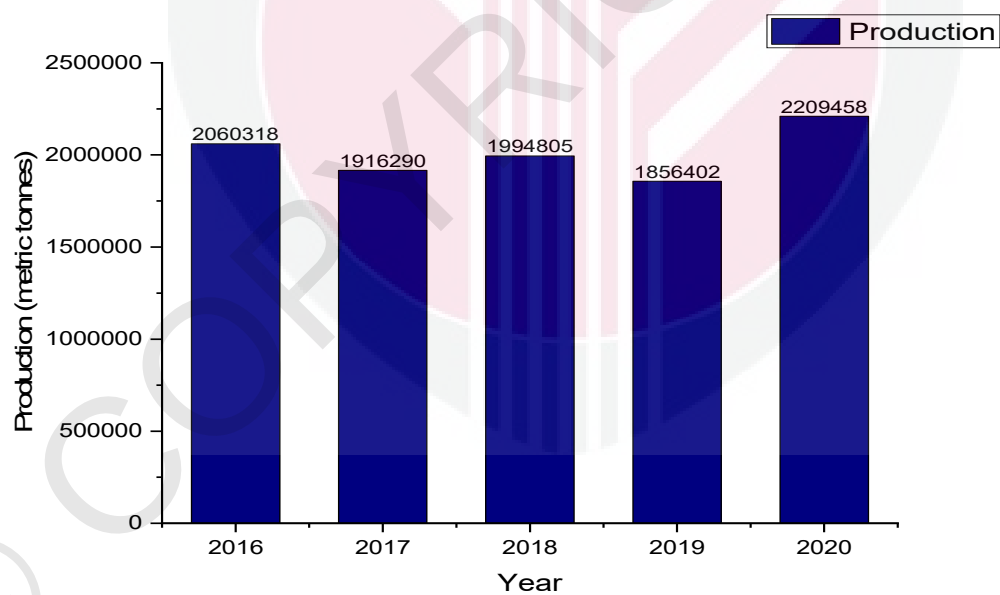


Figure 2.2: Annual rice production in Malaysia from 2016-2020
(Dorairaj & Govender, 2023)

The challenges faced by rice cultivation in Malaysia include poor soil fertility, extreme weather conditions, and poor deployment of technology (Dorairaj & Govender, 2023). These problems have affected the progress of the rice industry and the achievement of self-sufficiency (SSL). Rice self-sufficiency in Malaysian (SSL) has decreased slightly to 69% due to the COVID-19 pandemic, which has interrupted the food supply chain and increased demand for staple foods. Additionally, the country's population has grown to more than 32 million, whereas rice production areas have remained relatively constant. However, the annual growth in rice production has increased by 1.6%, which is sufficient to satisfy the consumption needs of the growing population. To address these challenges, the adoption of advanced technology-driven mechanization practices can enhance the productivity of rice crops.

2.1.1 Glutinous rice cultivation

Glutinous rice was first cultivated in Southeast Asia between 1000 and 1500 years ago by Tai-speaking immigrants. It is now grown in 37 countries around the world (Sattaka, 2016), with a production area of approximately 0.5 million square kilometers (Falvey, 2000). The crop is consumed by more than 20 million people daily (Sattaka et al., 2019) and accounts for approximately 16% of the global rice production. However, only 5% of glutinous rice is exported because it is primarily consumed domestically.

In Malaysia, the cultivation of glutinous rice stopped in the 1980s because of its low yield and high production costs compared to white rice (Bhattacharya,

2013). Presently, the glutinous rice production area in the country is limited to 38.96 hectares, which restricts overall output. This small cultivation area is primarily concentrated in specific regions, and the limited area indicates challenges for scaling up production to meet increasing demand (Zainal & Shamsudin, 2021).

As a result, glutinous rice is mostly imported from neighbouring countries (Castillo & Fuller, 2013). Efforts to revive the cultivation of glutinous rice in Malaysia are currently underway in certain states with suitable conditions, such as Langkawi (Malaymail, 2019). These efforts aimed to increase local production and reduce dependence on imports. As of 2023, Malaysia spent USD 815.85 million to import 1.40 million metric tons of glutinous rice, up from 1.21 million in 2022 (TRIDGE, 2023). Therefore, it is crucial to improve local glutinous rice production by utilizing appropriate machinery and technologies to maximize yield, reduce import costs, and increase self-sufficiency. Glutinous rice is often sold at a higher price than normal white rice varieties, which makes it a lucrative crop for farmers. Therefore, focusing on production can increase income and improve productivity, efficiency, and crop diversification. Furthermore, due to its cultural and traditional significance, its production can contribute to greater financial stability for local farmers and improve food security.

2.1.2 Characteristics of Glutinous Rice and White Rice

Glutinous rice and white rice differ in their fundamental characteristics due to differences in starch composition (Sattaka, 2016). Glutinous rice has a higher

amylopectin content, making it sticky when cooked, whereas white rice has a higher amylose content, making it fluffy (Shakri et al., 2021). Glutinous rice is shorter, plumper, and has a translucent appearance, while white rice is longer, slender, and opaque (Shuang Qiu, 2021).

Glutinous rice has a chewy texture and is slightly sweeter than white rice, which is soft and less sweet. Both types of rice have different culinary uses and cultural significance. Glutinous rice is commonly used in traditional Asian dishes and festive meals, while white rice is a staple in many parts of the world. Glutinous rice is more limited in production and is mostly imported into Malaysia, whereas white rice is widely cultivated. The fundamental physical characteristics that differentiate the two rice cultivars are presented in Table 2.1.

Table 2.1: Physical characteristics of glutinous rice and white rice

Physical Characteristics	Glutinous Rice Cultivar		White Rice Cultivar		
	Susu	Siding	Pusa-3	SKAU-345	PR-106
Length (mm)	6.63	6.24	6.62	8.32	6.61
Width (mm)	1.88	1.98	2.62	2.02	1.75
Thickness (mm)	1.5	1.48	2	1.79	1.4
Aspect ratio (%)	28	32	40	24	26.58
L/B ratio	3.82	3.17			
Sphericity (%)	40	42	49.29	37.4	38.28
Volume (mm ³)	9.81	9.87	18.51	15.84	5.1
Surface area (mm ²)	19.02	19.45	28.77	35.84	20.1
Bulk density (kg/m ³)	800.54	772.73	805.7	736.49	805
True density (kg/m ³)	1500.36	1229.51	1484.42	1270.81	1521
Porosity (%)	46.65	37.15	46.07	46.7	47.07
1000 weight Kernel (g)	18.88	17.04	22.92	21.84	17.4
Angle of repose (deg.)	39.45	38.85	29.93	31.13	34.86

(Bhattacharya, 2013; Ghadge & Prasad, 2012; Shittu & Olaniyi, 2012; Zainal & Shamsudin, 2021)

2.2 Overview of combine harvesters in Malaysia

A combine harvester was introduced in the Malaysian rice industry in 1970 as a solution to the challenges faced in manual harvesting, labor shortages, and increased harvesting wages (Mardi, 2010). Currently, the country's rice industry operates with approximately 1500 combine harvesters from various models. In most regions, a large combine harvester with a cutting width of 4-5 m is commonly used (Ahmad et al., 2020). Initially designed for wheat harvesting, these combine harvesters were modified and imported to the country for rice harvesting. However, these machines are becoming obsolete because of problems such as high grain loss, aging equipment, limited availability of spare parts, and soil damage. According to Baharudin & Waked, (2021), large combine harvesters cause damage to rice fields, and the efficiency of the machine in terms of energy output and productivity is very low, indicating the need for modern machinery to enhance the efficiency and productivity of rice harvesting.

2.2.1 Impact of combine harvester operations on paddy harvesting

Combine harvesters are commonly used to harvest various types of grains, and are among the most challenging types of machinery used in agricultural operations (Yin et al., 2018). The machine combines multiple operations, including harvesting, threshing, cleaning, separation and sometimes bagging, into one efficient process (Praweenwongwuthi et al., 2010).

Combine harvesters have both positive and negative effects on rice cultivation in Malaysia (Johari et al., 2020). The positive impact is the availability of the machine, and its physical design is suitable for wet rice cultivation, considering the soil conditions in rice fields. However, improper operation and management of the combine harvester can have negative impacts on the quantity and quality of grains. Excessive grain loss is a major issue caused by improper combine harvester operation which leads to an overall reduction in crop production and farmers' profits.

In the range of crop and field conditions, combine harvester harvest and threshes all forms of grains such as rice, wheat, corn, and soybean (Chaab et al., 2020). It is essential to maintain combine harvester operating conditions and output effectively to improve efficiency in farming and rice production (Elsoragaby et al., 2019). Furthermore, considering labor shortages, using a combine harvester increases labor productivity and reduces production costs. However, inappropriate crop conditions and machine settings have adverse effects on the total grain yield. Chuan-udom & Chinsuwan, (2010) reported that combine harvester play a vital role in the harvesting process; it increases efficiency and productivity of rice harvesting, but improper operation of the machine can lead to harvesting losses. According to Chuan-Udom & Chinsuwan, (2011), the adoption of combine harvesters results in increased net benefits for farmers, enhanced labor efficiency, reduced yield loss during manual harvesting, and decreased production costs. Sharifuddin & Mustaffha, (2021) reported that the use of combine harvesters reduces harvesting time but increases grain loss; understanding and addressing these factors is

essential for improving harvesting practices, reducing losses, maintaining food security, and increasing agricultural profitability.

The impact of combine harvesters can be assessed based on various factors, including machine efficiency, grain quality, damage kernel, and processing loss. According to Myhan & Jachimczyk, (2016), efficient design and control measures can help reduce grain loss and improve the overall performance of combine harvesters.

2.2.2 Process of combine harvester operation

It is important to understand the operations that occur in combine harvesters before making changes or adjustments to reduce losses. The various operations of the combine harvester are illustrated in Figure 2.3. The operations start at the header unit, where the cutting and gathering of grains from plants occur. The materials move to the threshing unit using a conveyor, where threshing and separation of grains from stalks occur. The grains were further cleaned using a cleaning fan to remove light straws; thereafter, the clean grains were transported to the grain storage tank through a screw conveyor. Subsequently, the straw and chaff are discharged from the rear of the combine harvester onto the field. Grains lost from the machine could be found at this point as a result of incorrect machine settings. Once the grain tank is full, an auger discharges the grain into the trailer or truck. Therefore, to improve the performance of the combine harvester and reduce grain loss, it is important to consider operational parameters, such as machine parameters, crop factors, and field conditions.

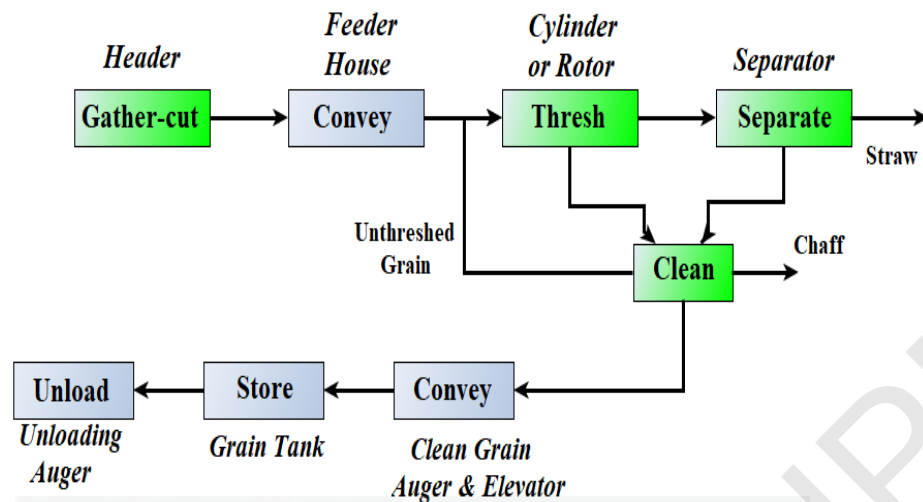


Figure 2.3: Combine harvesters' operation process

2.2.3 Combine harvester losses in harvesting operation

The grain loss in combine harvester operations is divided into three categories: losses at the front of the combine harvester (header loss), combining losses, losses at the threshing and separation units, and losses at the cleaning unit. These types of losses occur in the field during combine harvesting because of the inappropriate performance of the machine (Figure 2.4).

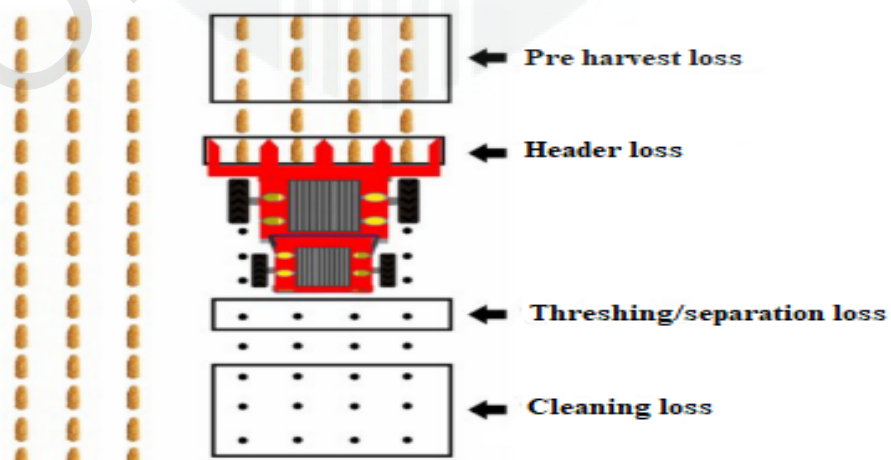


Figure 2.4: Operation losses of combine harvester
(Wang et al., 2021)

2.2.3.1 Header loss

These losses occur during the cutting of the crop from the plant, which is the process of gathering the crop into the machine before threshing (Tkachuk, 2017). It is expressed as the quantity of grain obtained at the header per unit area or as a percentage of crop yield (Khir et al., 2017). The grain loss obtained from the cutter bar was significant because the header was a component that vigorously hit the panicles. The factors that affect header loss include the reel height, cutter/header height, distance between the blade bar and the reel centre, and the reel speed relative to the machine speed (Bawatharani, Jayatissa, et al., 2014). According to (Bawatharani et al., 2016), the height at which the crop is cut at harvest plays a major role in determining grain yield and ensuring optimum performance by minimizing grain loss and optimizing grain quality. Zareei & Abdollahpour, (2016) utilized the following four parameters as factors influencing combine harvester header loss: the reel index, cutting height, horizontal distance of the reel, and vertical distance of the reel from the cutter bar. (Jarolmasjed et al., 2013) also reported that header loss results from cutter bar stroke, the height of the reel, reel peripheral speed, travel speed of the machine, the width of harvest, the height of the cutting crop, crop moisture content, height and density of the crop, and the feed rate.

2.2.3.2 Threshing loss

Threshing is the most important function of a combine harvester among the various operations involved in the machine. It involves an impact and rubbing

action to dislodge grains from plant heads (Thet et al., 2019). It works based on the frictional force among the harvested plant, threshing cylinder, and combine concave. Grain loss and damage during harvesting are significantly affected by the threshing performance (Khir et al., 2017). An important adjustment related to the threshing operation was the clearance between the combined concave and rotational cylinders. If the clearance between the cylinder and concave becomes too wide, threshing will not be effectively carried out with many grains remaining unseparated. However, if the clearance is too tight, the grain is broken and damaged. In addition, there are two different types of threshing mechanisms in a combine harvester: an axial threshing system and a tangential flow threshing system, as shown in Figure 2.5 and 2.6, respectively.

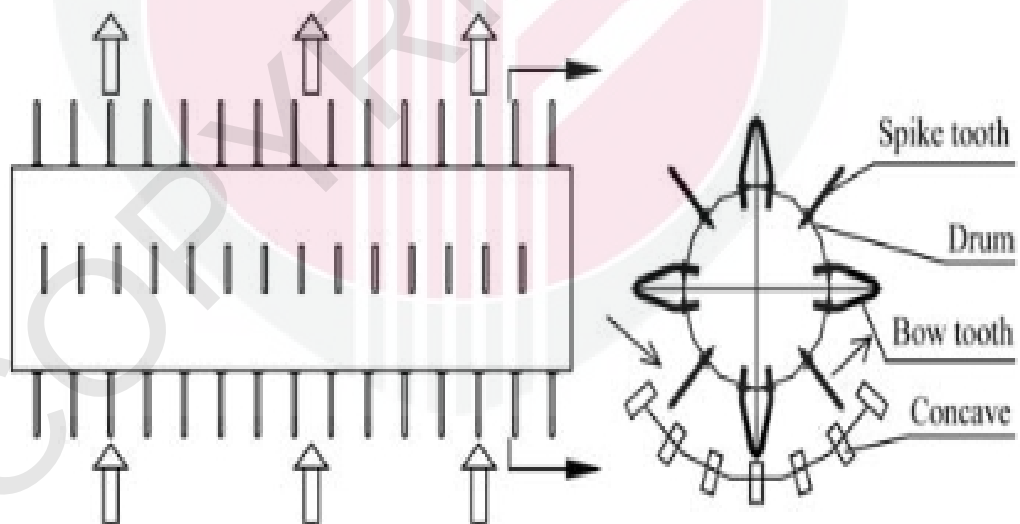


Figure 2.5: Tangential (conventional) threshing system
(Fu et al., 2018)

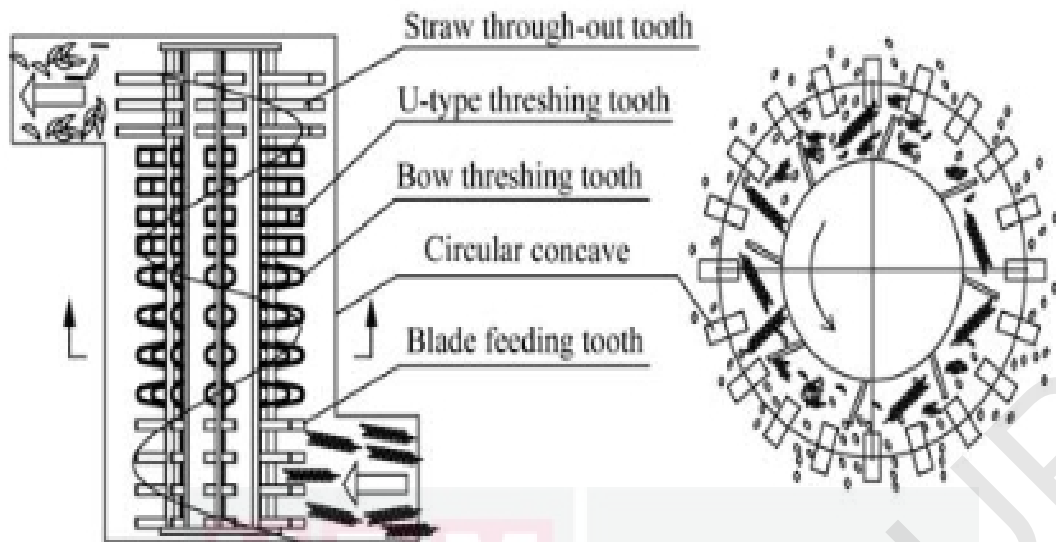


Figure 2.6: Vertical axial flow threshing system
(Fu et al., 2018)

A grain loss of 2.58 – 4.38% was reported in a fully axial threshing harvester machine as compared to 5.79 – 6.46% in a tangential flow system (Fu et al., 2018). The study further stated that grain loss and grain damage were lower in axial flow threshing than in tangential flow threshing. The threshing efficiency was lower in the tangential flow because threshing took place in the first portion of the cylinder where the threshing action was of the cross low type. Mairghany et al., (2018) also reported a threshing efficiency of 98.2% in axial flow combine harvester and 97.73% in tangential flow combine. Comparing the axial and tangential threshing systems, the axial threshing combine harvester had a lower grain loss.

These losses are directly affected by different operational parameters, such as threshing drum speed, feed rate, operating forward speed, concave clearance, and grain moisture content (Sudajan et al., 2005; Olaoye et al., 2011; Suliman

et al., 2012; Abich 2018; Bhardwaj et al., 2021). Other factors that contribute to threshing loss include crop conditions, concave type and style, guide vanes, rasp bar or rotor tine styles and conditions, feed rate, and cleaning-system settings (Bhardwaj et al., 2021).

2.2.3.3 Separation loss

Grain separation losses are significant factors to consider when evaluating the performance of a combine harvester (Liang et al., 2015). The amount of free grain that does not pass through the grates of the separation section in an axial flow is referred to as separation loss (Al-sammarraie & Alhadithi, 2021). Machine adjustments that improve threshing have a negative effect on separation efficiency. When the straw moisture level is low, the cylinder finely splits the straw, enabling more materials to pass through the sieve and causing a separation problem. Furthermore, crop conditions, machine settings, and operational decisions that affect separation efficiency exhibit features similar to those of threshing systems. The factors that contribute to the quality of separation in the straw walker includes; kinematic parameters, physical properties of grain and straw moisture content, and rheological properties of the straw layer (Derevjanko et al., 2020). Overall, it is critical to examine these parameters to achieve high-quality separation in combine harvester and straw walkers.

2.2.3.4 Cleaning loss

Cleaning loss is the number of grains mixed in the screenings of a combine harvester and is commonly quantified by the rate of cleaning loss (Zhan & Jing, 2011). Grains are blown out by the airflow during the cleaning process, and this loss is unavoidable (Lian et al., 2021). Cleaning systems in combine harvesters use a combination of air blasts to remove chaff and straw and a shaking action to drive grain downward through sieves while moving larger unwanted particles to the rear of the machine. Furthermore, the moisture content of the harvested grains is a conditional factor that influences the performance of the cleaning system (Y. Li et al., 2020). Chuan-udom & Chinsuwan, (2010) reported that the factors that affect harvesting losses of the cleaning unit in rice combine harvesters include cleaning air velocity, sieve inclination, barrier plate height, grain moisture content, grain feed rate, and sieve length. However, factors such as the grain moisture content, grain feed rate, and sieve length had insignificant effects on grain loss in this operation.

2.2.4 Factors contributing to combine harvester grain loss

Determining the appropriate harvesting parameters is essential for successful combine harvester operations to minimize grain loss and enhance grain quantity and quality. Improper cutting height, combine forward speed, reel speed, concave clearance, drum speed, fan speed, sieve opening, crop moisture content, and horizontal and vertical distances of the reel from the

cutter bar are all factors that cause grain loss in the combine harvester. These factors affect the machine settings, field efficiency, and field capacity.

According to Gundoshmian et al., (2010), the following factors contribute to the grain loss of the combine harvester: improper cutting height, inconsistent placement of the reel with respect to the cutting bar, improper kinematic index ratio, and inappropriate velocity of the cutting bar or damaged blades. Mostofi, (2010) used the combine forward speed, drum speed, crop moisture content at harvest, length of the harvesting area, specific area of the harvested crop, and effective width as factors to estimate grain loss while operating a combine harvester. The results show that the drum speed substantially influences the combine processing loss.

Zareei & Abdollahpour, (2016) stated that the reel index, cutting height, horizontal distance of the reel from the cutter bar, and vertical distance of the reel from the cutter bar are all factors that affect header loss on combine harvesters. With respect to crop conditions and machine ground speeds, major losses are generated by machines that have not been properly adjusted. Throughout the harvesting season, losses in rice output attributed to the use of inappropriate machinery and procedures are estimated to be approximately 25–30% (Esgici et al., 2016).

The results obtained during field experiments reported by Špokas et al., (2016) revealed that combine harvester performance is dependent on the cutter bar operating width, grain yield, and forward speed of the combine harvester.

These parameters are controlled by machine operators based on field conditions. The field speed resulted in excessive grain loss during harvesting. According to Hunt, (2016), the most critical aspect for optimizing the performance of a combine harvester is the field speed of the machine. Hamzah et al., (2019) further reported that incorrect travel speed of the combine harvester is a contributing factor to paddy harvesting losses. In addition, Jawalekar & Shelare, (2020) stated that the machine forward speed is the primary element affecting the performance of the combine harvester. (Ahmad et al., 2020) stated that farmers' satisfaction with automated rice harvesting in Malaysian paddy fields was significantly affected by the field speed of the combine harvester. As a result, the field speed of the combine harvester is a major concern during mechanical harvesting. Therefore, determining the optimum speed for operating a combine harvester is a major challenge.

The study conducted by Ahmad et al. (2020) measured the daily field speed of rice combine harvesters in Malaysia to assess its impact on grain loss in paddy fields. The speed ranged from 3.87 to 11 km/h, with the best speed of 3.87 km/h resulting in a grain loss of approximately 67%. The finding is consistent and within the anticipated range of 3.0 – 6.50 km/h for a large combine harvester (ASABE, 2011).

Al-sammarraie & Alhadithi (2021) reported a correlation between field speed and grain loss with a reduction in forward speed. This resulted in significant grain loss. However, a higher field speed reduces field efficiency due to grain spillage, emphasizing the need for an optimum speed to prevent grain loss.

The major loss is attributed to the improper adjustment and calibration of the harvester components during harvesting. As a result, farmers often overlook the significance of these factors as well as the role of interaction factors, such as field conditions, crop variety, and maturity.

2.2.5 Conventional methods for measuring grain loss

The conventional method for measuring grain loss has a certain level of accuracy; however, it is often time-consuming, tedious, and labor-intensive. This method is the most widely employed method worldwide, with a wide scope of procedures according to the different types of losses obtained in combine harvester operations, as reported in the literature. According to Liang et al., (2015), header losses are typically collected by placing a roll of cloth behind the combine harvester to collect threshing and separation efflux from the rear of the machine. The loose grains as well as the complete and incomplete ear heads of the crop, which are found in the field after harvesting, are determined to be header loss. These losses occur because of improper cutter-bar operation. To measure the threshing and separation losses, two rolls of cloth, 30 m in length and one and a half times the width of the threshing and separation outlet of the combine harvester, were used. The cloth was placed behind the machine to collect the straw and chaff efflux. As the roll cloth unrolls, one sheet captures the threshing loss, whereas the other sheet captures the separation loss. The unrolling process began in advance and finished 5 m before the combine harvester reached the end of the swath.

Tkachuk (2017) reported that header losses were determined when the combine harvester stopped during the harvesting process and were reversed by a distance of 15 – 20 ft. A quadrant measuring one square foot was randomly placed at four different locations. The grains collected from this location were measured as header loss. A similar approach can be used to measure the threshing loss behind the combine harvester.

Mairghany et al., (2018) determined harvest losses by selecting 12 random locations within a rice field. A square wooden frame measuring 50 × 50 cm was used to obtain an area of 0.5 m in the direction of travel of the combine harvester. All threshed and unthreshed grains were collected manually when the machine passed over the frame. The collected grains were weighed to determine the extent of the grain loss. Esgici et al., (2016) measured header loss when a combine harvested was allowed to move forward for a distance of 50 m. Then, a 1 m² quadrat was placed in front of the parked combine harvester, as shown in Figure 2.7. The grains and panicles that fell within this area were collected manually. The weight of the collected grains was measured as header loss.



Figure 2.7: Manual method of collecting grain losses

The method of using three-quarter square frames, as shown in Figure 2.8, was employed to assess the combine harvester losses using a frame measuring 50 × 50 cm (Esgici, 2020). To determine harvest losses, the location of the crop divider trace was identified, and the frames were poisoned accordingly. The grain loss was determined by measuring and recording all grains within the frame.

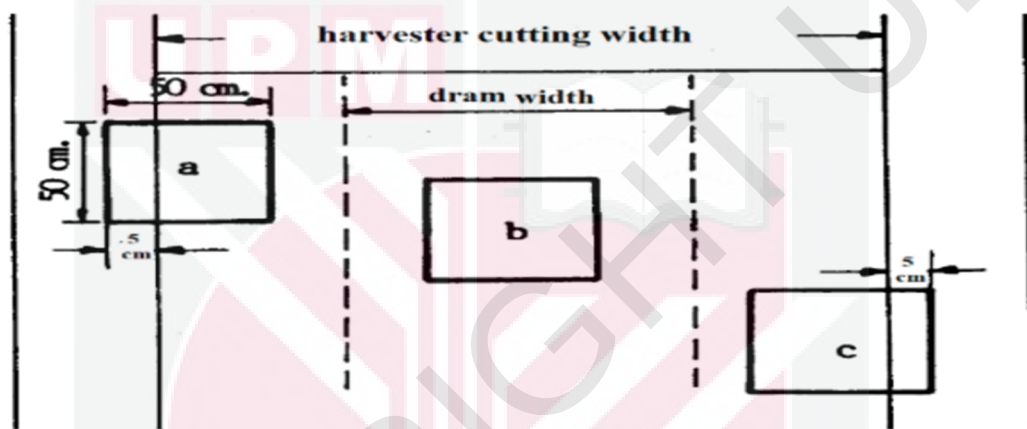


Figure 2.8: Frame sampling location for three quarter square frame
(Esgici et al., 2016)

In a study by Paulsen et al., (2013), combine harvester losses were measured using the Embrapa method in which losses behind the combine harvester were measured when the machine was running in the field at full capacity and normal operating speed. The losses were measured across the full width of the combine header in a rectangular pattern of sufficient length to provide a 2.0 m² area, as shown in Figure 2.9. The grains collected in the rectangular pattern in the field after the passage of the combine harvester were collected and measured as grain loss.



Figure 2.9: Collecting grain losses in a 2 m² area
(Paulsen et al., 2013)

Ahmad et al., (2020) determined grain loss as the cumulative grain loss incurred during field harvesting because of the combine harvester movement. To measure losses, a sampling process was carried out on the designated subplots to mark the plots and remove pre-harvest losses. Five square quadrants measuring 1 × 1 m were randomly placed within each subplot. After the combine harvester operation, the grains found within the quadrats were collected manually and weighed as the average grain loss per plot.

In a study by Bawatharani et al., (2016) the combine harvester header was lifted and reversed after reaching a steady-state speed under full load conditions. A quadrant frame measuring 1 x1 m was randomly placed in front of the machine along the cut swath. The grains were manually collected within the frame and weighed for header loss. According to Sumner & Williams, (2012), the combine harvester was stopped 100 ft away from the row ends, and a wooden frame or four wooden stakes and strings were placed along the 100 ft swath width. The combine harvester was backed up by 20 ft, and the

kernels in the 10 square foot plots over each row in front of the machine were collected and counted, as shown in Figure 2.10. The grains collected in the field were measured as the combine harvester field-operation grain loss.

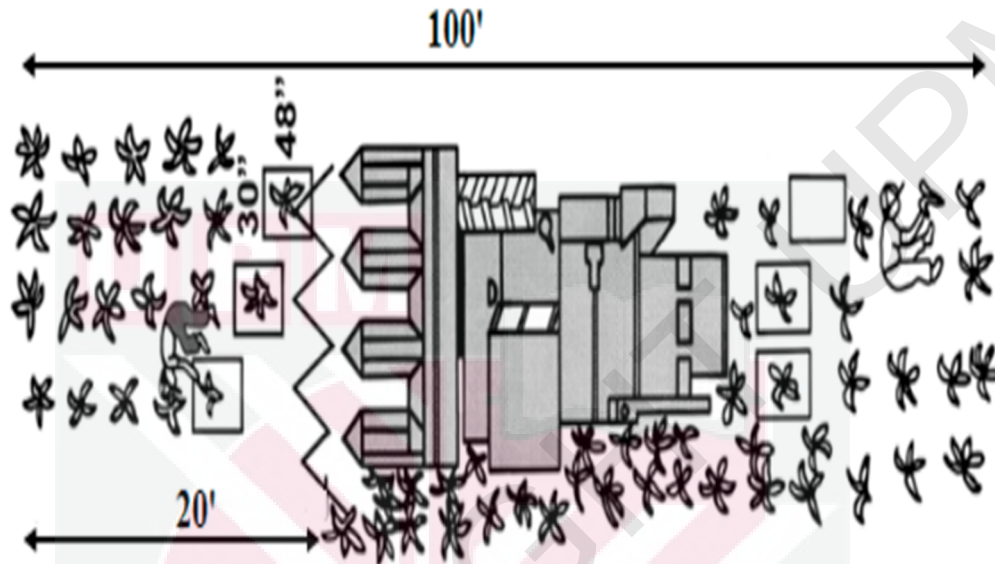


Figure 2.10: Grain loss measurement by backing up 20 ft in a 10 square foot frame
(Sumner & Williams, 2012)

Furthermore, the losses of ears and heads were measured both ahead and behind the combine harvester at 1/100 of an acre, based on a specific row spacing and swath width. This was achieved by either placing a rectangular frame or marking the area with a stick and string, as illustrated in Figure 2.11. Once the combine harvester passed over the marked areas, the grains collected within those areas were identified as ear and header loss.

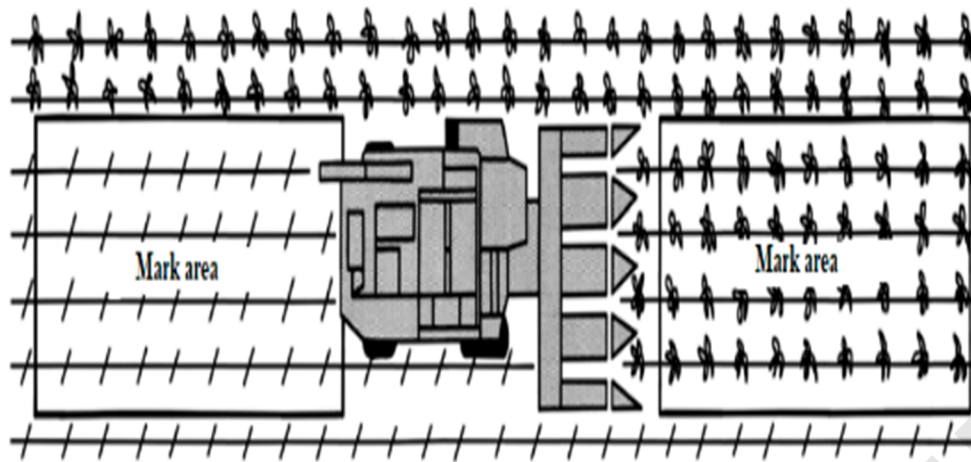


Figure 2.11: Measurement ear and header losses from the front and end of the combine harvester
(Sumner & Williams, 2012)

In a study by Sattar et al. (2015), a 4 m² steel frame was positioned at ten different locations in the field. The shattered grains and materials ejected from the combine harvester are collected within the enclosed area of the frame. Subsequently, the collected samples were threshed, winnowed, cleaned, weighed, and recorded as harvesting and threshing losses. Amponsah et al. (2017) utilized the continuous method of assessing combine harvester grain loss as described by Smith (1981). In this method, two woven plastic sacks are attached to the rear of the machine. The sacks were positioned such that one sack captured the efflux from the concave, whereas the other captured the efflux from the straw walker, as illustrated in Figure 2.12. The sacks were placed at the beginning of a 20-meter swath. Once the machine reached the end of the swath, the sacks were removed, and the machine was brought to a halt. The grains were manually separated from chaff and straw. The grains collected from the concave efflux were identified as threshing losses, whereas those collected from the straw walker were measured as separation losses.



Figure 2.12: Grain loss collection in a woven sack from the concave and rear of the combine harvester
(Amponsah et al., 2017)

According to Srivastava et al. (2013), the combine harvester was driven in the field until it reached steady-state conditions, at which point it was stopped. The machine was then backed up at a distance equal to the longitudinal distance between the cutter bar and discharge chute. The area in front of the combine harvester was marked and the losses collected from the area were weighed as the header loss. Wang et al., (2021) reported that a frame was positioned over each row behind the combine harvester. The loose grains were collected from the ground within each frame. The number of grains still attached to the threshed cobs was measured as “cylinder loss.” Additionally, the frame was placed in front of the combine harvester in areas where the machine did not pass. Loose grains gathered inside the frame were counted as a header loss.

In conclusion, the current methods for estimating grain loss are conventional and time-consuming, making it very challenging to measure grain loss in real-time. This necessitates the need for the development of real-time grain loss

measurement techniques to aid machine operators in optimizing the operational variables of the combine harvesters. This can improve the overall performance of the equipment and minimize grain loss.

2.3 Grain loss sensing technology

The sensing technology is currently automated, remote, and prospective. It is used to monitor various agricultural operations including grain quality and loss identification. It provides an opportunity to deploy and install capabilities more quickly (Kaushik & Singhai, 2018). The word "sensor" refers to a device or system that responds to a physical or chemical quantity to generate an output that is a measure of that quantity (e.g., gas concentration, ionic strength measurement) (Sureshraj, 2007). A grain loss sensor is an important monitoring element in combine harvesters (Jarolmasjed et al., 2013). Sensors have a wide range of applications in agriculture. When utilized appropriately, it might be one of the most effective instruments for assisting in determining how effectively a combine harvester operates (Liang et al., 2020). Grain loss monitors are installed on combine harvesters that allow the measurement of grain loss in various parts of the machine (Mostofi Sarkari, 2010).

2.4 Principle of grain loss monitoring

The principle of grain loss monitoring (measurement) using sensors, as shown in Figure 2.13, occurs when a grain hits a sensitive plate and sends an impact that causes vibration. The sensor, which is attached to the sensitive plate, transforms the vibration into an electric signal, and the corresponding signal-

processing circuit processes the grain impact (collision) signal into a waveform for counting, whereas the signals for the material other than grain (MOG) are filtered out. The signal representing the number of grain impacts is sent to the cab at a fixed interval. The in-cab monitor interprets the signal and provides a readout for the operator, usually as a graph or accumulated number of grains.

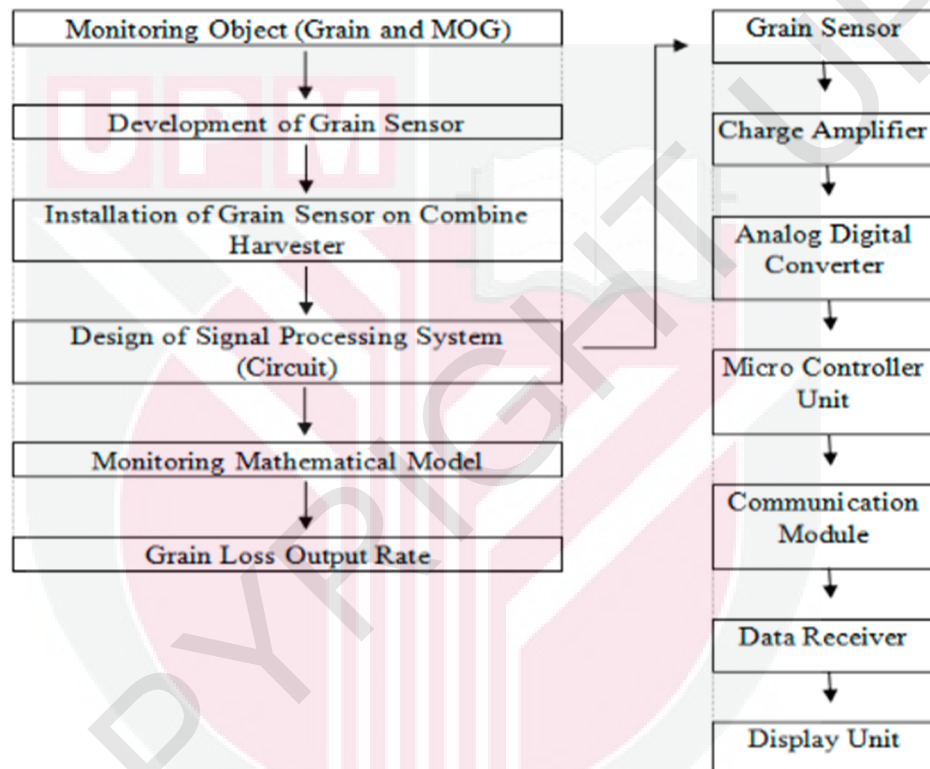


Figure 2.13: Flow chart representation of grain loss monitoring

2.5 Related research on grain loss monitoring systems

Table 2.2 summarizes the existing developed grain loss monitoring systems, indicating the type of losses each system focuses on, the sensors used, the locations where the sensors are installed on the combine harvester, and the measurement errors obtained from each system.

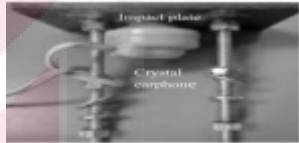
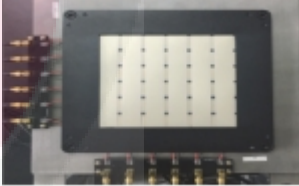
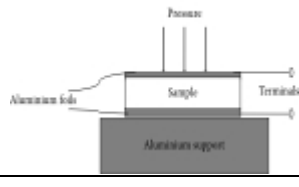
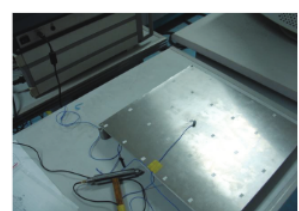
Table 2.2: Summary of existing grain-loss sensors and measurement errors

Authors	Type of Losses	Sensor Used	Sensor Position	Measurement Error (%)
(Lian et al., 2021)	Cleaning loss	PVDF film sensor	Under the concave screen of the lab test	0.7 highest error, 1.3 lowest
(Liang et al., 2020)	Separation/cleaning	Piezoelectric ceramic	Under the sieve	≤3.46%
(Liang et al., 2015)	Separation loss	Piezoelectric ceramic	End of the walker	4.63
(Liang et al., 2016)	Cleaning loss	Piezoelectric ceramic	Under the cleaning sieve	4.48
(Liang et al., 2017)	Separation loss	Piezoelectric ceramic	Under the threshing sieve	3.83
(L. Zhou et al., 2019)	Separation/Cleaning	PVDF film sensor	Under the cleaning/separation sieve	Rice 2.5, Wheat 4.8
(Tan et al., 2019)	Cleaning loss	PVDF film sensor	Below the threshing and cleaning sieve	1.8–3.15
(Sun et al., 2019)	Grain losses	Two crossed PVDF film	Test bench in the laboratory	Not specified
(L. Xu et al., 2019)	Cleaning loss	Displacement sensor	Under the cleaning sieve	Not specified
(Wu et al., 2020)	Cleaning loss	PVDF film sensor	Test bench in the laboratory	Reduced from 12 to 3
(Chedong et al., 2018)	Cleaning loss	PVDF film sensor	Rear of the vibrating cleaning sieve	Not specified
(Yilmaz & Caner, 2015)	Separation loss	PVDF film sensor	Under threshing/separation rotor	3.40

2.6 Sensor platforms used for grain loss monitoring systems

Table 2.3 provides an overview of the various structures of the sensor platforms utilized in previous studies for monitoring grain loss, along with their limitations.

Table 2.3: Overview of sensors used in grain loss monitoring

S/N	Type of Sensor	Critical Point (Comments)	Photo
1	Piezoelectric ceramic sensor	Because of the brittleness of the sensor material, it is susceptible to breakage due to vibration and has a lower level of reliability than the other materials. The vibration interference of the combine reduces the sensor's measurement accuracy (Liang et al., 2016).	
2	Acoustic sensor	The sensor's sensitivity severely diminished due to the mechanical vibration of the machine (Wu et al., 2020). It has a limited degree of precision (Zhan & Jing, 2011).	
3	PVDF piezoelectric	It is the most utilized grain loss sensor. It has a negligible effect on the structure of the testing system. It also offers a considerable advantage in terms of sensing components (Zhan & Jing, 2011).	
4	Force sensor	The sensor can only detect a fraction of the discharge grain and the surface of the sensor is very small to be installed on the combine harvester (Kawamura, 2013).	
5	Pressure sensor	The conventional pressure sensor is incapable of distinguishing between grain and residue. Additionally, the sensor's response time is very lengthy (Yilmaz & Caner, 2015).	
6	Piezoelectric crystal sensor	This type of sensor increase not only the signals of the grain cleaning loss but also provide consistent sensitivity for the sensitive element stable performance, and high signal to noise ratio were the key characteristics of the sensor (Ni et al., 2015)	

2.7 Machine learning algorithm

Machine learning is a form of artificial intelligence that enables systems to learn and make predictions using data. They are used for prediction or data classification, with numerous applications in agricultural production, both in pre- and post-harvest studies (Meshram et al., 2021). Machine learning iteratively learns from data to predict outcomes and provides training data to produce models. It is important in the field of agriculture and is increasingly being used to predict and classify various agricultural variables and outcomes (Domingues et al., 2022). Machine learning has shown promise in prediction compared with traditional scientific models. They are flexible in terms of complex and unexpected relationships between numerous variables (Kang et al., 2020). It helps to address various factors that affect crop yield, including soil fertility, water availability, pests and diseases, climate, and postharvest losses (Balducci et al., 2018). It can analyze these factors and make predictions, leading to more accurate and consistent predictions. A standard process for utilizing machine learning involves data collection, preparation of the dataset, processing, extraction of features, selection of the most relevant features, selection and application of appropriate machine learning algorithms, and performance evaluation of the model (Yang & Guo, 2017).

2.7.1 Advantages and limitations of machine learning algorithms

Table 2.4 presents a summarized review of machine learning algorithms with their advantages and disadvantages.

Table 2.4: Advantages and limitations of various machine learning algorithms

Types of Algorithms	Advantages	Limitations
Linear Regression (Amornsamankul et al., 2019)	- Easy to understand - Predictions are numerical	- Too simple to capture complex relationship - Tendency for model overfitting
Logistic Regression (Omary & Mtenzi, 2010; Reed & Wu, 2013)	- Useful in establishing a relationship between different variables - Update the classification model easily to incorporate new data	- Large number of input variables (data) results in inaccurate parameter estimation - Does not handle missing data and can be sensitive to extreme values of continuous variables
Support Vector Machine (Fatima & Pasha, 2017; Zekić-Sušac et al., 2016)	- Overfitting of data unlikely to occur and can withstand noise from the data	- Slow in training data and difficult to obtain optimal parameters when data cannot understand the structure of the algorithm
Naïve Bays (NB) (Kourou et al., 2015; William et al., 2018)	- Low generalize error and easy to interpret results - Easy to understand and takes less time on training data - Easy to obtain a probability for prediction and can deal with noisy and missing data	- Susceptible to correlated inputs and irrelevant features - Less accurate when the data are not mutually exclusive - Prone to bias when increasing the number of training sets
Decision Tress (Amornsamankul et al., 2019; Zekić-Sušac et al., 2016)	- Easy to understand, past prediction and effect of training order - Handle missing values and can accept both numerical and categorical data	- Error in training data results in wrong prediction decision - It can lead to overfitting in some instances

Table 2.4: Continued

Artificial Neural Network (Amornsamankul et al., 2019; Omary & Mtenzi, 2010; Zekić-Sušac et al., 2016)	-	Learn the data with noise and missing data	-	It requires a lot of computer power when the data is too large
	-	Tolerance to correlated inputs and can accept the combination of different inputs variables	-	Not robust to outliers and susceptible to irrelevant features
Random Forest (Omary & Mtenzi, 2010; Reed & Wu, 2013)	-	Provides accurate predictions and results in high quality models	-	Biased in favour of categorical variables with different number of levels
	-	Parameters can be set easily and also easy to understand	-	Can be slow to output predictions relative to other algorithms
K – Means (Ray, 2019)	-	Relatively efficient and can process large data.	-	Applicable only when mean is defined and cannot handle noisy data
	-	Ease in implementation and interpretation of the clustering results are the attraction of this algorithm.	-	
K - Nearest Neighbor (KNN) (Amornsamankul et al., 2019)	-	It is extremely flexible classification scheme and well suited for Multi-modal classes.	-	Not suitable for categorical data
	-	Robust to outliers on the predictors	-	Difficult to interpret results and handling mixed data
			-	Performance relies on the number of dimensions

2.7.2 Review of grain loss prediction using machine learning

Hiregoudar et al., (2011) introduced an artificial neural network (ANN) to assess grain loss in the field. The study identified that moisture content and forward speed are two important factors for minimizing postharvest losses and quantitative losses by applying ANN. The model exhibited a good fit and could generalize the relationship between the input and output parameters without overtraining. Overall, the findings suggest that the ANN model can be a useful tool for farmers to improve their harvesting efficiency and reduce grain loss. By considering crop and machine parameters, the ANN model can assist in determining the optimal harvest time and minimizing postharvest loss. Additionally, models for quantitative and qualitative grain loss in combine harvesters have been developed using artificial neural networks (Komleh et al., 2012).

Komleh et al., (2012) utilized an ANN to predict seed corn harvesting losses based on the travel speed of a combine harvester and cylinder. The accuracy of the model was 93%. The results of this study indicate that the ANN model with a 2-7-10-1 topology accurately predicted seed corn loss. Cylinder speed was the most significant factor affecting harvesting losses. The study concluded that ANN is a valuable tool for predicting seed corn harvesting losses based on the machinery factors that affect harvesting quality.

Gundoshmian et al., (2019) employed a combination of the radial basis function (RBF) and adaptive neuro-fuzzy inference system (ANFIS) as

machine learning methods to predict various variables of the combine harvester for optimal performance. The accuracy rates of the models are 84%, 92 %, and 98% for cutter bar, threshing, and separation losses, respectively. The study showed that the hybrid machine learning modelling approach using a combination of the radial basis function (RBF) and adaptive neuro-fuzzy inference system (ANFIS) can accurately predict various variables of combine harvester performance for optimal efficiency. This study showed that ANFIS method outperformed the RBF method in predicting the performance variables.

Nadai, (2020) utilized a hybrid model combining ANN and particle swarm optimization (PSO) for performance analysis of combine harvesters. The results showed that ANN-PSO had an average prediction accuracy of 97%, whereas ANN had an accuracy of 95.45%. The findings of this study indicate that the hybrid model of ANN and PSO, known as ANN-PSO, outperforms the ANN model in terms of accuracy when analyzing the performance of combine harvesters.

Li et al., (2020) predicted the cleaning loss of a combine harvester using ANN. The findings of this study indicate that the neural network model can accurately predict the cleaning loss rate of a combine harvester based on cleaning system parameters. The experiment demonstrated that increasing the forward speed of the machine could reduce the cleaning loss rate. The results of the study provide a 68.70% prediction accuracy with a mean squared error of 269.82. However, the prediction accuracy of the neural network model must be

improved because of the limited amount of sample data. Further research is required to enhance the accuracy of this model.

Li & Mao (2022) developed a grain loss prediction algorithm for different stages of grain production. The algorithm integrates multiple classification models, including the K-nearest neighbour (KNN), decision tree, XGBoost, and Softmax regressions. The results of this study indicate that these methods can improve the accuracy of the test datasets by 94%. The multiple-classifier-based grain loss prediction algorithm can contribute to minimize the loss and waste of grains.

Ma et al., (2023) developed an ANN model with inputs such as rotation speed, threshing clearance, separation clearance, and feeding quantity. The model accurately predicted the crushing rate, impurity rate, and loss rate of the threshed material. The sensitivity analysis showed that the rotational speed, threshing clearance, and separation clearance were the most important factors influencing the performance of the machine. These findings indicate the potential of using ANN models to optimize the design and performance of flexible threshing systems in rice harvesting to improve the efficiency of grain production.

A review of the grain loss predictions showed that in almost all the studies, only the neural network was used for the prediction of various grain losses. It has been reported that there are some limitations to these algorithms which are recommended for further studies. Therefore, it is necessary to consider the

use of other machine learning algorithms to predict grain loss and compare the performance of these algorithms to determine the best algorithm that can predict grain loss.

2.8 Summary of literature review

This chapter reviews the relevant literature. The results showed that the occurrence of grain loss in the combine harvester operation was significantly related to the machine operational factors and inappropriate settings of these parameters by the operators of the machine during harvesting. This review highlighted that conventional methods for measuring grain loss are ineffective in addressing these problems. It was reported that an advanced technology method is required for the operation to monitor the losses, optimize the operational parameters of the combine harvester to guide the operators the condition of the machine operation in real-time during harvest. One of these methods is a sensor-based grain-loss monitoring system. Introducing these systems in combine harvesters saves time and reduces the difficulty involved in the conventional methods. Real-time measurement of grain loss can guide combine harvester operators to adjust the machine settings immediately, thereby improving the general performance of the combine harvester. Although existing monitoring systems have been reported in the literature, they have numerous limitations that must be addressed to improve the system. The aim of this study is to develop a grain-loss monitoring system to enhance existing systems and address the problems of grain loss in combine harvester operations in Malaysia. Based on previous research presented in the literature,

the ANN model has been employed to predict grain loss with varying levels of accuracy owing to disparities in the datasets, operational parameters, and types of combine harvesters used in the studies. This suggests the necessity of utilizing other machine learning algorithms and models to evaluate their predictive accuracy.



CHAPTER 3

MATERIALS AND METHODS

This chapter presents the materials and methods used in this research, including the study area, the combine harvester used, the experimental design of the study, field performance evaluation of the combine harvester, a method for measuring grain loss, and optimization of the combine harvester operational parameters to minimize grain loss. It further presents the procedure for developing a grain loss monitoring system, experimental modal analysis for determining an optimum plate thickness for the sensitive plates, calibration of the monitoring system, and evaluation of the system on the combine harvester. Finally, a technique for predicting the performance of the grain loss monitoring system using machine learning algorithms is presented.

The flowchart shown in Figure 3.1 highlights the methodology used in this study. It presents a clear, step-by-step methodology that is systematic and replicable. It outlines the essential research steps, from data collection and analysis to optimization and system development, all aimed at reducing grain loss. The approach ensures that the system will perform optimally under field conditions.

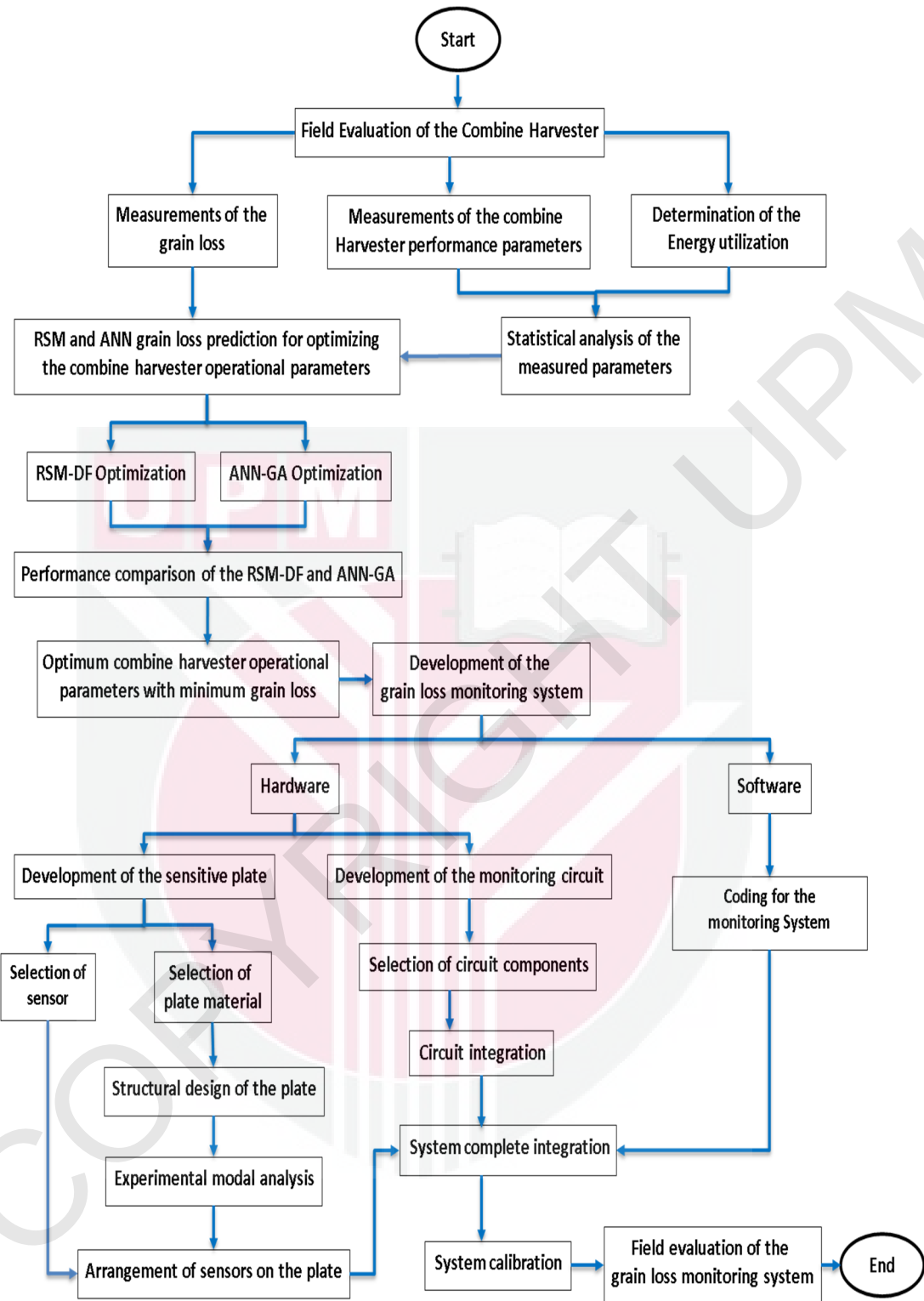


Figure 3.1: Flow chart of the research methods

3.1 Field performance characteristics of the combine harvester and energy utilization in glutinous rice harvesting

The field performance characteristics of combine harvesters are crucial for optimizing the efficiency and productivity of rice harvesting. Therefore, understanding the performance metrics of the machine is essential for enhancing operational effectiveness. Additionally, energy utilization in rice harvesting significantly impacts economic viability and environmental sustainability. By analyzing energy use and improving machine performance, farmers can maximize yields while minimizing production costs and resource consumption, leading to more sustainable agricultural practices.

3.1.1 Study area

This research was conducted on farmers' rice fields in Ayer Hangat village (06°25'14.7"N 99°48'23.00"E) Langkawi Island, Kedah, Malaysia, as shown in Figure 3.1. The following topographical data were obtained during the experiment: atmospheric temperature, 33°C; humidity, 83%; wind speed, 5 km/h; wind direction, E; and atmospheric pressure, 1008 Pa. The location data were obtained from online weather data. This location was selected because of its favourable topographical conditions that suit the production of glutinous rice in Malaysia.

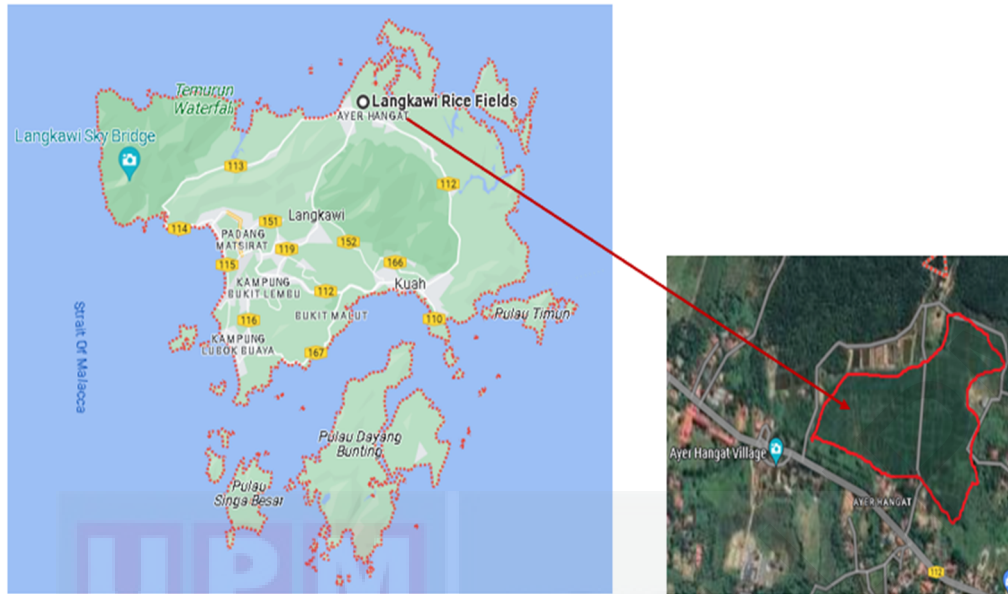


Figure 3.2: Location of rice fields in Ayer Hangat Village, Langkawi, Malaysia

3.1.2 Rice variety

The variety of rice used in this study was glutinous rice pulut Siding (MR4). It is the most widely used glutinous rice cultivar produced by local farmers in Malaysia. The rice was planted in November 2021 and harvested in March 2022. The crop reached maturity 116 days after germination, with an average plant height of 95 cm and moisture content of 19.60 % during harvest. The paddy moisture content was within the range of 19.10 – 20.10 % reported by Amponsah et al., (2017) to minimize threshing unit clogging due to high grain moisture content and physical grain losses caused by increased shattering due to low moisture content.

3.1.3 Combine harvester used

A medium-sized combine harvester (Worldstar WS 7.0 Plus) manufactured by the Worldstar Agricultural Machinery Company was used in this study, as shown in Figure 3.2. The combine harvester was recently introduced in rice harvesting in Malaysia to replace the existing large models due to issues with high soil compaction and obsolete spare parts (Nasir et al., 2021; Wagiman et al., 2019). The use of this machine results in higher quality work during harvesting operations with less damage to the terrain surface compared with large combine harvesters. This type of combine harvester is an axial flow-type machine that adopts an I-type threshing system. This system is an advanced technology for combine harvesters due to its higher efficiency and better performance. The specifications of the combine harvester are presented in Table 3.1.



Figure 3.3: Medium-sized combine harvester

Table 3.1: Technical Specification of the medium-sized combine harvester

Parameters	Specifications
Model	WS 7.0 Plus++ (4G33-TC)
Overall Dimension (mm)	5150 x 2620 x 3030
Weight (kg)	3400
Power (kW/hp)	10/108
Rotational speed (rpm)	2600
Fuel tank capacity (L)	130
Track type	Rubber track
Cutting width (m)	2.36
Feeding capacity (kg/s)	6
Threshing type	Axial flow, beater bar
Threshing cylinder (mm)	620 x 2010
Fan type	Centrifugal fan
Grain tank capacity (m ³)	1.7
Unloading discharge (kg/s)	1.68

3.1.4 Tools and Equipment Used

The following equipment and instruments were used for measurements and data collection during the harvesting experiment: a measuring tape to measure the size of the plots and the length of machine swath; a stopwatch to measure the harvesting time during the combine harvester operation; a sensitive weighing scale to measure the weight of grain loss obtained from the field, volumetric cylinder to measure the fuel used during the machine operation, digital moisture meter to measure the moisture content of the grains, tachometer to measure the speed of the cleaning fan, plastics for grain sample collection, woven sacks for collecting the samples of harvest debris from the combine harvester, and field marking poles to identify the length of the swath distance of the machine.

3.1.5 Field and crop conditions

The performance of the combine harvester varies according to the type and condition of the machine, field, crop, and topography (Šotnar et al., 2018; Kukhmazov & Konovalov, 2021). These parameters were inspected before harvest. The combine harvester was in good condition without technical problems, the rice field was relatively flat without surface irregularities, and the condition of the crop was studied by measuring the crop yield, moisture content, and height of the crop as well as the topographical data of the location. The study was conducted in March 2022 on a one-hectare paddy field with three plots used in the study; the size of each plot was 0.33 ha. Before the experiment, the following data were measured and recorded: the area of the rice field, cutting width of the machine, and the swath distance.

3.1.6 Determination of the crop field yield

The yield is required to state the combine harvester losses as a percentage of the total field yield (Paulsen et al., 2015). The field yield was determined before the harvesting operation. A square frame measuring 1 m × 1 m was randomly placed at five locations within each experimental plot, as shown in Figure 3.3. The crop plants inside each frame were harvested manually, the grains were manually separated from the chaff and stalk, and the collected grains were weighed and recorded to determine the yield.



Figure 3.4: Placement of a square frame for grain yield measurement

3.1.7 Measurement of grain loss

Grain loss was measured by placing a sack behind the combine harvester at the start of the swath distance to collect threshed heads and grain residues discharged from the rear of the machine, as shown in Figure 3.4a. This process was repeated 30 times across the experimental plots, as depicted in Figure 3.4b, using various machine operational parameters determined by the experimental design. At the end of each swath, the combine harvester was stopped to remove the sack containing the collected sample as shown in Figure 3.4c. The plot length was 30 m, representing the swath distance, while the 2.36 m width of the combine harvester header was the cutting width for each run. The samples were manually screened to separate grains from non-grain materials as shown in Figure 3.4 (d, e, and f) (Srivastava et al., 2013; Amponsah et al., 2017). The weight of the recovered grains from each sample sack was recorded as the measured grain loss.

The grain loss recorded per unit area (G_A) was determined from the relationship given in equation (1):

$$G_A = \frac{G_w}{A_c} \quad (1)$$

Where G_w is the average weight of grain collected behind the combine harvester (kg) and A_c is the area covered by the combine harvester during harvesting (ha).





Figure 3.5: Procedure for measuring grain loss. (a) placing a sack behind combine harvester, (b) combine harvester experimental run, (c) removing a sack behind combine harvester, (d) major separation of grain, (e) and (f) minor separation of grain from non-grain materials.

3.1.8 Experimental design of combine harvester operation

The experiment was designed using a four-factor five-level design (CCD) to determine the effect of the numerical factors on the response variable. The numerical factors include the forward speed (A), height of header (B), cleaning fan speed level (C), and feed rate (C) while the response variable was the grain loss. The design matrix presented in Table 3.2 was developed using Design-Expert software (version 13.1.5; Stat Ease Inc., Minneapolis, MN, USA). Thirty (30) runs of the experiment were generated in three blocks, with each block comprising ten (10) runs. The experiment was conducted in a randomized order to minimize the effects of external variables (Jha & Sit, 2021).

Table 3.2: Experimental design metrics of combine harvester field experiment

Block	Run	Factor 1 Forward Speed (km/h)	Factor 2 Header Height (mm)	Factor 3 Cleaning Fan Speed (rpm)	Factor 4 Feed Rate (kg/s)
Plot 1	1	2.26	350	1500	3
	2	2.01	250	1300	4.5
	3	1.76	350	1500	6
	4	2.26	150	1500	6
	5	2.26	150	1100	3
	6	1.76	150	1500	3
	7	1.76	350	1100	3
	8	1.76	150	1100	6
	9	2.01	250	1300	4.5
	10	2.26	350	1100	6
Plot 2	11	1.76	150	1500	6
	12	2.26	350	1100	3
	13	2.01	250	1300	4.5
	14	1.76	150	1100	3
	15	1.76	350	1500	3
	16	1.76	350	1100	6
	17	2.26	350	1500	6
	18	2.01	250	1300	4.5
	19	2.26	150	1100	6
	20	2.26	150	1500	3
Plot 3	21	1.51	250	1300	4.5
	22	2.01	250	1300	1.5
	23	2.01	250	1300	4.5
	24	2.51	250	1300	4.5
	25	2.01	250	1300	7.5
	26	2.01	250	900	4.5
	27	2.01	250	1700	4.5
	28	2.01	450	1300	4.5
	29	2.01	50	1300	4.5
	30	2.01	250	1300	4.5

In generating the design metrics, the forward speed varied from 1.76 to 2.26 km/h, the height of the header varied from 150 to 350 mm, the cleaning fan speed varied from 1100 to 1500 rpm, and the feed rate varied from 3 to 6 kg/s. The parameter ranges for each factor were selected within the constraints of previously reviewed studies. A summary of the independent variables and their corresponding levels are presented in Table 3.3.

Table 3.3: Independent variables and their coded levels for combine harvester operation

Independent variable	Symbol	Coded Levels				
		α	-1	0	1	α
Forward Speed (km/h)	A	1.51	1.76	2.01	2.26	2.51
Height of Header (mm)	B	50	150	250	350	450
Cleaning Fan Speed (rpm)	C	900	1100	1300	1500	1700
Feed Rate (kg/s)	D	1.5	3	4.5	6	7.5

Real levels of independent variables were coded according to equation (2) with each value coded at 5 levels between -1 and 1 (Shafi et al., 2018).

$$H_i = \frac{H_0 - H_c}{\Delta H_i} \quad (2)$$

where H_i and H_0 represent the coded and real levels of the independent variable, respectively, ΔH_i represents the step change (i.e. the difference between the values at the centre point and the coded levels), and H_c indicates the actual value at the central point.

The specific equations for each independent variable were derived from equation (2) to code their actual values. Specific equations for combine

harvester forward speed (A), height of header (B), cleaning fan speed (C), and feed rates (D) are presented equations (3) – (6).

$$H_1 = \frac{(A-2.01)}{0.25} \quad (3)$$

$$H_2 = \frac{(B-250)}{100} \quad (4)$$

$$H_3 = \frac{(C-1300)}{200} \quad (5)$$

$$H_4 = \frac{(D-4.5)}{1.5} \quad (6)$$

3.1.9 Machine factors (Independent variables)

Four machine factors were selected to evaluate the performance of the combine harvester due to their impact on the operation and optimum performance of the machine. These variables are usually controlled by operators which is one of the major problems reported in the literature that cause grain loss in rice fields in Malaysia. These factors are as follows:

3.1.9.1 Forward speed

The forward speed of the combine harvester is the rate at which the machine engine rotates. It was measured in revolutions per minute (rpm). The speed may vary depending on the field conditions, crop type, yield, and skill of the operator. The machine speed can be adjusted to optimize the performance and efficiency of the combine harvester (Masroon et al., 2020). However, operating at very high or very low speeds affects the quality of harvested grains

and results in high fuel consumption. The different models and settings of combine harvesters have different speed ranges.

3.1.9.2 Height of header

The header is a part of the combine harvester that cuts and collects grains and materials other than grains from the field and feeds them into the machine threshing mechanism. The header is of different types and sizes, depending on the type of crop. The height of the header can be adjusted to effectively cut the crops. However, the inadequate adjustment of the header causes grain loss in the field (Yuan et al. 2023).

3.1.9.3 Cleaning fan speed

The speed of the cleaning fan of the combine harvester is the rate at which the fan rotates. It was measured in revolutions per minute (rpm). The cleaning fan speed affects the quality and quantity of the harvested grain as well as the fuel consumption and power output of the combine harvester. Different crop conditions require different cleaning fan speeds to achieve optimal results (Guan et al., 2020). The speed depends on factors such as the type of crop, yield, moisture content, speed of the machine and the field conditions.

3.1.9.4 Feed rate

The feed rate of the combine harvester is the amount of crop that enters the machine per unit time. It is measured in kg/s. The feed rate depends on the width of the header, the cutting speed, and the crop yield. A higher feed rate can increase the productivity and capacity of the combine harvester. However, it can also cause problems, such as congestion, increased fuel consumption, reduced grain quality, and high threshing losses. To achieve optimum settings, it is important to choose a header that can match the feed rate to the threshing capacity of the combine harvester (Jiang et al., 2022).

3.1.10 Performance response of the combine harvester (Dependent variables)

The performance of the combine harvester was evaluated based on the following parameters.

3.1.10.1 Measurement of harvesting time

The amount of time required for the combine harvester to complete a given operation is a good indication of its efficiency. In this study a stopwatch was used to record each run of harvest operation. Among these are the time taken to harvest the crop, turning and reversing times, unloading time, and others, such as the time taken to refuel, adjust, or set the machine. The total field time represents the time spent when a combine harvester engine is turned on, run, and turned off once the job is completed (Olt et al., 2019). The data were used

to compute the field performance metrics, which include forward speed (FS), effective field capacity (EFC), field efficiency (FE), and field machine index (FMI).

3.1.10.2 Determination of field speed of operation

The field speed (FS) of the combine harvester is the distance travelled by the machine divided by the time taken to travel. This was determined based on the relationship in equation (7), as reported by Ahmad et al., (2020):

$$FS = \frac{D}{t} \quad (7)$$

where D is the distance travelled by the machine during operation (km) and t is the time taken to cover the distance travelled (h).

3.1.10.3 Determination of theoretical field capacity

The theoretical field capacity (TFC) is the product of the machine field speed and effective working width of the machine. This was determined based on equation (8) reported from ASABE, (2011):

$$TFC = \frac{W \times S}{10} \quad (8)$$

where W is the width of the machine (m) and S is the speed of the machine (km/h).

3.1.10.4 Determination of effective field capacity

The effective field capacity (EFC) is the ability of the machine to harvest the crop under the actual field conditions (K. Zhou, 2015). The EFC was determined as the area harvested by the machine divided by the total working time in the field (Elsoragaby et al., 2019). This was obtained using equation (9):

$$EFC = \frac{A}{T} \quad (9)$$

where A is the area of the harvested plot (ha) and T is the total working time required to harvest the plot (h).

3.1.10.5 Determination of field efficiency

The field efficiency (FE) is the ratio between the combine harvester's productivity under actual working conditions and the theoretical maximum possible productivity (Elsoragaby et al., 2019). This describes the efficiency of the time required to conduct the operation using the machine. It was determined using the relationship in equation (10), as reported by ASABE, (2011):

$$FE = \frac{EFC}{TFC} \quad (10)$$

3.1.10.6 Determination of fuel consumption

The fuel consumption (FC) was recorded using a measuring cylinder of known volume by refilling the fuel tank to its full capacity after each harvesting task run (ASABE, 2011). Before starting the harvesting operation, the fuel tank of the combine harvester is filled. At the end of the harvesting operation of each plot, the fuel tank was refilled using a measuring cylinder. The fuel consumption was determined using the following relationship in equation (11) reported by Hasan et al., (2019):

$$FC = \frac{F_a}{A} \quad (11)$$

where F_a is the amount of fuel used during operation (L) and A is the area of operation (ha).

3.1.11 Determination of energy sources of glutinous rice field harvesting operation

Energy usage during harvesting is an important factor for evaluating the performance of agricultural machinery. Reducing energy loss is vital for minimizing operating costs, especially during harvesting. The energy sources used during harvesting include machine, fuel, and human energy.

3.1.11.1 Machine Energy (ME)

"Machine energy" is an indirect energy assumed to be embodied in a piece of equipment during operation (Elsoragaby et al., 2019). To measure machinery

energy, the total useful life and EFC of the machine were considered (Muazu et al., 2014). The weight of the machine was included by equally distributing its weight over total economic life. This was determined using equation (12), as described by Masroon et al., (2020):

$$ME = \frac{C_f \times W}{EFC \times L} \quad (12)$$

where ME is the machinery energy (MJ/ha), C_f is the energy conversion coefficient of the combine harvester, W is the weight of the combine harvester in kg according to the manufacturer specification (3400 kg), EFC is the effective field capacity (ha/h), and L is the economic life of the combine harvester (h). The machinery energy conversion factor used for the combine harvester was 87.63 MJ/kg (Masroon et al., 2020).

3.1.11.2 Fuel Energy (F_e)

The fuel energy per unit area is a function of the type of fuel (diesel or petrol) and quantity of fuel consumed by the machinery to power engines in the harvesting operation. This was obtained from the expression in equation (13) reported by Masroon et al., (2020):

$$F_e = \frac{F_{con} \times F_c}{A} \quad (13)$$

Where F_e is the fuel energy (MJ/ha), F_{con} is the quantity of fuel consumed (lit), F_c is the fuel energy conversion coefficient (MJ/lit), and A is farm area (ha).

The fuel energy conversion factor used for the combine harvester was 47.80 MJ/kg (Masroon et al., 2020).

3.1.11.3 Human Energy (HE)

Human energy expenditure in harvesting operations was evaluated based on the number of farm workers engaged in harvesting operations per unit area and the time spent performing the operations multiplied by the energy conversion coefficient. This value was obtained using equation (14), as reported by Masroon et al., (2020):

$$HE = \frac{n \times H \times I_c}{A} \quad (14)$$

where HE is human energy (MJ/ha), n is the number of workers engaged in an operation, H is the duration of the operation (h), I_c is the energy conversion coefficient for human labour, and A is the farm area covered (ha). The human energy conversion factor used for harvesting operation was 1.96 MJ/kg (Masroon et al., 2020).

3.1.11.4 Total Energy Consumption (TE)

The overall energy input per hectare in the harvesting operation was calculated as the sum of all the energy sources. It was calculated using equation (15) (Elsoragaby et al., 2019):

$$TE = ME + F_e + HE \quad (15)$$

3.1.11.5 Mechanization Index (MI)

The Mechanization index (MI) is expressed as the percentage of machine energy to the total energy consumed during the combine harvester field operation. This value was computed using equation (16), as described by Elsoragaby et al. (2019):

$$MI = \frac{ME}{TE} \quad (16)$$

3.1.12 Analysis of Results

One-way analysis of variance (ANOVA) was conducted using SAS statistical analysis software (SAS), employing the general linear model (GLM) method. The mean results were compared for p-values with 95% confidence and a 5% significance level (0.05).

3.2 Optimization of the combine harvester operational parameters to minimize grain loss

In the optimization process, the results of grain loss obtained from the field evaluation of the combine harvester were utilized to optimize the combine harvester operational parameters based on the models that represent the relationship between the combine harvester operational parameters and the amount of grain lost during harvesting.

The prediction models treat grain loss as a function of the four operational parameters of the combine harvester (forward speed, header height, cleaning

fan speed, and feed rate). The model functions help in understanding how each parameter contributes to grain loss and analyzing the functions a parameter that has the most significant effect on grain loss can be determined. By adjusting the parameters an optimum operational parameter that reduced grain loss was achieved.

In this study, RSM and ANN prediction models were used as the mathematical functions for this optimization while RSM with desirability function (RSM-DF) and ANN with genetic algorithm (ANN-GA) were used to optimize the operational parameters of the combine harvester based on the established prediction models to minimize grain loss.

The RSM and ANN offer a data-driven approach to optimize combine harvester performance, helping to reduce grain loss by adjusting the operational parameters based on the predictive conditions. Time and resources can be managed appropriately because the models can predict outcomes without the need for extensive field trials. Additionally, combine harvester operators can continuously adjust the machine's settings as conditions change (such as crop type, moisture level, or terrain), leading to real-time optimization and reduced grain loss.

The goal of this optimization is to find the set of operational parameters that minimize grain loss while maintaining the efficiency of the combine harvester.

3.2.1 Response surface method (RSM) prediction modeling

The RSM quadratic model defines grain loss as a second-degree polynomial function of the combine's operational parameters. It provides a concept on how small changes in these parameters can affect grain loss, enabling a more precise prediction.

In this study, the second-order polynomial model using response surface methodology (RSM) was used to predict grain loss in a medium-sized combine harvester during glutinous rice harvesting. The grain loss data were analyzed and modelled using Design Expert software. The fitted model equation presented in equation (17) indicates the predicted grain loss as a function of the independent variables.

$$Y = \beta_0 + \sum_{i=1}^n \beta_i X_i + \sum_{i=1}^n \beta_{ii} X_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{ij} X_i X_j \quad (17)$$

Where Y represents predicted grain loss response; β_0 is the intercept constant, β_i , β_{ii} , β_{ij} represent the regression coefficients; and X_i , X_j represent the independent variables in the coded values.

3.2.1.1 RSM model analysis

The model was analyzed using analysis of variance (ANOVA). Numerous statistical parameters, such as the lack-of-fit test, predicted and adjusted multiple correlation coefficients, and coefficient of determination (R^2), were calculated to determine the adequacy of the model. The coefficient of variation

(CV) was calculated to determine the relative dispersion of the experimental points from model predictions. To understand the effect of the independent variables on the response variables, response plots were generated using the Design Expert software. Significant differences were determined using analysis of variance (ANOVA) by calculating the F-values at probabilities of 0.5, 0.1, and 0.01.

3.2.2 Artificial Neural Network (ANN) prediction modeling

A neural network fitting tool using MATLAB software (Matlab 2022b, Mathworks Inc., MA, USA) was used to model the experimental data to predict grain loss. A feed-forward (FF) back-propagation (BP) multilayer perception (MLP) using the Levenberg-Marquardt algorithm was used to provide a nonlinear mapping between the input and output variables using the same set of experimental data used for the RSM. The ANN model in this study had four (4) input layers, ten (10) hidden layers, and one (1) out layer, as shown in Figure 3.5. The input layer comprised the forward speed, height of the header, cleaning fan speed, and feed rates, whereas the output layer was the grain loss.

Back Propagation is a distributed and parallel model that employs supervised learning for the training datasets to minimize errors between the output and input variables using the expressions given in equations (18) and (19) reported by Ramezanpour & Farajpour, (2022).

$$\text{Error} = \frac{1}{n} \sum_{n=1}^n (y_s - \hat{y}_s)^2 \quad (18)$$

Where n is the number of observations in the study, y and $\bar{y}$ are the sth observed and predicted variables respectively.

$$\bar{y} = f \left[\sum_{j=1}^p w_j g \left(\sum_{i=1}^k w_{ij} X_i + w_{jo} \right) + w_o \right] \quad (19)$$

where p and k are the number of neurons in the hidden layer and output variables, respectively. X_i is the i th output variable, w_j is the weighted input data into the j th hidden neuron, f is the activation function for the output neurons, w_{ji} is the weight of the direct relationship of the input neuron i to the hidden neuron j , w_{jo} is the bias for the j th node, w_o is the bias connected to the neuron output, and g is the activation function for the hidden neuron.

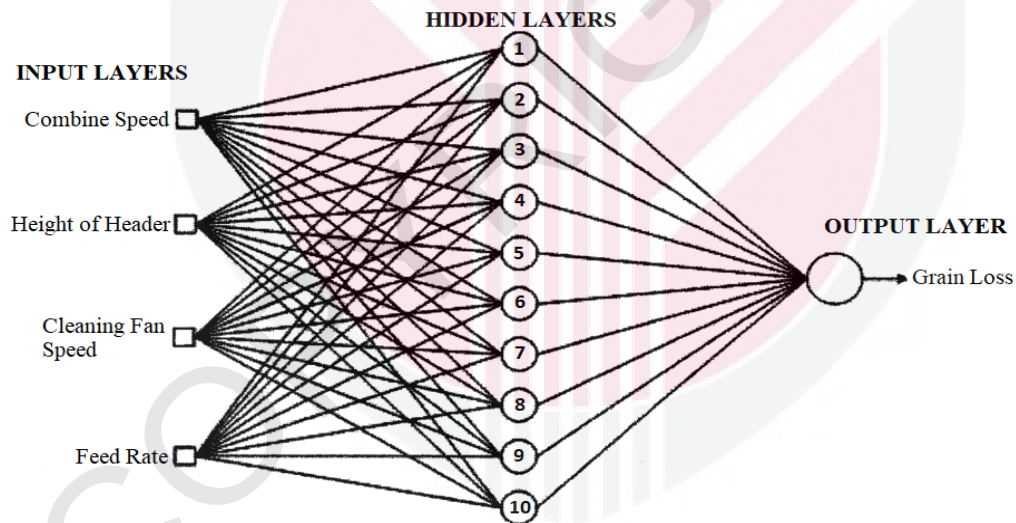


Figure 3.6: Schematic architecture of the ANN input and output layers

The input layer is typically passed through the hidden layer using a set of weights and biases, which are variable parameters for the network. The neurons in the hidden layer sum up the weighted inputs and the bias, as presented in Figure 3.6, whereas the input of the output layer comes from the

output produced by the hidden layer. Lian et al., (2021) reported that the number of neurons in the hidden layer influences the performance of the ANN model because the lower the number of neurons in the hidden layer, the less accurate the ANN model process results, and the network may not train well. However, the excessive number of neurons may cause the network to memorize the data rather than train it. Therefore, this study utilizes the optimal number of neurons suggested by the network.

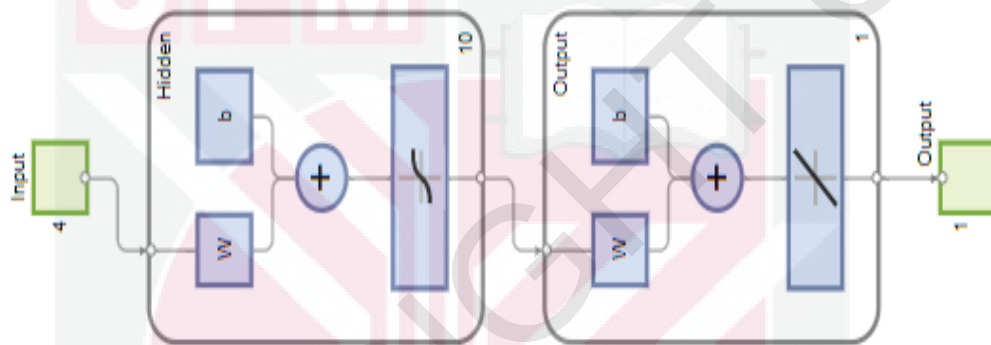


Figure 3.7: General architecture of the feed-forward back-propagation multilayer perceptron (MLP) using MATLAB software

The model was developed by splitting the datasets into three groups: 74% for training, 13% for testing, and 13% for validation. The model was trained until the error between the experimental and the predicted response values was minimal. The trained network model was validated using a validation dataset (experimental data not used to train the model). Figure 3.7 shows the processes involved in ANN prediction modeling. The flowchart illustrates the methodology for developing and training an ANN model in MATLAB to predict grain loss in a combine harvester during paddy harvesting. The process begins by launching MATLAB and initializing the ANN toolbox, followed by inputting datasets consisting of key operational parameters from the field experiments,

such as forward speed, header height, cleaning fan speed, and feed rate. The dataset, comprising 30 runs, undergoes preprocessing and is divided into three subsets: 72% for training, 13% for testing, and 13% for validation. The ANN is trained using the training data, and its performance is validated using the validation dataset. After training, the ANN is tested using the testing dataset to evaluate its predictive accuracy. If the model's predictions are not sufficiently accurate, the network is re-trained by adjusting key parameters, including the learning rate, number of hidden layers, neurons, and weights. This iterative process continues until the ANN achieves satisfactory accuracy, at which point it is used to predict grain loss.

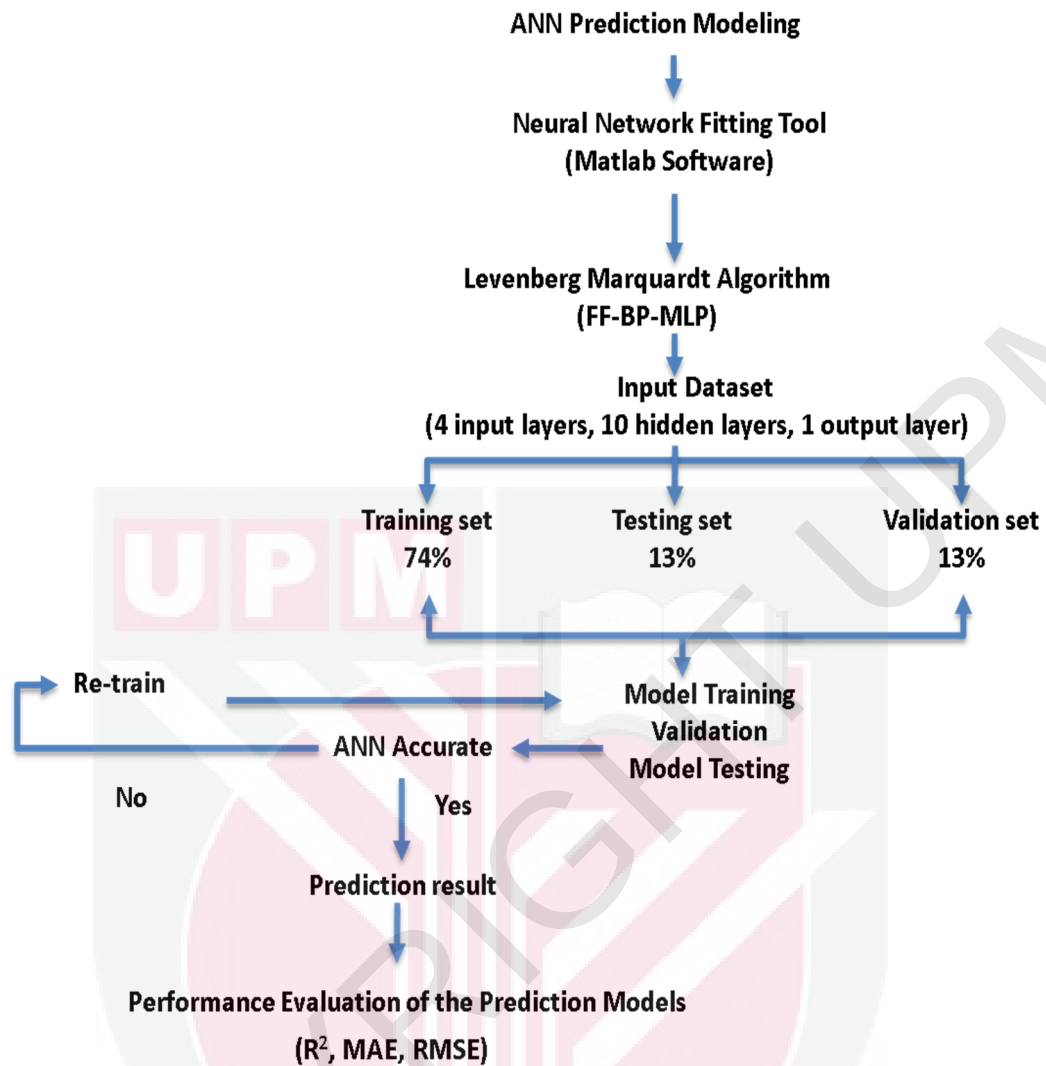


Figure 3.8: The flowchart of the artificial neural network prediction process in this experiment

3.2.3 Evaluation of the grain loss prediction models

The performances of the RSM and ANN models were compared using the coefficient of determination (R^2) when the intercept was zero, the mean absolute error (MAE), and the root mean square error (RMSE), as reported by Gendy et al., (2020). If R^2 is close to 1, the experimental and predicted values are closely related. The random association between the outputs and targets is represented by zero. MAE is the sum of the absolute differences between

the experimental and predicted values divided by the total number of data points, and RMSE is the square root of the sum of the differences between the predicted and experimental values divided by the total number of data points. The model fits better if R^2 is close to one, while the MAE and RMSE become smaller. The relationships for the performance of the models are given in equations (20) – (22), as reported by Nadai, (2020).

$$R^2 = \frac{\sum_{i=1}^n (Y_{pi})^2}{\sum_{i=1}^n (Y_{ei})^2} \quad (20)$$

$$MAE = \frac{\sum_{i=1}^n |Y_{pi} - Y_{ei}|}{n} \quad (21)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Y_{pi} - Y_{ei})^2}{n}} \quad (22)$$

where n is the number of data points in the experiment, Y_{pi} is the value predicted by the models, and Y_{ei} is the experimental value.

3.2.4 RSM-DF optimization procedure

The RSM desirability function approach was numerically optimized using design expert software. The quadratic model obtained in this study was used to optimize the operational parameters of the combine harvester using RSM-DF optimization. The optimization criteria presented in Table 3.4 were aimed at minimizing the grain loss due to machine variables. A total of 100 solutions were generated, each with a different combination of the input variables. The

solution with the lowest desirability value for grain loss was selected as the optimized set of operational variables for the combine harvester.

Table 3.4: RSM-DF optimization parameters criteria

Parameter	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
Forward speed (km/h)	range	1.76	2.26	1	1	3
Header Height (mm)	range	150	350	1	1	3
Cleaning fan speed (rpm)	range	1100	1500	1	1	3
Feed rate (kg/s)	range	3	6	1	1	3
Grain Loss	minimize	17.68	70	1	1	3

3.2.5 ANN-GA optimization procedure

A genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution (Yu, 2020).

The procedure for optimizing the operational parameters of the combine harvester using ANN-GA is shown in Figure 3.8. The ANN-GA optimization was performed in MATLAB software using a genetic algorithm optimization toolset. The genetic algorithm (GA) optimization begins by randomly selecting an initial population of individuals, where each individual represents a set of artificial neural network (ANN) weights. Each individual's fitness function was determined by evaluating the ANN outputs and comparing them with the experimental data to calculate the error. Individuals with lower error values were ranked higher in terms of fitness. The best individual was selected for survival by using the elitism mechanism. The roulette-wheel selection method

was used to select parents to generate offspring, with individuals of higher fitness having a higher probability of being selected. The crossover operation combines the genetic material from two parent individuals to create new offspring with random exchanges of weights between parents to generate variations in the population. The mutation operation introduces random changes in the genetic material to maintain the diversity in the population. The best individuals from each generation were selected as parents to generate the next generation. After a defined number of cycles, the GA training was completed. A set of weights from the best individual of the last generation is selected as the optimal weight.

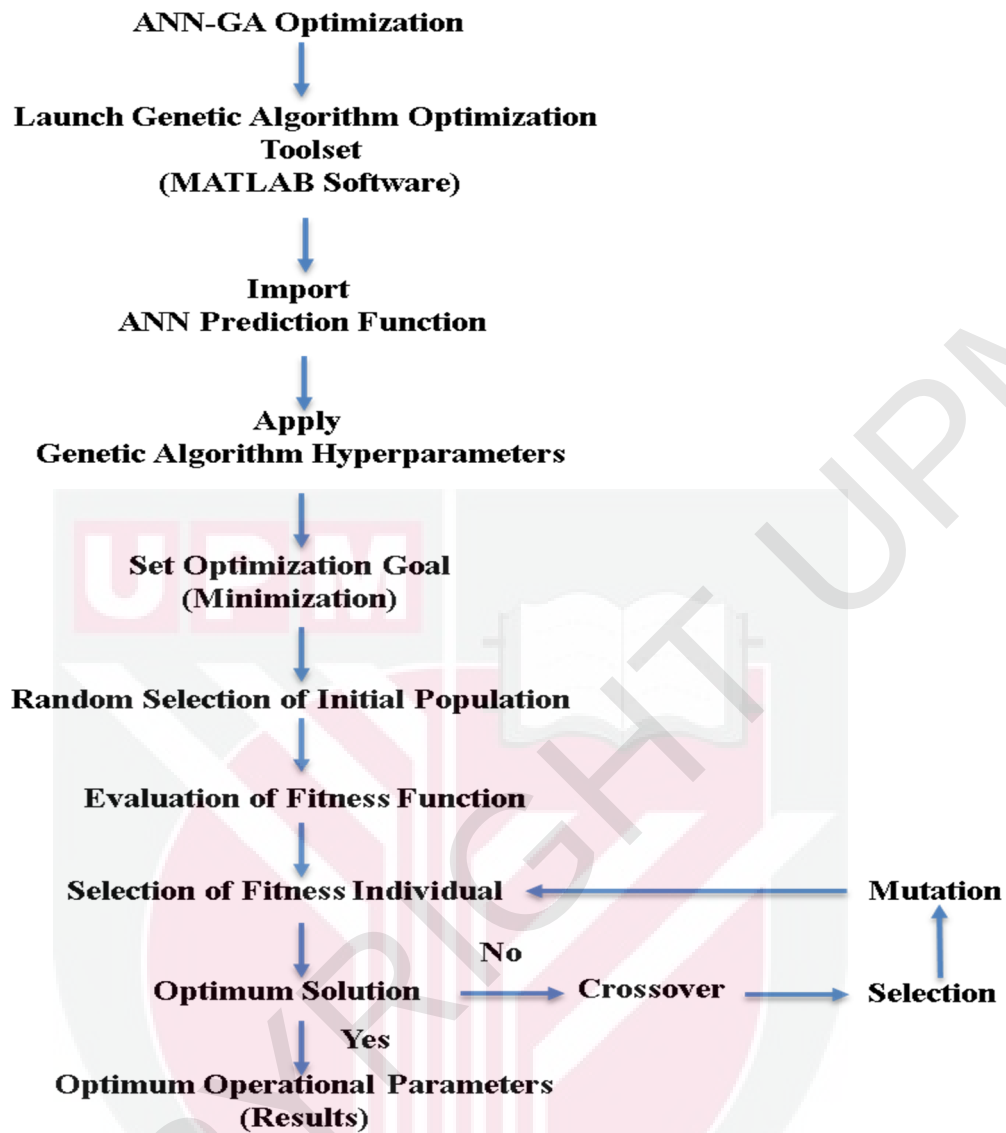


Figure 3.9: The flowchart of the Genetic Algorithm optimization process

The hyperparameters used for the ANN-GA optimization are presented in Table 3.5. These parameters were obtained after running the algorithms with different parameters and were repeated to provide solutions for each new generation until an optimum solution was achieved.

Table 3.5: ANN-GA optimization hyperparameters

Hyperparameters	Parameters
Population size	100
Mutation Probability	0.01
Crossover probability	50
Maximum generations	500
Stall generation limit	10
Crossover function	Crossover scattered
Selection function	Selection roulette
Lower boundary	[1.76 150 1100 3]
Upper boundary	[2.26 350 1500 6]

3.3 Development of grain loss monitoring system

The monitoring system was developed to monitor and measure real-time grain loss in a combine harvester during rice harvesting. It was developed into two major sub-units connected to form a complete system; a sensitive plate and a monitoring circuit. The flow chart in Figure 3.9 presents the procedure used to design and develop the grain loss monitoring system.

The development of the grain loss monitoring system involved hardware and software components. On the hardware side, it included the development of sensitive plates and monitoring circuits. The process of developing the sensitive plates began with selecting appropriate sensor and plate materials, followed by performing experimental modal analysis on the plate's geometry to determine the optimum thickness for the system. Subsequently, the structural design of the plate was completed based on the specifications of the combine harvester's separation and cleaning outlets. Finally, the sensors were attached to the plate using double-sided tape, black rubber foam, and damping material. The monitoring circuit incorporated components such as a microcontroller, amplifier module, LCD screen, sound buzzer module, and

microSD card module. These components were then arranged and integrated onto a circuit board.

The software was developed using the Arduino Integrated Development Environment (IDE) to write code capable of reading and processing material impacts to differentiate grain from non-grain materials. Finally, the complete grain loss monitoring system was assembled by connecting the sensitive plates to the monitoring circuit and uploading the software to the system. The system was calibrated to determine the optimum impact voltage for detecting grains.

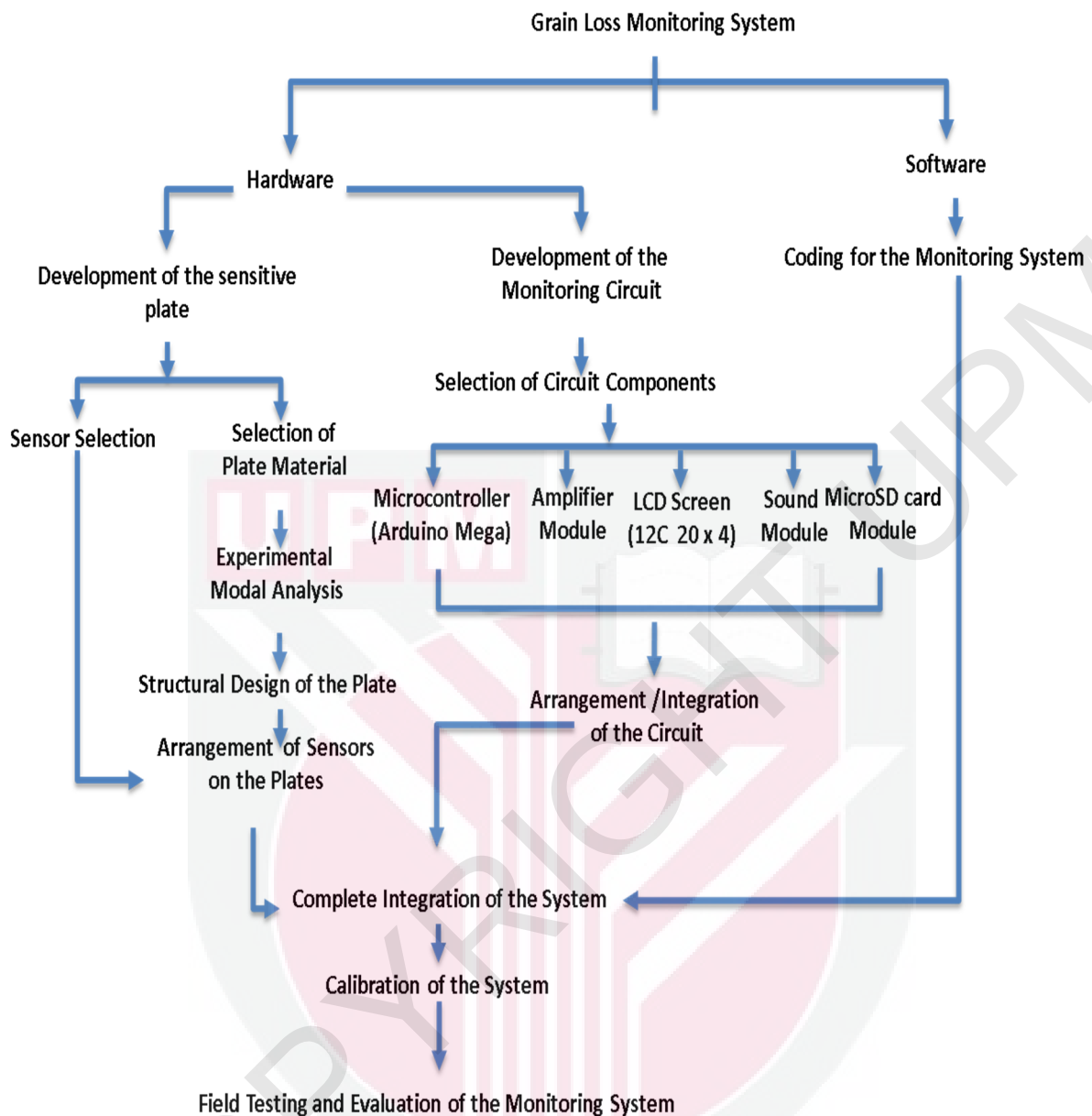


Figure 3.10: Flow chart for the development of the grain loss monitoring system

3.3.1 Selection of sensor

A Piezoelectric Polyvinylidene Fluoride (PVDF) thin-film sensor produced by the TE Connectivity Company was used in this study, as shown in Figure 3.10. This sensor has a wide range of measurement applications and unique characteristics. The PVDF piezoelectric thin-film sensor was selected as a

grain loss monitoring sensor due to its high feasibility and superior advantage compared to other types of sensors used in previous studies, such as piezoelectric ceramic, acoustic, force, piezoelectric crystal, and pressure sensors, as reviewed in the literature. In addition, the measurement accuracy of the sensor is a key factor in monitoring the performance of the system.



Figure 3.11: Piezoelectric PVDF thin film sensor

The PVDF thin-film sensor was polarized and protected by the PET film. The length, width, and thickness of the sensor are 170, 22, and 0.23 mm respectively. The PVDF layer was 0.52 μm thickness, and the PET layer was 0.2 mm thickness. The sensor can detect either continuous or impulsive vibrations or impacts. The sensor was made from a piezoelectric polymer material, which has numerous advantages, such as a high piezoelectric voltage constant, lightweight, low density, better toughness, wide frequency response, low acoustic impedance, better sensitivity and stability, and easy

processing and installation (Xu & Li, 2010). The properties of the sensor are presented in Table 3.6.

Table 3.6: Specifications and properties of piezoelectric PVDF thin film sensor

Description	Parameters	Values
Sensor Model	DT4-052K	
Electromechanical coupling coefficient	K33	0.14
Piezoelectric constant PC/N	d31, d33	23, 21
Relative permittivity	Tr3	10
Mechanical quality factor	Qm	0.018
Sensitivity		4uC/cm2 for 10Gpa
Curie temperature/C	Tc	80
Density	g/cm3	1.78
Output voltage (depending on the force)		10 mV - 100 V
Minimum input impedance	Ω	1
Prepared impedance	Ω	10
Capacitance	nF	5.7
Resonance Frequency	V/g	6
Voltage Sensitivity (open circuit, at resonance)	V/g	6
Upper Limiting Frequency (+3 dB)	Hz	42
Charge Sensitivity (baseline)	pC/g	260

Based on the study by Xin et al., (2016), PVDF sensors can measure impact and vibration based on direct effects. They are good for measuring impact due to their advantages such as high thermal stability, low permittivity, flexibility, and membrane-forming properties. Ramadan et al., (2014) reported that PVDF sensors have been widely used for vibration measurements, large stress ranges, and large signal-to-noise ratios. Compared with the most common piezoelectric ceramic sensors, the magnitude of the piezoelectricity of the PVDF sensor is much lower. Its flexibility, wide frequency range, and low cost render it a satisfactory material for practical applications (Xin et al., 2016). Tan et al., (2019) and Sun et al., (2019) reported that PVDF sensors have better voltage output characteristics and good machinability because their size is determined according to the need and can withstand large bending

deformation. Wu et al., (2020) reported that in terms of sensing elements, PVDF sensors have a significant advantage because the accuracy of acoustic sensors is low, piezoelectric ceramic can guarantee the accuracy but its ductility and reliability in a vibration environment are low. The PVDF thin film sensor is very sensitive to collision signals, and its high sensitivity to weak impacts and signals can attenuate rapidly, unlike piezoelectric ceramic sensors, which have a long attenuation time (Wu et al., 2020).

Therefore, a piezoelectric thin film sensor was selected because of its suitability for detecting grain loss due to its sensitivity, accuracy, response time, and durability (Zhou et al., 2019). This type of sensor is also cost-effective, readily available, and has been successfully used in similar applications (Tan et al., 2019; Wu et al., 2020).

3.3.2 Selection of sensitive plate material

Stainless steel plate 304 was selected as the optimal material for the sensitive plate due to its superior properties compared to other steel mate (Wang et al., 2016; Liang, 2020; Li et al., 2022). A stainless steel plate was selected because it is a food-grade material that offers better sensitivity to grain impact due to its mechanical properties. This is because the material for grain impact (sensitive plate) must possess a specific hardness to resist fatigue deformation and sufficient toughness to prevent brittle fracture and withstand external vibrations from the combine harvester. Some properties of the plate materials are listed in Table 3.7.

Table 3.7: Mechanical properties of 304 stainless-steel plate

Description	Units	Values
Density	kg/m ³	7930
Poisson's ratio		0.27
Young modulus	Pa	185×10^9
Yield strength	Pa	210×10^9
Uniform elongation	%	25
Coefficient of restitution		0.57
Coefficient of static friction		0.8
Coefficient of rolling friction		0.01

3.3.3 Structural shape of the sensitive plate

The structural shape and materials of the sensitive plate significantly affect sensor signal acquisition and recognition (Ni et al., 2015). To improve the performance of the sensing platform, it is important to design the geometry of the instrumented plate. Therefore, when developing a grain loss monitoring system, it is essential to determine the effect of plate thickness and size in terms of its dynamic behaviour, such as its natural frequency, damping ratio, and modal shape. This enabled the selection of an appropriate thickness for the sensitive plate. The natural frequency and vibration mode of the plate depend on its thickness, length, and width (Liang et al., 2017). Wang et al., (2016), further reported that the natural frequency and damping ratio of the sensitive are key factors in improving the accuracy of the sensor. The plate thickness can be optimized by selecting a plate with a higher natural frequency and damping ratio to minimize excessive vibrations and ensure the stability of the sensitive plate on the combine harvester. The geometry, shape, size, and thickness of the sensitive plate, as well as the thickness, significantly affect the performance of the sensor attached to the plate.

The shape of the sensitive plate was determined based on the size and configuration of the separation and cleaning outlet of the combine harvester where the sensitive plate was installed. This was to ensure that the plate was designed to fit within the precise dimensions and shape of the combine harvester separation and cleaning outlet to enhance the efficiency and effectiveness of the grain loss monitoring. This ensures optimal performance and accurate detection of grain loss throughout the harvesting process. Finally, the shape of the sensitive plate was designed to be removable, and its angled structure allows for easy removal of materials from the plate's surface during operation, preventing material accumulation that could affect the sensor's sensitivity.

As shown in Figure 3.11, the plate was designed to have a T-shaped structure with a total length of 180 mm and a width of 250 mm. The plate was bent at an angle of 45° at the intersection point of the T-shape, as shown in Figure 3.12. This facilitates the downward flow of the materials in contact with the plate when installed on the combine harvester and prevents material accumulation on the surface of the sensitive plate. The thickness of the plate was selected using an experimental modal analysis.

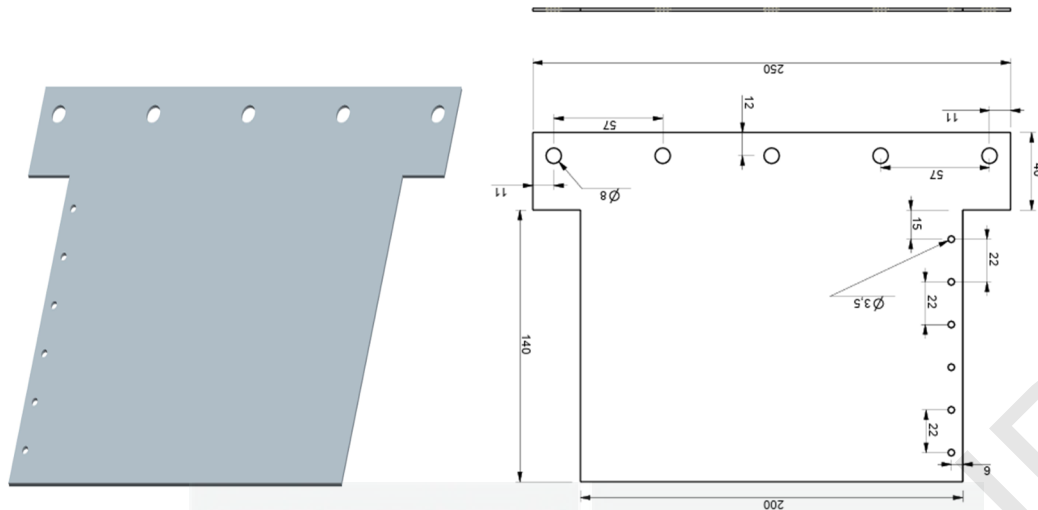


Figure 3.12: Structural design of the plate with measurement



Figure 3.13: Final shape of the plate

3.3.4 Experimental modal analysis of the stainless-steel plate

Experimental Modal Analysis (EMA) is a useful tool for describing, comprehending, and modelling the dynamic behaviour of a structure (Minardo et al., 2014). A modal experiment is a type of experiment used to identify a system's natural frequencies and mode shapes (Riaz et al., 2020).

Understanding the natural frequency and mode shape of a structure aids in designing a structural system in a noisy and vibrating environment, which is a common environment for a combine harvester. The objective of this analysis was to determine and analyze the dynamic characteristics of four different stainless steel plate thicknesses to select an appropriate plate thickness for the sensitive plate of the grain-loss monitoring system.

3.3.4.1 Experimental procedures

The experiment was conducted in a dynamic and vibrational laboratory without excessive noise or vibrations that could affect the experimental setup. Before starting the experiments, 78 measurement points were marked on each of the four stainless steel plates with thicknesses of 1, 1.5, 2, and 2.5 mm, as presented in Figure 3.13. These plate thicknesses were selected within the limitations of the previous studies (Liang, 2020; Li et al., 2022). The plates were placed on a rigid platform to prevent unwanted vibrations and movements during the experiment. A roving hammer method was employed in the experiment, using a percussion hammer as the input device and a sensor as the output. An impact hammer was set up for three impacts at each measurement point. The measurement points were across different point locations on the plates. An illustration of the experimental layout and setup is presented in Figures 3.14 and 3.15, showing how the piezoelectric accelerometer sensor was attached to the centre of the plate, the impact hammer, and the PC connected to the signal acquisition system.

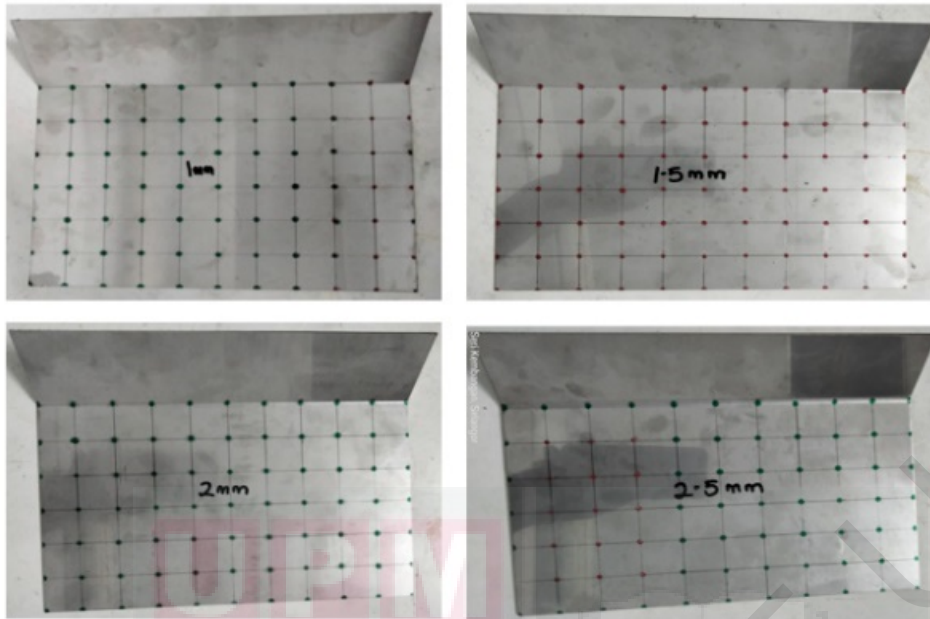


Figure 3.14: Experimental plates with their respective thicknesses

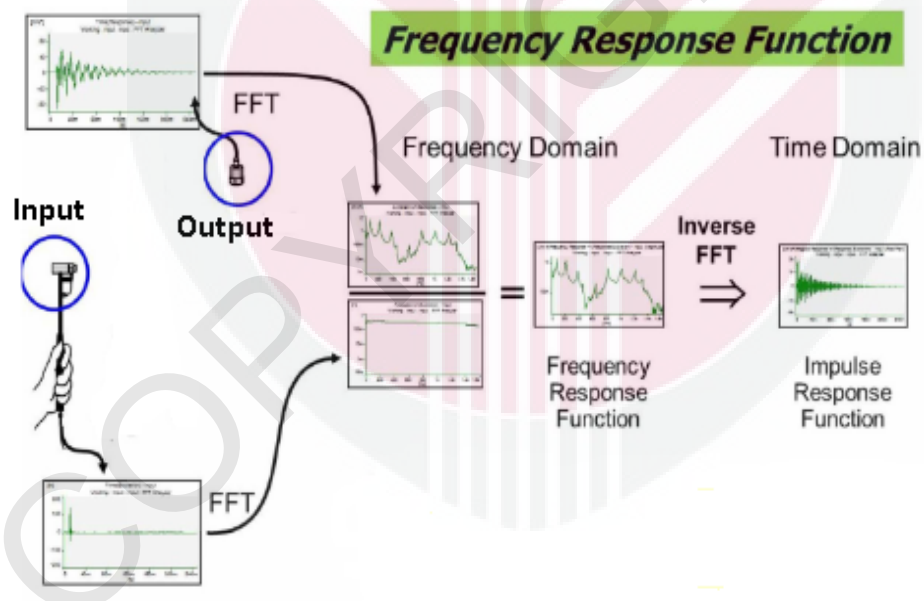


Figure 3.15: Illustration of the experimental layout



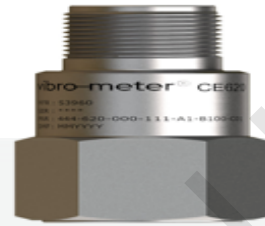
Experimental Set-up



Impact Hammer



National Instrument (NI)



Piezo accelerometer Sensor

Figure 3.16: Modal analysis experimental setup

To set up the devices for the experiment, the output cables of the piezoelectric accelerometer and impact hammer were connected to the input ports of the NI data acquisition device, whereas the output of the NI data acquisition device was connected to the USB port of a PC for data collection. The sensitivity of the sensor was set at 2.25 mV/EU:95 mV/EU:95 mV/EU:95 mV/EU. The specifications of the instruments used in this study are listed in Table 3.8.

Table 3.8: Experimental instruments and their specifications

Components	Parameters	Range	Manufacturer
Piezoelectric Accelerometer Sensor (3-Dimensional)	Sensitivity	100 mv/g	Meggit SA Sensor
	Response-Frequency Range	0.5 - 14000 Hz 80 gpk±5%	
National Instrument Model: 9233/9234	Lateral Sensitivity		National Instrument Corp. USA
	Number of Signal Channel Sampling	4 Channels	
	Bandwidth	13.0172 MHz	
Impact Hammer Model: PCB-086D05	AD Resolution	24 Bits	PCB Piezoelectronics USA
	Sensitivity	0.23 mV/N± 22.240	
	Range Resonance Frequency	N pk ≥ 22,000 Hz	

To increase the quality of the obtained data, signal processing techniques such as filtering, averaging, and windowing were applied to each hammer impact. The window type was set to "Force: Exponential: Exponential: Exponential," and the window value was 50:1:1:1. To improve coherence in the plate impact experiment, the number of samples and the sample span were set to 1024. In the software, the measurement was set in the frequency domain using a transfer function (FRF) and coherence. The frequency response was calculated using equation (23):

$$FR = \frac{OUTPUT}{INPUT} = \frac{Motion}{Force} = \frac{Response}{Excitation} \quad (23)$$

After connecting the devices, the MEscape modal analysis software was installed and run on a PC to confirm that the setup was correctly connected before starting the experiment. The measured sensor signal data were transferred into the software for modal analysis and extraction of modal parameters.

3.3.4.2 Data analysis

The experimental modal parameters were examined using polynomial fitting analysis in Origin statistical analysis software and Bode graphs obtained from MEscape analysis software. Polynomial model fitting is a data analysis and visualization technique that provides statistical measurements to assess the best fit of a dataset, such as the coefficient of determination (R^2), adjusted R^2 , root mean square error (RMSE), and analysis of variance. These parameters were used to evaluate and compare the performance of the polynomial model.

A Bode plot is a plot that displays the frequency response of the plates to interpret their behavior when subjected to vibration and noise (Wan et al., 2020).

There are two curves in the plots: the magnitude response plot in decibels (dB) and the phase response plot in degrees. The magnitude response shows how the amplitude of the plate vibration changes with frequency, whereas the phase response shows how the phase of the plate vibration changes with frequency. The plot also shows the natural frequency of the plate as the peak in the magnitude response. The peak was determined at the location where the frequency of the plate vibrated with the highest amplitude. The bandwidth of the plates was also shown as the width of the peaks in the phase response.

The most important observation from these graphs is to identify a plate thickness that can withstand the rigorous condition of the combine harvester, resulting from the high vibration and noise generated by the machine. A plate with the narrowest bandwidth or maximum phase response is suitable for this application because the higher the phase response of the plate, the lower is the vibration frequency outside the bandwidth (Wan et al., 2020).

3.3.5 Arrangement of the sensitive plate

In this study, three (3) sensitive plates were developed and assembled at the outlet of the cleaning and separation unit of the combine harvester. Each plate was equipped with five (5) sensors, resulting in a total of fifteen (15) sensors being used for the grain loss monitoring system. Three (3) materials were used

to fix the sensors to the plates: black soft rubber foam, double-sided rubber tape, and viscoelastic damping material.

3.3.5.1 Black soft rubber foam

The black soft rubber foam used in this study was EVA rubber foam. EVA rubber foam is a type of foam that is made from copolymer of ethylene and vinyl acetate. It has multiple applications across various industries and is available for different thicknesses and sizes. Some of the advantages of the EVA form over other types of foams include its light weight, flexibility, durability, and resilience. It can withstand wear and tear, water resistance, and UV resistance, which means that it can withstand moisture and heat, and it is not harmful to other materials. Therefore, because of the exceptional properties of the EVA foam, it was selected in this study to attach the sensors to stainless steel plates. It also provided a flexible surface for the sensor to achieve maximum deformation on the plate. The foam thickness used in this study was 2 mm.

3.3.5.2 Double sided rubber foam tape

Double-sided soft rubber tape is an adhesive tape with a soft rubber layer on both sides that can stick to various surfaces and materials. They are often used for sealing cushioning, damping, and mounting applications. One of the most important properties of this type of tape is that it can absorb shocks, vibrations, and noise; reduce wear and tear; and improve the performance of the system.

It can also resist heat, moisture, cold, ultraviolet (UV) rays, and chemicals. The use of this type of tape to attach the sensors to the plates reduces the effects of combine harvester vibrations and noise, which may affect the accuracy and performance of the sensors. The double-sided foam used in this study was 2 mm thick.

3.3.5.3 Viscoelastic damping material

Viscoelastic damping materials are high-energy dissipative polymers used to effectively control resonance-induced vibrations in structures or devices. This is a crucial requirement when designing an electronic system to reduce or eliminate the noise caused by resonance and vibration in electronic systems and ergonomic applications. One of the aims of this study was to reduce and eliminate noise from the effect of vibration from sensitive plates when mounting it to the combine harvester. Therefore, it is necessary to select an ideal damping material for the sensitive plate structure to enhance the performance of the monitoring system. The thickness of the damping material used in this study is 2 mm.

3.3.5.4 Attachment of sensors to the plates

To fix the sensors onto the plates, as shown in Figure 3.16, a 2 mm thick black rubber foam was used as an intermediary between the sensors and the double-sided tape. The rubber foam offers flexibility and improved deformation resistance, which is crucial when grains impact the surface of the sensors.

Once the sensors were securely attached to the black rubber foam, they were affixed to the surface of the stainless-steel plate using 1 mm thick double-sided tape with a soft texture.

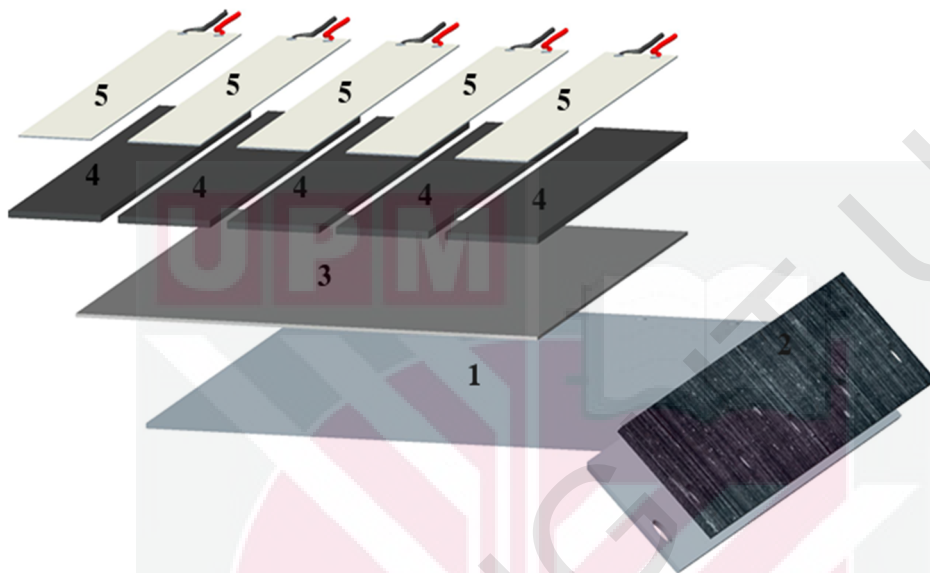


Figure 3.17: Illustration of sensors arrangement to the plate (1-stainless steel plate, 2- viscoelastic damping material, 3-double sided foam tape, 4-black rubber foam, 5-PVDF sensor)

This assembly resulted in the development of a sensitive plate for the grain loss monitoring system, as shown in Figure 3.17. To enhance the sensor accuracy, a 2 mm thick viscoelastic damping material was applied to the surface of the stainless-steel plate, which was mounted on the combine harvester. This strategic application effectively absorbed and reduced the machine vibration, which could potentially affect the precision of the sensor during operation.

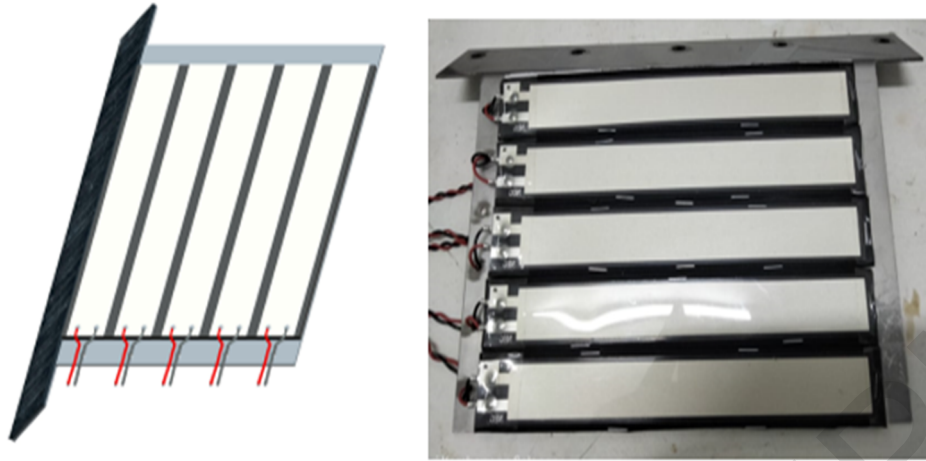


Figure 3.18: Illustration and pictorial view of the assembled sensitive plate

3.3.6 Design of grain loss monitoring circuit

The monitoring circuit was designed using Fritzing software Version 0.9.10 (Fritzing GmbH, Germany). The Fritzing software tool is an online circuit simulator and ultimate tool that can be used to create electronic circuits and component diagrams for use with rapid-prototyping development boards such as the open-source Arduino. The monitoring circuit comprises a charge amplifier module, microcontroller, LCD module, microSD card module, and sound buzzer module, as shown in Figure 3.18. This circuit was first developed to verify its operation using a single sensor and amplifier module. The single sensor circuit design with the real image of components used is presented in Appendix C1.

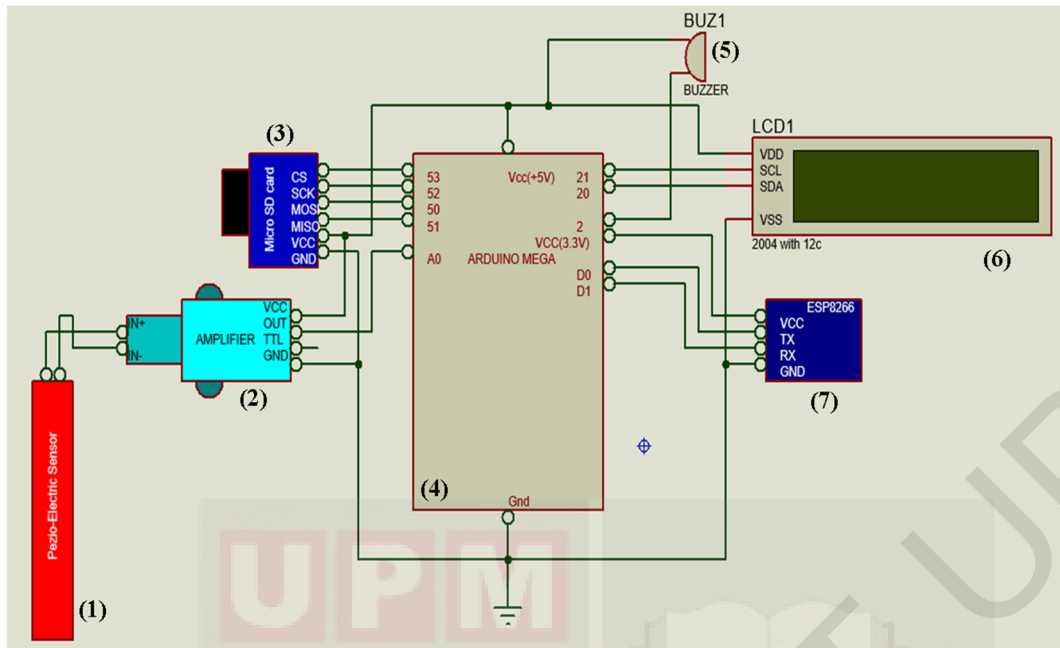


Figure 3.19: Single sensor circuit (1-PVDF sensor, 2-amplifier module, 3-microSD card module, 4-microcontroller module, 5-sound buzzer module, 6-LCD display module, 7-WiFi module)

After successful testing, the main grain loss monitoring circuit was developed, comprising 15 amplifier modules that accommodated 15 piezoelectric PVDF thin-film sensors, as shown in Figure 3.19. The charge amplifier converts the raw electrical signal generated from the piezoelectric PVDF sensors into a voltage reading, the microcontroller performs digital filtration of the sensor signals, processing, thresholding, and counting of the grain impact voltage detected from each sensor, as well as data transfer and communication. The LCD screen displayed the counted impact of grains detected from the sensors, while the SD card was used to record and save the grain loss data generated by the system for further analysis. The sound buzzer notifies the operators of grain loss from the system. The grain loss monitoring system design with complete components connection is given in Appendix C2.

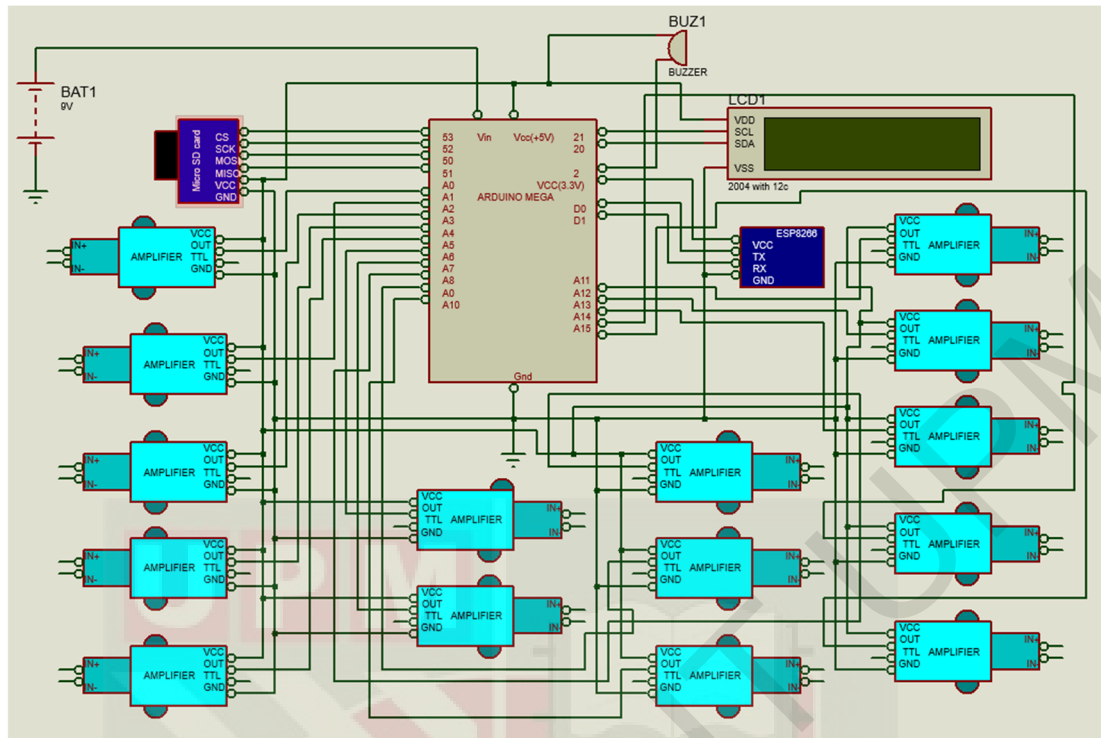


Figure 3.20: Integrated grain loss monitoring circuit design

3.3.7 Integration of the monitoring system

The monitoring system involves hardware integration which involves complete wiring of the monitoring circuit by connecting all component modules to the microcontroller on a circuit board, as shown in figure 3.20.

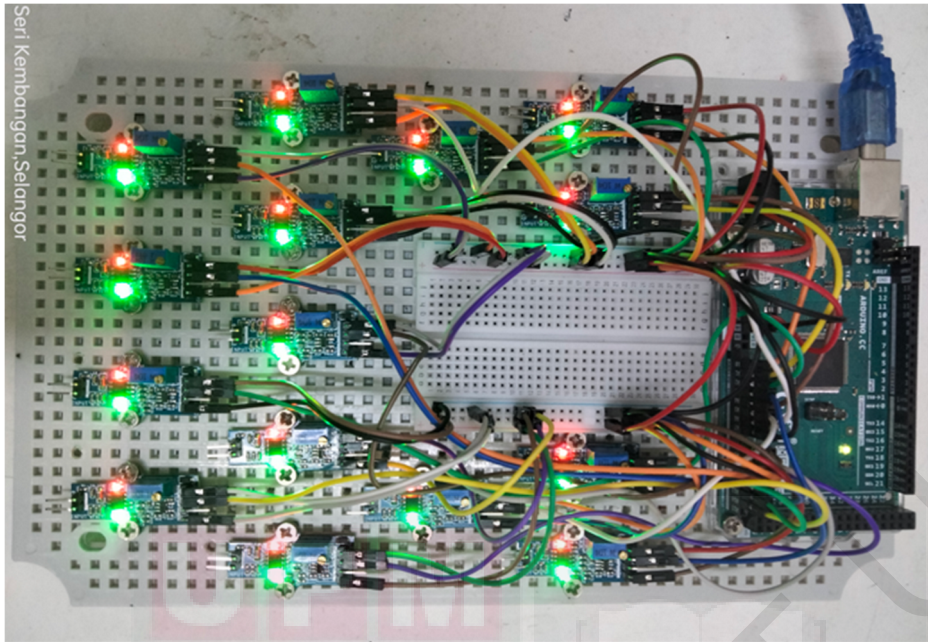


Figure 3.21: Assembled grain loss monitoring circuit

3.3.7.1 Sensors - amplifier module connection

Figure 3.21 shows the wiring integration of the piezoelectric PVDF sensor to the amplifier module. A piezoelectric charge amplifier module with a comparator was used as the charge amplifier. The amplifier was used to amplify and process electric signals generated by the piezoelectric sensor. It can convert a small electric charge due to vibration or impact into a measurable voltage signal (Emad, 2020). The module can also detect and process weak signals, allowing it to be used in conditioning monitoring and impact-detection systems. Therefore, it is important to develop a grain-loss monitoring system based on the function of the amplifier module. The sensor has two outputs (positive and negative), while the amplifier features two input pins (positive and negative). The positive and negative outputs are connected to the corresponding positive and negative inputs of the amplifier module, respectively.

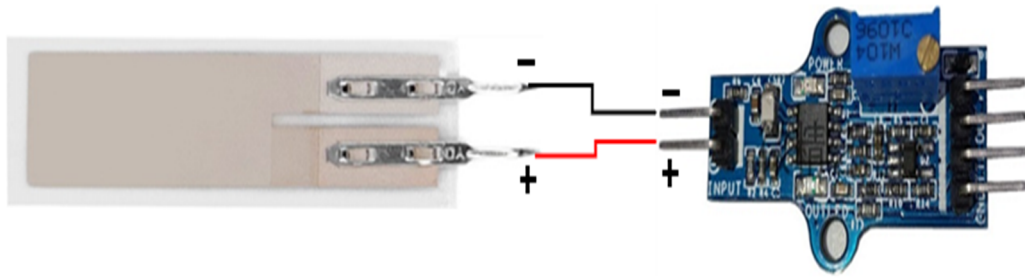


Figure 3.22: Integration of PVDF sensor and amplifier module

3.3.7.2 Amplifier module – microcontroller board connection

Figure 3.22 shows the wiring integration of the amplifier module to the microcontroller. The microcontroller used in this study is an Arduino Mega 2560, which serves as the central processor of the system and connects all the other component modules. The Arduino Mega is a microcontroller board that can be used for various projects that require more input and output pins, serial ports, or memory than the Arduino Uno. It is based on the ATmega2560 chip and has 54 digital input/output pins, 16 analog inputs (A0 – A15), 4 UARTs, a 16 MHz crystal oscillator, a USB connection, a power jack, an ICSP header, and a reset button. In this monitoring system, 15 analogue pins (A0 – A14) were used, because the system involved 15 sensors, each with a separate analogue pin. The amplifier features four output pins (VCC, GND, TTL, and a data pin). However, only three output pins were used in this circuit (VCC, GND, and data pin). The VCC stands for the Voltage Common Collector, which receives a positive power supply from the microcontroller; the GND stands for ground, which provides a common ground (zero voltage reference point) between a microcontroller and any module connected to it. The VCC and GND of the amplifier were connected to the VCC and GND of the

microcontroller, respectively, while the data pin was connected to the analogue pins of the microcontroller. The same connection was replicated for the 15 amplifiers.

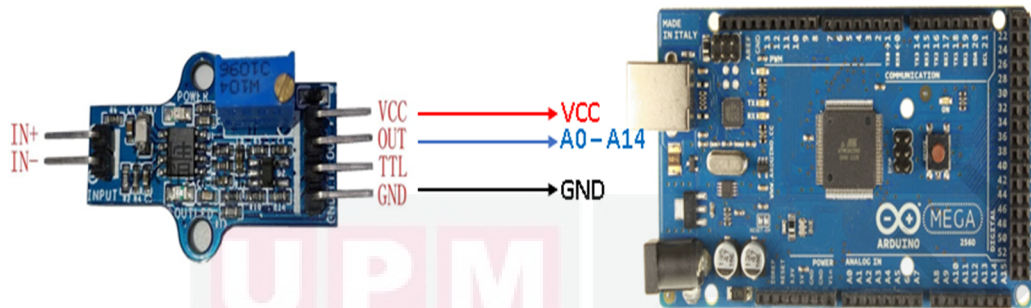


Figure 3.23: Integration of amplifier module and microcontroller board

3.3.7.3 LCD module – microcontroller board connection

Figure 3.23 shows the wiring of the LCD module to the Arduino Mega microcontroller board. The LCD module used in this study is a 20 × 4 module with an I2C interface. It is an alphanumeric liquid-crystal display (LCD) that can display up to 20 characters in each of its four rows. The LCD module was connected to the microcontroller by using four input pins (VCC, GND, SDA, and SCL). The VCC and GND of the LCD module are connected to the corresponding VCC and GND pins of the microcontroller. SDA represents the "Serial Data Line", which is used for data transfer between the microcontroller and the LCD module, while SCL represents the "Serial Clock Line", which is used for synchronizing the data transfer between the microcontroller and the LCD module. These pins are essential for connecting the I2C devices to the Arduino Mega. The SDA and SCL pins of the LCD module are connected to the SDA and SCL pins on the microcontroller.

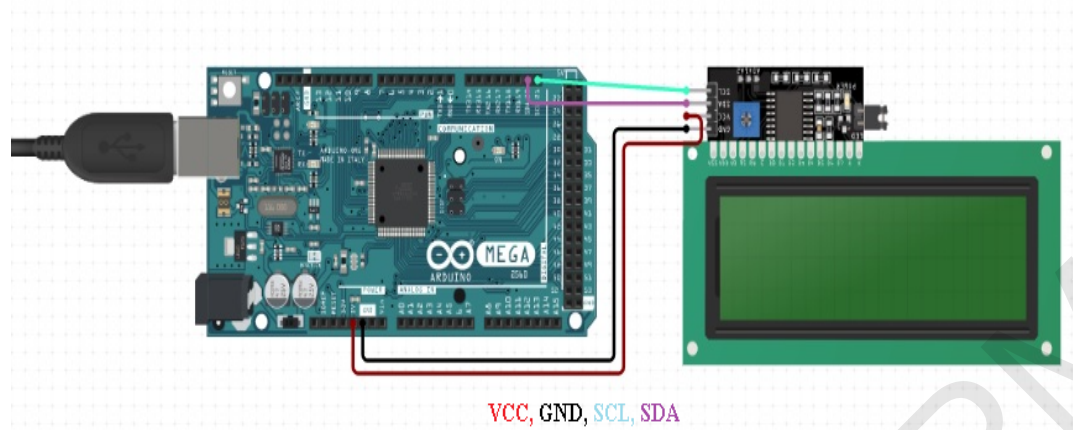


Figure 3.24: Integration of LCD display module and microcontroller board

3.3.7.4 MicroSD card module – microcontroller board connection

Figure 3.24 shows the wiring of the microSD card module to the Arduino mega microcontroller board. The microSD card module is connected to the microcontroller using six input pins (MISO, MOSI, SCK, SS, VCC, and GND). MISO, which stands for a master-in-slave-out, transmits data from the microSD card module to the microcontroller. The MOSI, which stands for master-out-slave-in, transmits data from the microcontroller to the microSD card module. SCK, which stands for Serial Clock, is a clock signal line that provides timing for data transmission between the microcontroller and the microSD card module. SS, which stands for Chip Select, is a control signal line that was used by the microcontroller to communicate with the microSD card module. Therefore, the MISO, MOSI, SCK, and SS pins of the microSD card module were connected to pins 50, 51, 52, and 53 of the microcontrollers, respectively. Additionally, the VCC and GND of the microSD card module were connected to the corresponding VCC and GND pins of the microcontroller.

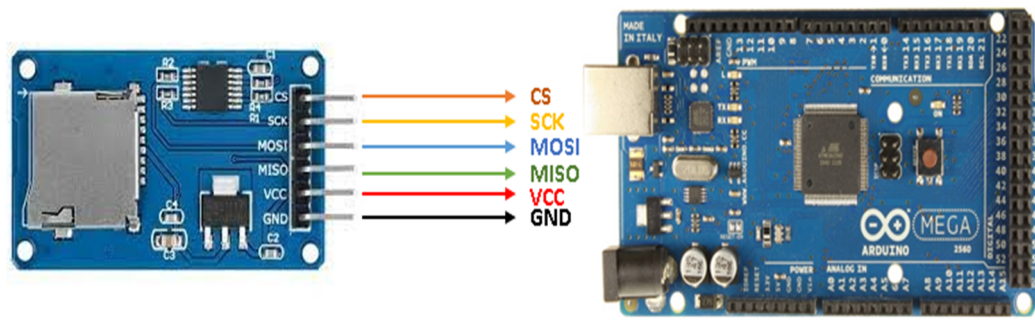


Figure 3.25: Integration of microSD card module and microcontroller board

3.3.7.5 Sound buzzer module – microcontroller board connection

Figure 3.25 shows the wiring of the buzzer module to the Arduino microcontroller board. The sound buzzer module is connected to the microcontroller using three input pins (VCC, GND, and D). The D pin on the sound buzzer module represents a digital pin that can be connected to any digital pin on the microcontroller. In this circuit, the digital pin is connected to digital pin 2 of the microcontroller, whereas the VCC and GND of the sound buzzer module are connected to the corresponding VCC and GND pins of the microcontroller.

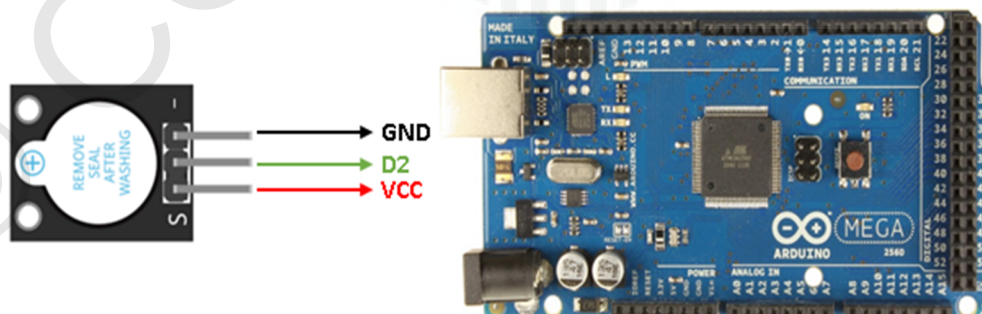


Figure 3.26: Integration of sound buzzer module and microcontroller board

3.3.7.6 WiFi module – microcontroller board connection

Figure 3.26 shows the wiring of the Wi-Fi module to the Arduino microcontroller board. The Wi-Fi module used in this circuit was an ESP8266 Wi-Fi module, which was connected to the microcontroller using four input pins: TX, RX, 3V3, and GND. The TX is a pin for serial data transmission, which sends data from the Wi-Fi module to the microcontroller. The RX is a pin for serial data reception that receives data from the microcontroller. 3V3 is a power supply pin that provides a regulated 3.3-volt power supply to the ESP8266 Wi-Fi module from the microcontroller. To connect the Wi-Fi module, the TX pin of the Wi-Fi module is connected to the RX pin of the microcontroller, whereas the RX pin of the Wi-Fi module is connected to the TX pin of the microcontroller. Additionally, the GND and 3V3 pins of the Wi-Fi module are connected to the GND and 3.3-volt pins of the microcontroller.

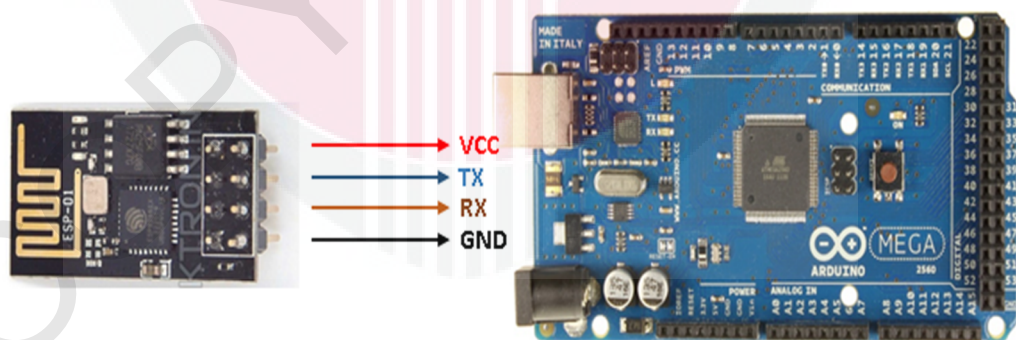


Figure 3.27: Integration of Wi-Fi module and microcontroller board

After effectively connecting all the components to the microcontroller and arranging them on the circuit board inside a circuit box, as shown in Figure 3.27, the circuit was powered by connecting it to a power source. This was

performed using a serial data transmission cable port on the microcontroller, which was connected to the USB port of the PC. This step was performed to verify the effectiveness of the connections and ensure that all the components received adequate power. The monitoring system was powered on the combine harvester using an auxiliary power outlet inside the operator's cabin, which is a de facto standard DC connector that provides electrical power to the portable devices.

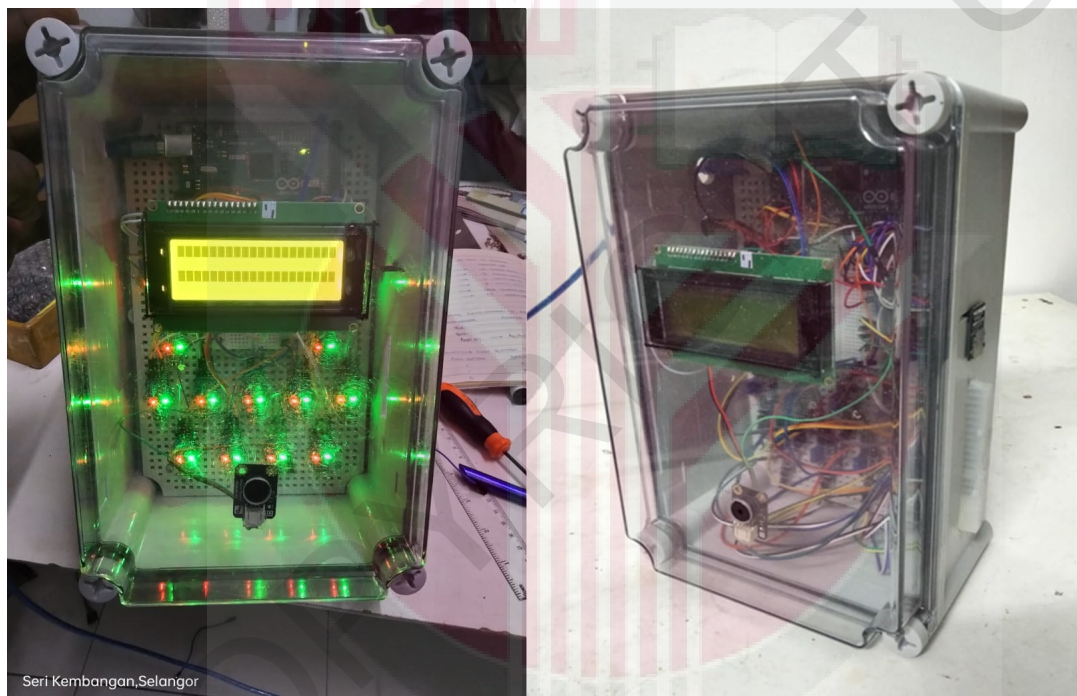


Figure 3.28: Completed monitoring system circuit box

3.3.8 Development of codes for the monitoring system

The codes for the grain loss monitoring system were written using the Arduino Integrated Development Environment (IDE), which is a suitable platform for code development and features various library modules for electronic system

development. The Arduino IDE interface in Appendix A displays a part of the grain loss monitoring code across the interface. This software allows users to write and upload code to Arduino boards and features a text editor with syntax highlighting, code completion, code navigation, and debugging capabilities. The code was written in the C++ programming language, which is compatible with various types of microcontroller boards. The process of determining grain loss using the monitoring system involved reading the raw sensor values when the grain impacts the surface of the sensitive plates, applying a high-pass filter for each sensor reading, converting the filtered sensor reading into voltage values, and applying grain impact detection logic for each voltage reading to detect the impact of grains from materials other than grains, sending a notification to the sound buzzer, counting the grain impact values, summing the counted grain impact values for each of the three sensitive plates, printing the grain impact values of each plate on the LCD screen, and saving the grain impact values counted on the microSD card.

The most significant components of the grain loss monitoring system include classifying the sensor readings, using thresholding logic to distinguish grains from other materials, and counting the number of grain impacts detected on sensitive plates using counting code. The coding for the individual steps mentioned above from reading the grain impact from the sensors to saving the grain impact counted from each sensitive plate are presented in Appendix B respectively.

In contrast to the existing systems that use filtering devices or complex mathematical formulas to filter sensor readings, this system employs digital high-pass filter coding as shown in Appendix B2, making it simple, effective, and advanced. Thresholding grain detection logic codes in Appendix B4 allow the system to distinguish grains from other materials by reading only the impact voltage of the grains. The counting codes in Appendix B5 count the number of grain impacts registered by the sensitive plates and present the results as the number of grains detected.

3.3.9 Calibration test of the grain loss monitoring system

The calibration of the grain-loss monitoring system is important to ensure its accuracy and reliability in detecting and measuring the impact of grain and non-grain materials. By conducting these calibrations, any potential system issues can be identified and resolved, resulting in precise and reliable data. The monitoring system was calibrated to determine the voltage impact of grains and non-grain materials to set a threshold for the monitoring system to record the impact of grains when various materials hit the surface of the sensitive plates. The experiment was conducted using a variable speed belt conveyor and an adjustable stand to install a sensitive plate, as reported by (Liang et al. (2016) and Xu et al. (2019)). The test was conducted under different conveyor speeds and drop heights of the materials from the conveyor. The specifications of the table-belt conveyor are listed in Table 3.9.

Table 3.9: Specifications of the table belt conveyor

Parameter	Specifications
Length	1000 mm
Height	820 mm
Width of the conveyor belt	200 mm
Prime mover details	Ele Delta Induction Motor
Speed range	0.76 – 2.60 m/s
Maximum Speed	1390 rpm
Speed gear reducer	1:10
Input	200-240 V, 50/60 Hz, 18.5 A
Output	0-230 V, 8.5 A
Frequency range	0-599 Hz
Power	0.75 kw (1 Hp)

3.3.9.1 Calibration experiment design

The experiment was designed using a central composite design (CCD) with two numerical factors. The numerical variables included the conveyor speed (m/s) and drop height of the materials from the conveyor (mm). The conveyor speed varied from 0.57 – 2.48 m/s and the drop height varied from 168.93 – 381.07 mm. Thirteen (13) experiments were conducted for each sample material at random, as listed in Table 3.10. The dependent variables were the impact voltages of the material samples (grain, short straw, long straw, grain and short straw, grain and long straw, and a mixture of grains, short straw, and long straw).

Table 3.10: Experimental design metrics of monitoring system calibration

Std	Run	Factor 1	Factor 2
		Conveyor Belt Speed (m/s)	Drop Height (mm)
7	1	1.53	168.93
5	2	0.57	275
12	3	1.53	275
6	4	2.48	275
13	5	1.53	275
9	6	1.53	275
1	7	0.85	200
4	8	2.2	350
2	9	2.2	200
8	10	1.53	381.07
11	11	1.53	275
10	12	1.53	275
3	13	0.85	350

3.3.9.2 Calibration test experiment procedure

The calibration experiment utilized six (6) categories of material samples, as shown in Figure 3.36, to set a voltage threshold value for the grain impact from non-grain materials on the sensitive plate. The material samples were as follows: full grains (1000 grains); 10 g short straws (30–90 mm straw length); 10 g long straws (100–300 mm straw length); a mixture of full grains and short straws; a mixture of full grains and long straws; and a mixture of full grains, short straws, and long straws, as reported by Liang et al., (2015) and Xu et al., (2019). The average weight of the thousand grains was 29.48 g at a moisture content of 19.67%.

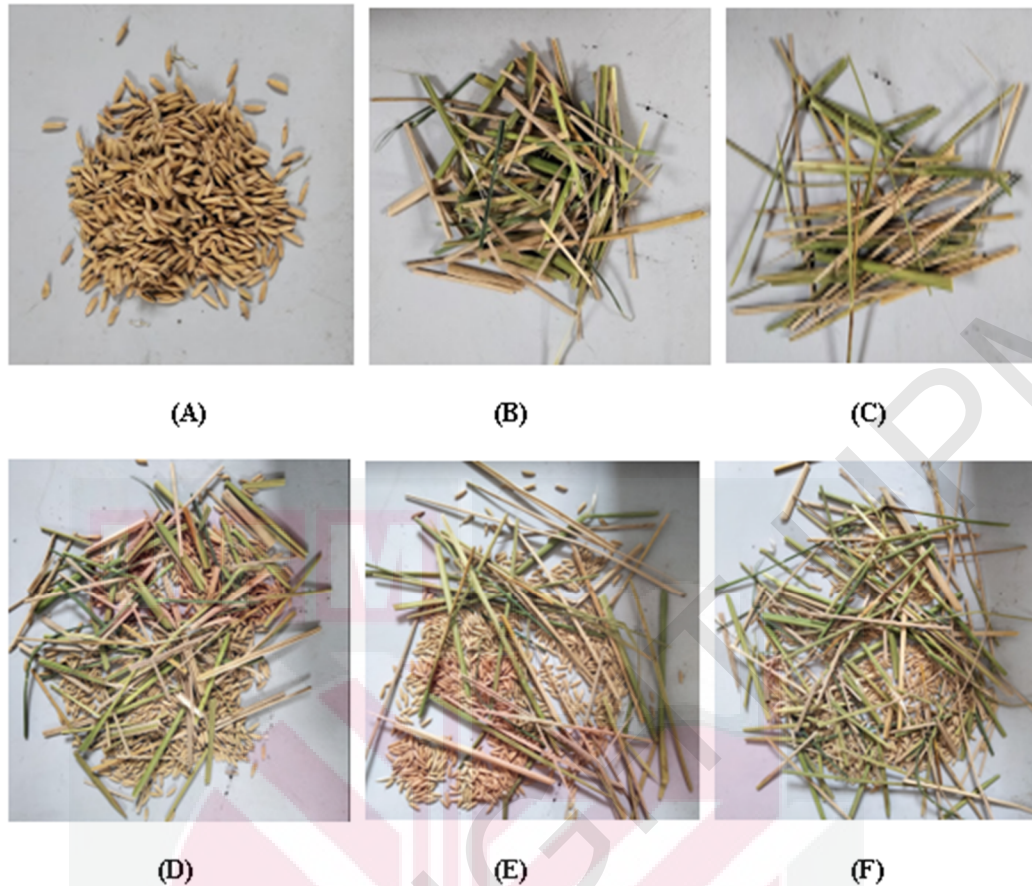


Figure 3.29: Calibration test material samples (A-Full grains, B-Short straws, C-Long straws, D-Full grains and short straws, E-Full grains and long straws, F-Full grains, short straws and long straws)

The sensitive plate was mounted on an adjustable stand at an angle of 45° , such that the materials dropped on the surface of the plate were subjected to gravity to avoid material accumulation, which could affect the performance of the system. After setting up the sensitive plate, the stand was positioned beside the conveyor belt where the material dropped from the conveyor hit the surface of the sensitive plate. A plastic container was placed on the ground between the conveyor and adjustable stand to collect the materials from the sensitive plate. The monitoring circuit was connected to the sensitive plate through a wire connection and the monitoring system was connected to a PC using a USB cable. An Arduino integrated development environment (IDE) was

launched on a PC using a serial monitor to record the impact voltage of the materials during the experiment. The experimental setup is illustrated in Figure 3.37.

The experiment was conducted 13 times for each material sample category, according to the design metrics. The material samples were placed on a conveyor belt, 1 m from the outlet of the conveyor, to test their impact on the surface of the sensitive plate by operating the conveyor at different speeds and setting the plate at different drop heights. The results of each run for the given categories of material samples were displayed on the LCD screen and recorded on an SD card on the monitoring system for further analysis.

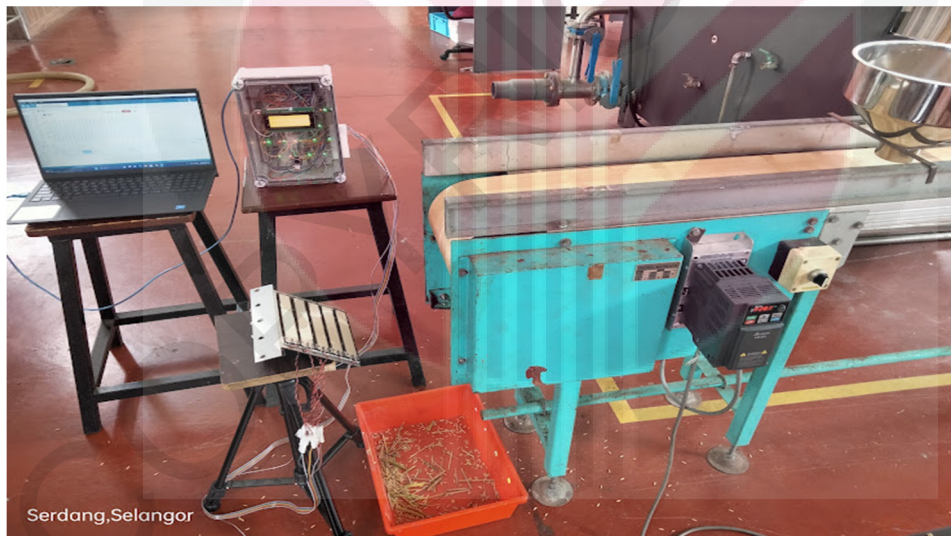


Figure 3.30: Experimental layout of grain impact calibration test

3.3.10 Field evaluation of grain loss monitoring system

Field evaluation of a grain loss monitoring system is crucial for assessing its accuracy and effectiveness under real conditions. It ensures the system can

reliably detect and measure grain loss during harvesting, thereby optimizing the combine harvester's performance. By providing real-time data, operators can adjust the machine's operational parameters to reduce grain loss and improve overall yield. Additionally, the field testing validates the system's functionality, contributing to the development of more efficient, cost-effective, and sustainable harvesting practices.

3.3.10.1 Installation of the grain loss monitoring system on combine harvester

The grain loss monitoring system comprised three sensitive plates and a monitoring circuit box. The monitoring circuit was equipped with an LCD screen, a sound buzzer, and a microSD for data display and recording. The sensitive plates were installed at the outlets of the separation and cleaning units of the combine harvester. The plates were set at 45 °according to the design and geometry of the machine outlet, such that the materials that touched the plates could easily go down to avoid accumulation on the surface of the sensitive plates. Bolts and nuts were used to mount the plates to the combine harvester with a 4 mm rubber washer to reduce the effect of vibration that can affect the performance of the system. The monitoring circuit box was placed in the operator's cabin of the combine harvester and linked to the sensitive plates using a connecting wire. The system was powered by an auxiliary power outlet inside the combined harvester. The installation of the system is illustrated in Figure 3.38.



Figure 3.31: Illustration of the grain loss monitoring system installation (A-Installed grain loss sensitive plates, B-Monitoring circuit box at operators' cabin)

3.3.10.2 Method of monitoring grain losses

Two measurement approaches using a grain loss monitoring system and the conventional method of measuring grain loss were simultaneously used to determine the grain loss: The grain loss data were used to determine the monitoring accuracy of the system.

In this process, the sensitive plates were installed behind the combine harvester at the separation/cleaning outlet, and a woven sack was placed at the rear of the combine harvester to collect the effluents from the machine, as shown in Figure 3.39. At the end of the swath distance, the combine harvester was stopped, and the sack was removed from the rear of the machine (Amponsah et al., 2017). The swath distance used in the study for each run

was 30 meters, and the width of the combine harvester header was used as the cutting width for each experimental run.



Figure 3.32: Experimental run for measuring grain loss

This operation was repeated according to the number of experiments obtained from the design metrics using different operational factors of the combine harvester. After the experiment was completed, the samples of the materials collected inside the woven sacks were separated to remove grains from the non-grain materials. The separation of grains from non-grain materials involves major and minor separations. Major separation was performed manually to remove large straws, while minor separation was carried-out using a grain cleaning and separation machine to separate the grains from the effluents, as shown in Figure 3.40.



Figure 3.33: Minor separation of grains from non-grain materials

For each run of the experiment, the grain loss detected by the sensitive plates was displayed on the LCD screen, recorded, and saved on an SD card in the monitoring circuit box, as shown in Figure 3.41. For the samples collected inside the woven sacks, the weight of the grains collected after separation was recorded as conventional grain loss.

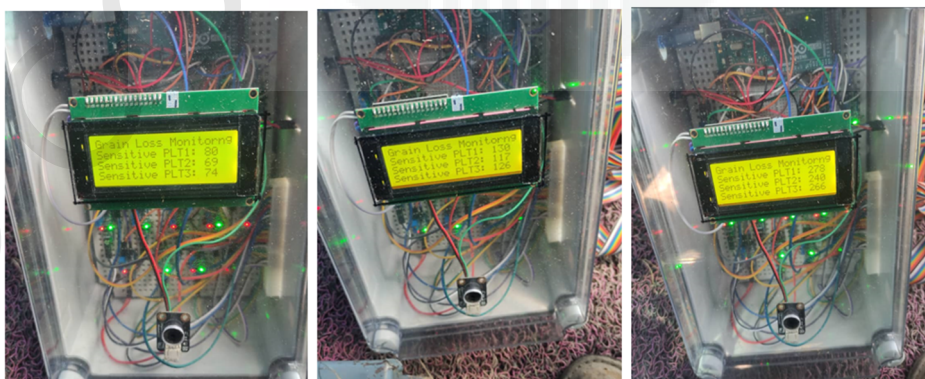


Figure 3.34: LCD screen displayed grain loss detected

3.3.10.3 Experimental design of field evaluation of grain loss monitoring system

The experiment was designed using a central composite design (CCD) with three numerical factors. The numerical variables included the combine harvester forward speed (km/h), header height (mm), and cleaning-fan speed. The forward speed varied from 1.76 to 2.26 km/h, header height varied from 200 to 350 mm, and cleaning fan speed varied from 1100 to 1500 rpm. Twenty experimental runs were conducted for the combination of combine harvester parameters, as listed in the design metrics in Table 3.11. The dependent variables were monitoring system grain loss, conventional grain loss, and monitoring accuracy.

Table 3.11: Design metrics of field evaluation of grain loss monitoring system

Std	Run	Factor 1	Factor 2	Factor 3
		A: Forward Speed (rpm)	B: Height of Header (mm)	C: Cleaning Fan Speed (rpm)
19	1	2.01	275	1300
8	2	2.26	350	1500
9	3	1.59	275	1300
14	4	2.01	275	1636
3	5	1.76	350	1100
7	6	1.76	350	1500
12	7	2.01	401	1300
17	8	2.01	275	1300
1	9	1.76	200	1100
15	10	2.01	275	1300
20	11	2.01	275	1300
2	12	2.26	200	1100
13	13	2.01	275	963
11	14	2.01	149	1300
4	15	2.26	350	1100
10	16	2.43	275	1300
6	17	2.26	200	1500
16	18	2.01	275	1300
18	19	2.01	275	1300
5	20	1.76	200	1500

3.3.10.4 Determination of percentage accuracy of the monitoring system

The accuracy of the grain loss monitoring system was determined using a standard relationship to calculate the percentage accuracy of the device or system, as given in equation (24-25). Accuracy measures the correctness of a system or process. The accuracy and error of a system are considered metrics for improving system performance (Deepthi et al., 2017).

$$\text{Percentage Error} = \frac{|\text{Conventional grain loss} - \text{Monitoring grain loss}|}{\text{Conventional grain loss}} \times 100 \quad (24)$$

$$\text{Percentage Monitoring accuracy} = 100 - \% \text{ Error} \quad (25)$$

3.3.10.5 Performance analysis of the monitoring system

Analysis of variance (ANOVA) was used to analyze the effect of the combine harvester operational parameters comprising forward speed (rpm), header height (mm), and cleaning fan speed (rpm) on the percentage accuracy of the grain-loss monitoring system. This was performed to determine the best combination of machine operational parameters with the highest monitoring accuracy. This provides a means to improve the accuracy of the system.

3.3.11 Prediction grain loss monitoring system output parameters using machine learning algorithm

Machine learning (ML) algorithms use datasets to learn patterns, correlations, and findings. Machine learning regression is a technique employed to determine a linear relationship between a dependent variable and multiple independent variables (Pejak et al., 2022). In this study, datasets were

obtained from the performance of a grain loss monitoring system using a medium-sized combine harvester. The monitoring system grain loss, conventional method grain loss, and monitoring accuracy of the system served as the output of the machine learning regression models, whereas the combine harvester operational factors, including forward speed, height of header, and cleaning fan speed, represented the input of the models.

3.3.11.1 Machine learning model selection

The selection of machine learning algorithms is based on the nature of the application and the accuracy of the prediction algorithm. According to Banu et al. (2023), it is important to evaluate and compare various options before selecting the best-fit model for a given dataset. In this study, four (4) machine learning regression models—linear regression (LR), support vector regression (SVR), random forest regression (RF), and decision tree regression (DT)—were tested and evaluated using a portion of the dataset. The models were compared to select the most effective prediction model for this dataset because of the advantages and disadvantages of machine learning algorithms, such as inaccessible data, data security, and implementation time when building a well-functioning predictive model (H. Khan et al., 2022).

The algorithms were implemented using the Scikit Learn Python library on the Jupyter Notebook interface. This library is widely used for implementing various artificial intelligence decision support systems. From the model training and testing performance, the two best-performing models using box and

whisker plot rankings were selected to predict the grain loss monitoring system performance parameters. The procedure for implementing the model selection is shown in Figure 3.41. The best-performing models obtained for this study were the random forest regression and decision tree regression algorithms.

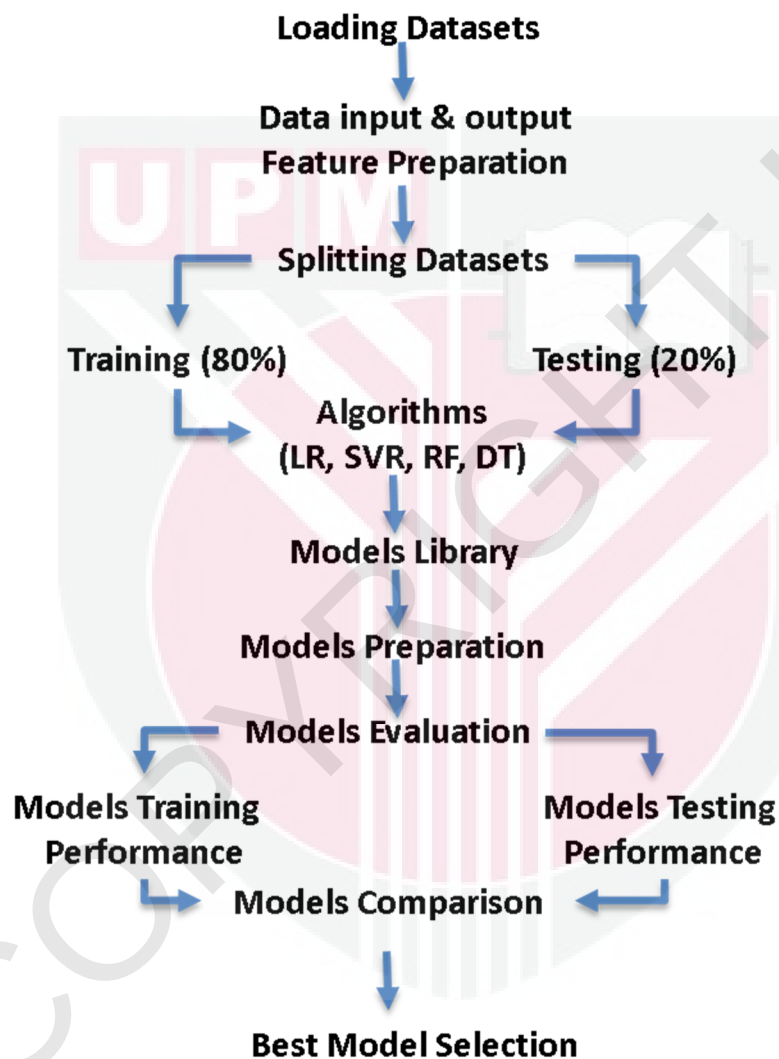


Figure 3.35: Flow chart for the selection of prediction algorithm

3.3.11.2 Implementation of decision tree and random forest prediction algorithms

The datasets in this study were prepared in Excel in the form of a CSV file format and uploaded to the Jupyter notebook Python interface for implementation of the algorithm prediction. The prediction of the algorithm was performed by separating the data into input and output sets using feature extraction, where the input data consisted of combine harvester speed, header height, and cleaning fan speed level, while the output data were the monitoring system grain loss, conventional method grain loss, and monitoring system accuracy. The datasets were further split into 80% and 20% for training and testing the algorithm, respectively. The model algorithms were then imported into the learning library. The DecisionTreeRegressor library was used for the decision tree algorithm with the following hyperparameters: max. depth = 5, sample split = 10, random state = 2. For the random forest algorithm, the RandomForestRegressor and GridSearch CV libraries were used with the following hyperparameters: n-estimators = 20, random state = 30, and max. depth = 10 and min-sample-split = 2-10. The hyperparameters were used to evaluate the model testing procedure by the hit and trial method using various levels of hyperparameters, based on which a combination of values was selected to provide the highest model prediction performance (Khan et al., 2022; Abbas et al., 2020).

3.3.11.3 Models' evaluation metrics

Statistical metrics used to assess the accuracy of the models in predicting values near the observed values were employed to evaluate the accuracy of the predictions generated by the DT and RF algorithms (Palanivel & Surianarayanan, 2019). These parameters include the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE), as presented in equations (20) – (22).

3.4 Summary of the chapter

This chapter begins by outlining the methods used to evaluate the performance of a medium-sized combine harvester during glutinous rice harvesting. Techniques for determining the combine harvester's performance parameters, energy utilization during harvesting, and grain loss measurements are presented. The grain loss data obtained from field evaluations was then used to develop prediction models through Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) for optimizing the operational parameters of the combine harvester.

Two optimization approaches, RSM-DF and ANN-GA, were employed in the study, and their results were compared to identify the optimal settings that minimize grain loss. A grain loss monitoring system was developed by designing three sensitive plates, selecting appropriate sensors and materials, conducting experimental modal analysis to determine the ideal plate thickness, and arranging sensors on the plates.

Concurrently, a monitoring circuit was developed by selecting components, integrating them onto a circuit board, and calibrating the system to distinguish grain impacts from non-grain materials. Code was written and uploaded to ensure the proper functionality of the monitoring system. Finally, the chapter presents the methodology for evaluating and assessing the effectiveness of the monitoring system under real harvesting conditions, and methods for predicting the system performance parameters using machine learning algorithms.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and discusses the performance evaluation results of the medium-sized combine harvester, time distribution during harvesting, energy utilization in harvesting glutinous rice, and grain loss prediction using Response Surface Methodology (RSM) and Artificial Neural Network (ANN) models. This chapter further discusses the results of the dynamic behavior of stainless-steel plates for selecting an optimum plate thickness for a grain loss monitoring system. This chapter also discusses the calibration of the monitoring system to determine the impact voltage of the grains for the thresholding process. Finally, the chapter discusses the results of the performance evaluation of the grain loss monitoring system installed on the medium-sized combine harvester and the prediction of the monitoring system performance responses using machine learning algorithms.

4.2 Performance evaluation of the medium-sized combine harvester

In this study, the comprehensive performance of a medium-sized combine harvester was evaluated to promote the efficient and effective harvesting of glutinous rice. The combine harvester was evaluated to determine the operational efficiency, productivity, and overall effectiveness of the machine in

glutinous rice harvesting. This enables farmers and machine operators to identify areas for improvement and make necessary adjustments to optimize the operational parameters of the machine to reduce losses and increase yields.

Table 4.1 presents the results of the performance of the medium-sized combine harvester over three plots in glutinous rice harvesting. The results show insignificant differences for each parameter at 5% significance level ($P \leq 0.05$) between the harvesting plots. In addition, there were no mechanical or technical problems during the machine operation.

Table 4.1: Performance evaluation results of the medium-sized combine harvester

Field Performance	Plot 1 (Mean $\pm$ SD)	Plot 2 (Mean $\pm$ SD)	Plot 3 (Mean $\pm$ SD)	Average (Mean $\pm$ SD)	P- Value
FS (km/h)	2.40 $\pm$ 0.41	2.38 $\pm$ 0.39	2.47 $\pm$ 0.43	2.42 $\pm$ 0.40	0.84
TFC (ha/h)	0.55 $\pm$ 0.09	0.57 $\pm$ 0.09	0.57 $\pm$ 0.10	0.56 $\pm$ 0.09	0.84
EFC (ha/h)	0.33 $\pm$ 0.04	0.33 $\pm$ 0.04	0.33 $\pm$ 0.04	0.33 $\pm$ 0.04	0.96
FE (%)	60.05 $\pm$ 2.44	60.30 $\pm$ 2.57	58.97 $\pm$ 3.90	59.77 $\pm$ 2.99	0.59
FC (l/ha)	15.61 $\pm$ 2.00	14 $\pm$ 1.63	14.28 $\pm$ 1.41	14.89 $\pm$ 1.68	0.69
GTC (kg/h)	1799.94 $\pm$ 30.25	1798.88 $\pm$ 35.40	1791.90 $\pm$ 40.35	1796.91 $\pm$ 35.33	0.75

P-values for experimental parameters at 95 % confidence level ($n = 10$). No significant differences were observed in the experimental parameters at 0.05.

4.2.1 Field speed and theoretical field capacity

Table 4.1 presents the average mean of FS and TFC of the medium-sized combine harvester were 2.42 km/h and 0.56 ha/h, respectively. Plot 3 shows a higher FS value of 2.47 km/h than plots 2 and 1, which has FS values of 2.38 and 2.40 km/h, respectively, indicating that plot 3 has 3.8 and 2.9% higher TFC than plots 2 and 1, respectively. The result of FS in this study is lower than the

results reported by Elsoragaby et al. (2019) and Hairie et al., (2020), but higher than the result reported by Amponsah et al. (2017). This finding is consistent with the moderate FS of 2.55 km/h reported by Masroon et al. (2020), who stated that when harvesting with a medium-sized combine harvester, a lower field speed should be used to avoid overloading the feeding rate, thereby reducing grain losses. Hamid et al. (2018) reported that a medium-size combine harvester operated at a higher FS of 4.3 km/h, lead to a lower yield, while a lower FS of 2.25 km/h led to a higher yield. Inappropriate FS has the potential to reduce grain yield due to unpredictable losses. This indicates that the FS obtained in this study is consistent with the findings of Hamid et al. (2018). Therefore, a moderate forward speed of the combine harvester can lead to a higher yield and minimum losses. The optimum field speed was evaluated based on the quantity of grain harvester and fuel consumed by the combine harvester with minimum grain loss.

4.2.2 Effective field capacity and field efficiency

The average mean EFC and FE for the medium-sized combine harvester in glutinous rice fields were 0.33 ha/h and 59.77%, respectively (Table 4.1). Plot 2 has an average FE value of 60.30%, which is higher than those of plots 1 and 3, with average FE values of 60.05 and 58.97%, respectively. This indicates that the FE difference between the three experimental plots was insignificant. The EFC and FE values in this study were higher than those reported by Masroon et al. (2020) and Hairie et al. (2020), but less than those reported by Elsoragaby et al. (2019). This indicated that the performance of

the medium-sized combine harvester investigated in this study was adequate to provide appropriate performance during the harvesting of glutinous rice with a higher yield. The operating distance covered by the machine during operation is a significant factor affecting the efficiency of the combine harvester performance. This study had a total working distance of 30 m, which was longer than the working distances of 20–25 m reported in previous studies (Amponsah et al., 2017; Elsoragaby et al., 2019; Hairie et al., 2020; Masroon et al., 2020). The efficiency results obtained in this study may be attributed to disparities in adjusting the operational parameters of the combine harvester between the plots and the swath covered by the machine. Such differences can lead to changes in the percentage of field efficiency, either by increasing or decreasing nonproductive time. Another contributing factor is the operator's proficiency in adjusting the operational settings of the combine harvester.

4.2.3 Fuel consumption

The results reported in Table 4.1 revealed that the average fuel consumption (FC) of the medium-sized combine harvester employed in a glutinous rice field was 14.89 l/ha. Specifically, Plot 1 had a higher FC value of 15.61 l/ha compared to Plot 2 and Plot 3, which had FC values of 14.78 l/ha and 14.28 l/ha, respectively. These results indicate that Plot 1 had 5.32% and 8.52% higher FC than Plots 2 and 3, respectively. Furthermore, Elsoragaby et al., (2019) and Masroon et al., (2020) obtained 18.46 l/ha and 37.25 l/ha for fuel consumption, respectively, which are 19.34% and 60% higher than the values obtained in this study. These findings demonstrate that the performance of the

medium-sized combine harvester for glutinous rice is adequate and cost effective for increasing glutinous rice production.

4.2.4 Grain throughput capacity

The average grain throughput of the combine harvester obtained in this study was 1796.91 kg/h at an effective machine operation of 0.33 ha/h (Table 4.1). The results showed an insignificant difference between the plots. This indicated that there was uniformity in the combine harvester performance among the three plots. The average speed at which the combine harvester operated was relatively effective. The goal was to optimize the operational factors of the combine harvester to achieve a higher grain yield while maintaining grain quality and minimum losses. Therefore, farmers and operators need to consider combine harvester settings, crop conditions, and operator proficiency to maximize grain throughput capacity.

4.2.5 Time distribution of medium-sized combine harvesting in a glutinous rice field

The field time distribution is a significant performance parameter for evaluating effective time utilization of a combine harvester in the field (Elsoragaby et al., 2019). This analysis is essential for improving operational efficiency and enhancing the machine's harvesting capacity under various conditions (Kataev et al., 2020). It ensures that the combine harvester operates optimally to minimize grain loss and provides data for efficient fuel consumption, contributing to the cost-effective utilization of the harvester.

The field time distribution for harvesting glutinous rice includes the effective harvesting time, turning/reverse time, and unloading time as presented in Table 4.2. The results showed insignificant differences at the 5% significance level ($P \leq 0.05$) between harvesting operations for each plot.

Table 4.2: Time distribution of the medium-sized combine harvester

Operation	Plot 1 (Mean $\pm$ SD)	Plot 2 (Mean $\pm$ SD)	Plot 3 (Mean $\pm$ SD)	Average (Mean $\pm$ SD)	P-Value
Effective Harvest (h/ha)	1.86 $\pm$ 0.10	1.89 $\pm$ 0.11	1.81 $\pm$ 0.13	1.85 $\pm$ 0.11	0.86
Turning-Reverse (h/ha)	0.41 $\pm$ 0.008	0.37 $\pm$ 0.001	0.37 $\pm$ 0.002	0.38 $\pm$ 0.004	0.25
Unloading (h/ha)	1.04 $\pm$ 0.004	1.04 $\pm$ 0.002	1.05 $\pm$ 0.001	1.05 $\pm$ 0.002	0.76
Total (h/ha)	3.31 $\pm$ 0.63	3.30 $\pm$ 0.66	3.23 $\pm$ 0.63	3.28 $\pm$ 0.64	0.96

P-values for experimental parameters at 95 a confidence level ($n = 10$). No significant differences were observed in the experimental parameters at 0.05.

4.2.5.1 Effective harvesting time

Table 4.2 shows 1.85 h/ha average effective harvesting time for glutinous rice using the medium-sized combine harvester. Plot 2 had a higher harvesting time value of 1.89 h/ha than plots 1 and 3, which have harvesting time values of 1.86 h/ha and 1.81 h/ha, respectively. The difference in time between the three plots was negligible, indicating that the effective harvesting time accounted for 56.40% of the total combine harvester operation time in the glutinous rice fields, as shown in Figure 4.1. According to Hairie et al. (2020) and Masroon et al. (2020), the harvesting time in glutinous rice fields was reported to be 2.68 h/ha and 2.14 h/ha, respectively, which were 30.97% and 13.55% higher than the harvesting time recorded in this study. Elsoragaby et al. (2019) obtained a harvesting time of 1.36 h/ha, which is 26.50% less than the time recorded in this study. These differences in harvesting time can be

attributed to the combine harvester specifications, terrain conditions, types and varieties of grain crops, and distance covered by the machine during operation.

4.2.5.2 Turning/reverse time

In a glutinous rice harvesting using the medium-sized combine harvester, the mean turning, and reversal time was found to be 0.38 h/ha as presented in Table 4.2. The overall findings show that Plot 1 had a higher turning/reverse time of 0.41 h/ha compared to Plots 2 and 3, which both had 0.37 hr/ha. The results of this experiment accounted for 11.59% of the total harvesting operation time, as shown in Figure 4.1. Hairie et al. (2020) reported a turning/reverse time of 0.50 h/ha, which represents 12.53% of the total harvesting operation time. In contrast, Elsoragaby et al. (2019) and Masroon et al. (2020) reported 0.26 h/ha and 0.17 h/ha, respectively, which accounted for only 5.98% and 8.95% of the total harvesting operation time. These findings indicate that the results of this study are reasonable compared to those of previous studies.

4.2.5.3 Unloading time

Table 4.2 and Figure 4.1, show the average unloading time of glutinous rice using a medium-sized combine harvester was 1.05 h/ha, which accounts for 32.01% of the total harvesting operation time. This is higher than the finding reported by Elsoragaby et al. (2019) who found that grain unloading accounted for 18.95% (0.36 h/ha) of total field time. In contrast, Masroon et al. (2020)

reported a grain unloading of 1.24 h/ha equivalent to 28.41% of the total field time. Hairie et al. (2020) reported that the time spent unloading grain using Kubota and WordStar medium-sized combine harvesters was 1.25 and 1.21 h/ha, respectively. The unloading time varies depending on the type of combine harvester, crop, and standard management practices. Inconsistent or inadequate farm machinery standard management practices during field operations may reduce total field time (Hairie et al., 2020). The results of this study indicate that the standard management procedures demonstrated were appropriate and consistent, as they resulted in lower unloading times than those reported by Masroon et al. (2020) and Hairie et al. (2020) but higher than the results reported by Elsoragaby et al. (2019).

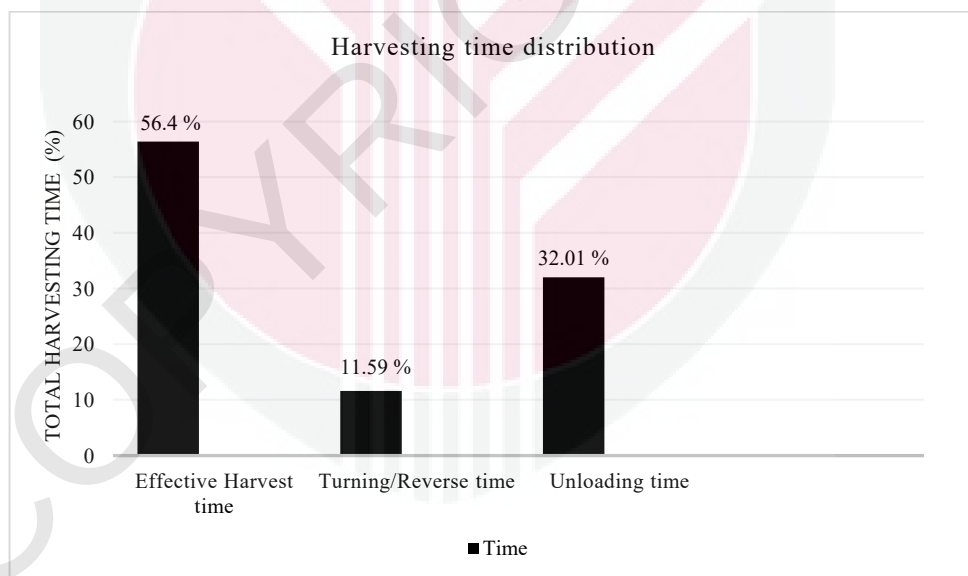


Figure 4.1: Harvesting time distribution in glutinous rice field

4.2.6 Energy Inputs for Harvesting Glutinous Rice

Monitoring and analyzing energy consumption is important during field harvesting operations. The operating cost of the combine harvester can be reduced by minimizing the energy losses during harvest. Table 4.3 shows the energy consumption of the three energy sources when harvesting glutinous rice using a medium-sized combine harvester. The results showed insignificant variation across the three plots.

Table 4.3: Energy input for harvesting glutinous rice field using medium-sized combine harvester

Energy Input	Plot 1 (Mean $\pm$ SD)	Plot 2 (Mean $\pm$ SD)	Plot 3 (Mean $\pm$ SD)	Average (Mean $\pm$ SD)	P- Value
ME (MJ/ha)	305.83 $\pm$ 40.96	307.45 $\pm$ 39.92	302 $\pm$ 44.05	305.34 $\pm$ 41.64	0.97
Fe (MJ/ha)	746.10	706	682.36	713.68	-
HE (MJ/ha)	3.64 $\pm$ 0.65	3.67 $\pm$ 0.60	3.54 $\pm$ 0.71	3.62 $\pm$ 0.65	0.9
TE (MJ/ha)	1055.57 $\pm$ 41.59	1017.73 $\pm$ 40.50	988.68 $\pm$ 44.73	1020.66 $\pm$ 42.27	0.006
MI	0.29	0.30	0.31	0.30	-

P-values for experimental parameters at 95 a confidence level (n = 10). No significant differences were observed in the experimental parameters at 0.05.

4.2.6.1 Machinery energy

Table 4.3 shows that the mean of machinery energy (ME) input in harvesting glutinous rice fields using a medium-sized combine harvester was 305.34 MJ/ha, which is equal to 29.73% of the total energy consumed during harvesting, as shown in Figure 4.2. The findings of this study are consistent with the 303.53 MJ/ha machinery energy input reported by Muazu et al. (2014). However, Elsoragaby et al. (2019) reported machinery energy of 275.65 MJ/ha for harvesting wetland rice using a mid-size combine harvester, which is equivalent to 26.14% of the total energy input during the harvesting operation. Masroon et al., (2020) also reported 24.77% machinery energy of the total

energy utilized in the harvesting operation. This study indicates a higher machinery energy input than previous studies due to differences in EFC, field and crop conditions, and operator expertise. Masroon et al., (2020) revealed that harvesting operations with lower EFC values use more machinery energy than those with higher EFC values.

4.2.6.2 Fuel energy

The fuel energy consumption (Fe) during harvesting of glutinous rice fields using a medium-sized combine harvester was determined to be 713.68 MJ/ha, as presented in Table 4.3. This represents 69.92% of the total energy utilized during operation, as shown in Figure 4.2. Masroon et al., (2020) recorded a fuel energy consumption of 1780.70 MJ/ha for harvesting wetland rice with a mid-size combine harvester, equivalent to 74.93% of the total energy input during harvesting. However, Elsoragaby et al. (2019) reported a fuel energy consumption of 882.39 MJ/ha, which accounted for 76.07% of the total energy input, while Muazu et al., (2014) reported a fuel energy of 853.54 MJ/ha, equivalent to 73.59% of the total energy utilized in harvesting wetland paddy. In this study, the fuel energy used by the medium-sized combine harvester was lower than that reported in previous studies, indicating that the fuel energy used was reasonable and cost-effective.

4.2.6.3 Human energy

The average value of human energy (HE) used in harvesting glutinous rice fields was 3.62 MJ/ha, which is equivalent to 0.35 % of the total energy

consumed during the harvesting operation, as shown in Figure 4.2. The percentage of human energy used in this study was consistent with the findings of Masroon et al. (2020). Elsoragaby et al., (2019) reported 0.23 % human energy of total energy input during harvesting, which is similar to the amount obtained by Muazu et al., (2014). The percentage of human energy in this study was higher than that in previous studies, which could be attributed to the harvested area and increased labour time per harvested area owing to the lower EFC.

4.2.6.4 Total energy

The average total energy (TE) consumed in harvesting glutinous rice using a medium-sized combine harvester was 1020.66 MJ/ha as presented in Table 4.3. Muazu et al., (2014) and Elsoragaby et al., (2019) reported a total energy input of 1159.77 MJ/ha and 1160 MJ/ha for harvesting wetland paddy using a medium-sized combine harvesters, the results are 12% greater than the total energy expended in this study. Compared to other type of crop, the total energy input for harvesting grain corn using a medium-sized combine harvester was recorded at 2376.96 MJ/ha by Masroon et al. (2020), which is 132.88% greater than the energy utilized in the present experiment. This study demonstrated a lower energy requirement for harvesting operations, which is suitable and cost-effective for boosting glutinous rice production in Malaysia.

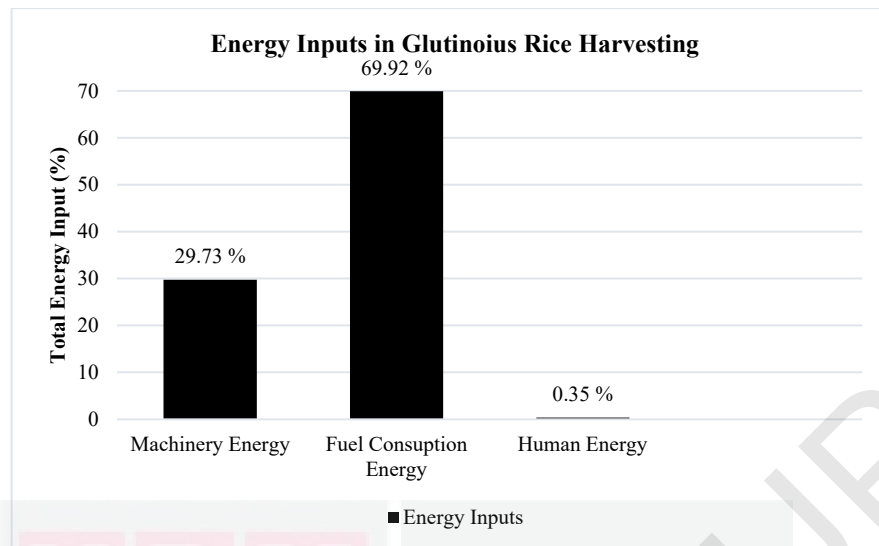


Figure 4.2: Percentage of Energy inputs in glutinous rice harvesting

The results presented in Table 4.4 compare the total energy utilization during harvesting by different types of combine harvesters used in various studies. The present study demonstrated the lowest energy utilization among the studies compared, indicating a more efficient use of energy in harvesting. This is significant as it suggests that the WORLD STAR combine harvester WS 7.0 Plus++ with a 2.36 m cutting width can achieve efficient performance with lower energy consumption compared to other models. The findings highlight the importance of choosing the right combine harvester model and configuration to optimize energy utilization during harvesting operations. Moreover, the results emphasize that factors such as cutting width, engine capacity, and machine design play a crucial role in determining the total energy consumed during harvesting activities.

Table 4.4: Comparison of total energy utilization during harvesting

Research conducted	Total energy utilized during harvesting (MJ/ha)	Type of combine harvester used
Present study	1020.66	WORLD STAR combine harvester WS 7.0 Plus++ (4G33-TC) with 2.36 m cutting width.
Machinery Utilization and Production Cost of Wetland, Direct Seeding Paddy Cultivation in Malaysia (Muazu et al., 2014).	1159.77	New Holland combine harvester 1545 Clayson with 4.27 cutting width
Comparative field performances between a conventional combine and mid-size combine in wetland rice cultivation (Elsoragaby et al., 2019).	1329.66	WORLD STAR combine harvester WS7.0 PLUS with 2.2m cutting width.
Performance of mid-size combine harvester of grain corn on the field efficiency and energy consumption at the northern Johor of Malaysia (Masroon et al., 2020).	2376.96	Kubota combine harvester DC 105X-V3800DI-TIE2-CT

4.2.7 Comparison of the key findings of the objective 1 and the previous studies

Table 4.5 below shows the comparison between the results of the field performance evaluation of the combine harvester used in this study and existing similar studies.

In summary, the present research recorded a field efficiency of 59.77%, which is below the 72% reported by Elsoragaby et al., (2019) but higher than the 34.97% achieved by Masroon et al., (2020). These differences might be due to field conditions, operator skills, and operational parameters utilized from the various studies. However, the results of the present study indicate that the combine harvester is relatively energy-efficient and there is a need for improvement in terms of field capacity and efficiency compared to other combine models. Overall, the findings highlight that the choice of the combine harvester model and its configuration significantly influence energy utilization, fuel consumption, and overall field performance.

Table 4.5: comparison between key results of objective 1 and previous studies

Objective	Present Research		Previous Research	
	To study the performance characteristics of the combine harvester and energy utilization in glutinous rice harvesting.	World Star WS 7.0Plus	Comparative performances between a conventional combine and mid-size combine in wetland rice cultivation.	Field performances and energy consumption for a typical mid-size combine harvester utilized for grain production under Malaysian farm conditions.
Type of combine harvester	World Star WS 7.0Plus	World Star WS 7.0Plus	World Star WS 7.0Plus	Kubota DC 105X
Key Findings				Kubota DC 105X
Theoretical Field Capacity (ha/h)	0.56	0.74	0.66	0.56
Effective Field Capacity (ha/h)	0.33	0.53	0.23	0.28
Field Efficiency (%)	59.77	72	34.97	50
Fuel Consumption	14.89	18.46	37.25	16.85
Grain Throughput Capacity (kg/h)	1760.91	—	—	—
Fuel Energy (MJ/ha)	713.68	882.39	1780.7	—
Machinery Energy (MJ/ha)	305.34	275.65	587.73	—
Human Energy (MJ/ha)	3.62	2.18	8.53	—
Total Energy (MJ/ha)	1020.66	1160	2376.96	—

Comparison of field performances between two typical mini combine harvesters in grain corn production.

4.3 Grain loss predictions

Grain loss prediction is crucial for optimizing the operational parameters of a combine harvester to provide an efficient and cost-effective utilization of the machine during harvesting. It provides farmers and operators with data-driven insights to make informed decisions to obtain optimum grain yield.

This study explored the potential of response surface methodology (RSM) and artificial neural networks (ANN) for predicting grain loss in medium-sized combine harvester operations in glutinous rice fields. To achieve this, the ability of the RSM to model the complex relationship between the various operating parameters of the combine harvester and grain loss was harnessed. In addition, the predictive capabilities of the ANN were used to determine nonlinearity within the datasets. By comparing the performances of these two methodologies, this study was able to investigate the relationship between the combine harvester operational variables and the predicted grain loss, thereby determining the accuracy and reliability of the resulting models. As a result, the findings of this innovative approach led to the optimization of combine harvester operations to minimize grain loss.

4.3.1 Statistical analysis and fitting of the RMS model

Response Surface Methodology (RSM) is a mathematical regression technique combined with statistical analysis that is used to display the analyzed data as plots and predict the correlations between dependent and

independent variables (Singh & Vinay, 2014; Homayoonfal et al., 2015; Gendy et al., 2020). In this study, experimental data obtained during glutinous rice harvesting using a medium-sized combine harvester with 30 runs of operation in three blocks of Central Composite Design (CCD) were analyzed using RSM in Design Expert Software version 13 by StatEase, Inc. Minneapolis, USA. The experimental and predicted results of grain loss along with their corresponding residual values are presented in Table 4.6. The coefficient of the polynomial model equation was computed from the experimental values to predict the values of response grain loss. The regression equation for the response variable prediction obtained from the RSM is shown in equation (4.1).

$$Y = -652.26 + 605.48A + 0.66B + 18.38C - 0.11D - 165.64A^2 - 0.0011B^2 - 10.79C^2 - 0.028D^2 - 0.06AB + 21.63AC + 0.36AD + 0.024BC - 0.0025BD + 0.055CD \quad (4.1)$$

Table 4.6: Experimental and RSM predicted responses for different combinations of experimental conditions

Run	A	B	C	D	Experimental Grain Loss (kg/ha)	RSM Predicted Grain Loss (kg/ha)	Residuals
1	2.26	350	1500	3	50.72	47.92	2.8
2	2.01	250	1300	4.5	69.57	67.27	2.29
3	1.76	350	1500	6	43.77	43.67	0.0966
4	2.26	150	1500	6	36.52	36.09	0.4348
5	2.26	150	1100	3	22.03	22.66	-0.628
6	1.76	150	1500	3	26.52	26.04	0.4831
7	1.76	350	1100	3	43.48	44.44	-0.9662
8	1.76	150	1100	6	31.88	35.22	-3.33
9	2.01	250	1300	4.5	67.1	67.27	-0.1691
10	2.26	350	1100	6	24.06	25.07	-1.01
11	1.76	150	1500	6	26.96	26.74	0.2186
12	2.26	350	1100	3	25.8	26.28	-0.4819
13	2.01	250	1300	4.5	67.83	67.59	0.2367
14	1.76	150	1100	3	33.48	35.48	-2
15	1.76	350	1500	3	44.93	45.1	-0.1679
16	1.76	350	1100	6	42.9	43.33	-0.4336
17	2.26	350	1100	6	49.42	47.68	1.74
18	2.01	250	1300	4.5	68.41	67.59	0.8164
19	2.26	150	1100	6	23.48	23.57	-0.0954
20	2.26	150	1500	3	35.65	35.48	0.1703
21	1.51	250	1300	4.5	35.36	32.71	2.66
22	2.01	250	1300	1.5	69.71	69.71	-0.0012
23	2.01	250	1300	4.5	68.84	69.71	-0.8647
24	2.51	250	1300	4.5	22.03	23.89	-1.86
25	1.51	250	1300	7.5	70	69.2	0.7959
26	2.01	250	900	4.5	24.06	19.98	4.08
27	2.01	250	1700	4.5	29.86	33.14	-3.29
28	2.01	450	1300	4.5	35.07	36.26	-1.18
29	2.01	50	1300	4.5	17.68	15.7	1.98
30	2.01	250	1300	4.5	67.39	69.71	-2.31

A: Forward speed (km/h); B: Header height (mm); C: Cleaning fan speed (rpm); D: Feed rate (kg/s)

The experimental response values were subjected to statistical analysis using the analysis of variance (ANOVA) presented in Table 4.7, to investigate the influence of combine harvester forward speed (A), header height (B), cleaning fan speed (C), and feed rate (D) on the prediction model. Statistical analyses were performed to evaluate the significance of the predictive model. The ANOVA revealed that the quadratic model for grain loss was highly significant ($P < 0.0001$), as indicated by the P-value and F-value of 100.92%. A high F-value of this amount could occur because of 0.01% noise.

The effects of various machine operational factors on grain loss in terms of the parameter's interactions are also presented in Table 4.7. The ANOVA results indicate that there is a direct relationship between grain loss and the linear and quadratic effects of the combine harvester forward speed, header height, and cleaning fan speed ($P < 0.0001$). Additionally, the interaction effects between these factors were significant for grain loss at $P < 0.05$ and $P < 0.0001$, respectively. However, the feed rate and its interactions had an insignificant effect on the grain loss.

Table 4.7: Analysis of variance of RSM model for grain loss prediction

Source of Variation	Sum of Squares	df	Mean Square	F-value	p-value
Block	35.02	2	17.51		
Model	9278.84	14	662.77	100.92	< 0.0001
A-CS	116.59	1	116.59	17.75	0.001
B-HH	633.8	1	633.8	96.51	< 0.0001
C-CFS	259.95	1	259.95	39.58	< 0.0001
D-FR	0.3859	1	0.3859	0.0588	0.8122
AB	35.74	1	35.74	5.44	0.0364
AC	467.88	1	467.88	71.24	< 0.0001
AD	0.2954	1	0.2954	0.045	0.8353
BC	89.43	1	89.43	13.62	0.0027
BD	2.21	1	2.21	0.336	0.572
CD	0.1063	1	0.1063	0.0162	0.9007
A ²	2939.21	1	2939.21	447.56	< 0.0001
B ²	3277.63	1	3277.63	499.09	< 0.0001
C ²	3191.3	1	3191.3	485.95	< 0.0001
D ²	0.1051	1	0.1051	0.016	0.9013
Residual	85.37	13	6.57		
Lack of Fit	81.12	10	8.11		
Pure Error	4.25	3	1.42	5.72	0.089
Cor Total	9399.23	29			
Std. Dev.	2.56				
	R²	Adjusted R²	Predicted R²	Adeq Precision	Mean
	0.9909	0.9811	0.9339	27.9957	42.48
					C.V. %
					6.03

The coefficient of variance (CV) was used to assess the degree of divergence between the experimental data and predicted values. A CV lower than 10% signifies high reliability, as reported by Rezaul et al., (2016). The CV value in the current study was 6.03%, indicating that the developed model for predicting the grain loss response was highly precise and reliable. To ensure adequate precision, an AP value greater than four is desirable and consistent for prediction models to describe the experimental process (Muhammad et al., 2021). Thus, as shown in Table 4.7, this study achieved a precision of 27.99, suggesting that the prediction model closely matches the operational parameters of the combine harvester, and can be effectively used to generate accurate results.

The coefficient of determination (R^2) is a statistical measure that evaluates the goodness of fit of the generated grain-loss model against the experimental data. An R^2 value close to 1 indicates that the model is well-suited to the data. Conversely, a lower R^2 value suggests that the response variables are inadequate for explaining the variation in performance (Myers et al., 2016). In this study, the grain-loss coefficient of determination (R^2) was 0.9909. Additionally, the corresponding adjusted R^2 value for the response is 0.9811. The difference between the predicted and adjusted R^2 values was less than 0.2, indicating that the two values were consistent, and there was a high correlation between the experimental and predicted values.

Therefore, the R^2 value in this study indicates that the quadratic polynomial model can adequately describe the influence of the forward speed (A), header

height (B), cleaning fan speed (C), and feed rate (D) of the combine harvester on the grain loss response. The insignificant lack of fit ($P>0.05$) presented in Table 4.7 for the operational factors of the combine harvester investigated in this study confirmed the goodness of fit of the RSM polynomial model relative to the pure error. This suggests that the model is satisfactorily accurate for predicting the response grain loss. A comparison of the experimental and predicted values for the grain loss response revealed that the polynomial regression model was appropriate for determining the optimal combination of the combine harvester operational parameters with minimum grain loss.

4.3.2 Effect of the combine harvester operational factors on grain loss

The grain loss rate during harvesting is a performance indicator that measures the number of grains lost in the field due to various factors including improper machine operation, and field and crop conditions. The optimal performance of the combine harvester is achieved when the grain loss is minimized, leading to increased machine output and enhanced profitability. According to (Bawatharani et al., 2014) it is vital to determine the effects of machine operational parameters to predict combine harvester performance and optimize operational factors.

Figure 4.3 - 4.5 presents the 3D response surface and contour plots generated from RSM analysis to visualize the effect of the input variables on grain loss. The use of response surface plots enables the determination of the optimal set of input variables that produces the maximum or minimum values of the

response variable (Muhammad et al., 2021). These plots depict the relationship between the operational parameters of the combine harvester and their impact on the grain loss. The contour plots in all plots in this study exhibit a well-defined elliptical shape, indicating perfect interaction between the combine harvester operational factors studied in this research.

4.3.2.1 Effects of the combine harvester forward speed and header height on grain loss

Figure 4.3 shows the effect of forward speed (km/h) and header height (mm) on grain loss (kg/ha). The figure presented 2D contour and 3D response surface plots to illustrate how these operational parameters influence grain loss during harvesting. According to the plots the contour lines represent different levels of grain loss. The closer the lines, the steeper the change in grain loss. The red portion indicates a higher grain loss while the green and yellow regions indicate lower grain loss.

At higher speeds and mid-level header heights, the grain loss was high while at lower speeds and higher/lower header heights (green/yellow), grain loss was minimized. The downward part of the surface plot shows the optimal range for minimizing grain loss when the combine harvester operates at a lower speed and specific header heights. However, the peak of the curve indicates higher grain loss at a particular combination of higher speed and mid-range header height. The grain loss ranges observed in the plots were 55 and 62 kg/ha. This study demonstrates that increasing forward speed and header height can lead to higher grain loss.

Therefore, operating the combine harvester at a higher speed and setting the header at inappropriate heights can increase grain loss. The combine harvester should be operated at a lower speed to minimize grain loss. Adjusting forward speed and header height within the optimal ranges can lead to more efficient harvesting and fewer losses. In summary, both parameters have a significant impact on grain loss, and optimizing these parameters can reduce grain during harvesting.

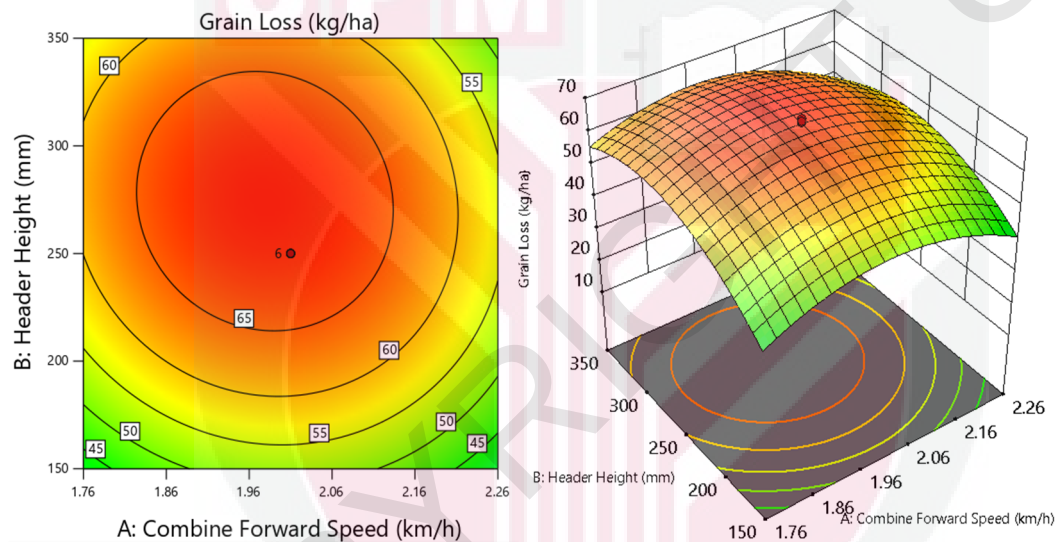


Figure 4.3: Effects of forward speed and height of header on grain loss

4.3.2.2 Effects of cleaning fan speed and forward speed on grain loss

Figure 4.4 illustrates the relationships between grain loss and two key variables (cleaning fan speed (rpm) and forward speed (km/h)) affecting a combine harvester performance in glutinous rice harvesting. The cleaning fan speed ranges from 1100 rpm to 1500 rpm while the forward speed ranges from 1.76 km/h to 2.26 km/h. The plots show grain loss increases as the cleaning

fan and forward speeds increase. Maximum grain loss occurs around a higher fan speed of 1400 to 1500 rpm and forward speed above 2.0 km/h (red area). However, a combination of a moderate fan speed of 1200 to 1300 rpm and a lower forward speed of less than 2.0 km/h results in lower grain loss (green and yellow region). To minimize grain loss, a combination of lower speeds in both variables seems to work better as represented by lower regions on the graph (green area).

A higher cleaning fan speed increases the air velocity for separating grains from non-grain materials, which can result in grain loss if not adequately controlled (Mirzazadeh et al., 2022). Conversely, a lower cleaning fan speed reduces grain loss but may result in impurities in the grain that negatively affect its quality (Singh & Vinay, 2014).

The numbers on the contour 40, 50, and 60 represent grain loss values in kg/h. The higher grain loss was concentrated in the central red area, while the green and yellow areas represent lower grain loss. In summary, the plots show that grain loss tends to increase with both higher cleaning fan speed and forward speed. Therefore, it is ideal to operate the combine harvester at moderate cleaning fan speed (1200 – 1300 rpm) and slower forward speeds (1.8 – 1.9 km/h).

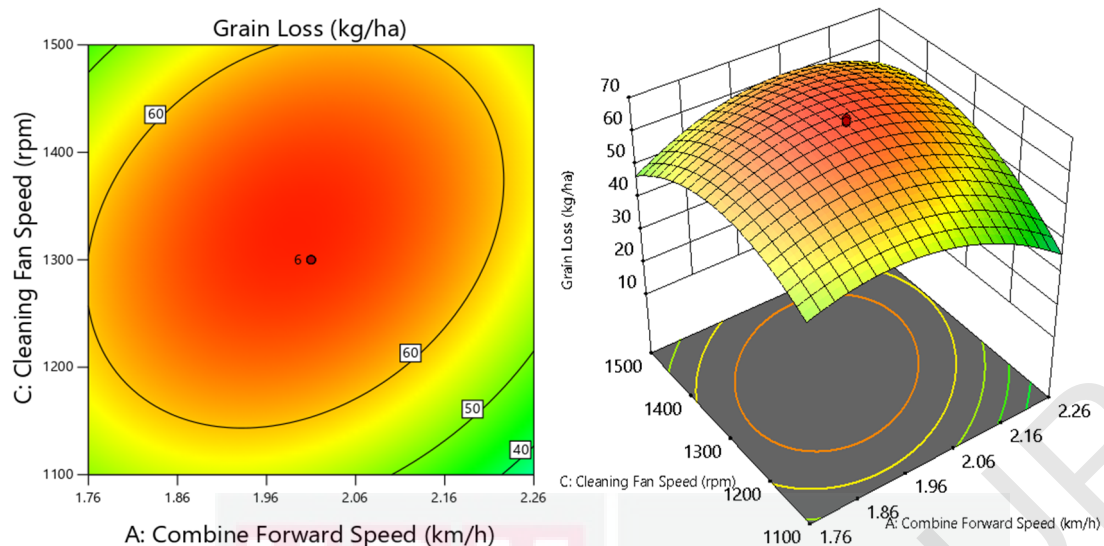


Figure 4.4: Effect of cleaning fan speed and forward speed on grain loss

4.3.2.3 Effects of header height and cleaning fan speed on grain loss

Figure 4.5 shows the effect of the cleaning fan speed and header height on the grain loss. The response surface for these variables exhibited an excellent circular contour, indicating a significant interaction between the operational parameters of the combine harvester.

The contour lines and the colour regions on the plots indicate levels of grain loss. The red zone shows a maximum grain loss of around 65 kg/ha while the green area shows a reduced grain loss of around 45 kg/ha. The closer the contours are to the red area, the higher the grain loss.

The header heights vary between 150 mm and 350 mm while the cleaning fan speed varies between 1100 to 1500 rpm. Higher fan speeds above 1400 rpm and lower header heights below 200 mm tend to increase grain loss. However,

lower fan speeds below 1300 rpm and higher header heights around 250 mm reduce grain loss. This demonstrates that adjusting header height and cleaning fan speed can optimize grain harvesting efficiency by minimizing grain loss.

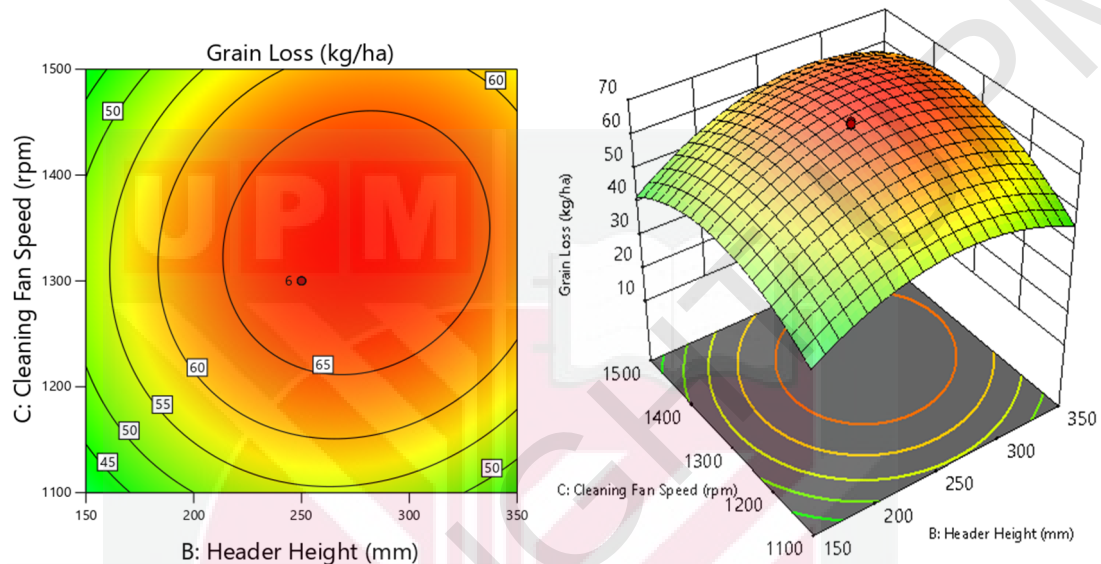


Figure 4.5: Effect of header height and cleaning fan speed on grain loss

4.3.3 Optimization of the combine harvester operational variables using RSM

To describe the effects of the combine harvester operational variables on the grain loss, a response surface graph was generated for three significant variables: forward speed, header height, and cleaning fan speed. These graphs were obtained by varying two input variables within the experimental ranges, while keeping the third variable at the centre point. The graph in Figure 4.3 was created by varying the forward speed and header height at a cleaning fan speed of 3. Similarly, Figure 4.4 was created by varying the forward speed and cleaning fan speed at a 250 mm header height while Figure 4.5 was

generated by varying the cleaning fan speed and header height at the central value of 2.01 km/h for the forward speed. These graphs illustrate the interactions between the input variables and provide a basis for optimizing the operational variables of the combine harvester to minimize the grain loss.

The quadratic model obtained in this study (equation 4.1) was used to optimize the operational conditions for the performance of the combine harvester. Numerical optimization of the operational factors was performed using a desirability function in Design Expert software to obtain the optimum solution. The goal criteria selected for the optimization were the target range for the combine harvester speed, height of the header, cleaning fan speed, and feed rate, whereas minimization was selected for grain loss. These criteria were selected because of the significant effects of the independent variables on the grain loss response obtained in this study. One hundred solutions were generated, each with a different combination of the input variables. The solution with the best desirability value for grain loss was identified as the optimized set of operational variables for the combine harvester.

Table 4.8 presents the optimal operating conditions for the medium-sized combine harvester along with the corresponding response variables obtained from the response surface method desirability function optimization (RSM-DF). The optimal conditions to achieve minimum grain loss were a forward speed of 2.26 km/h, header height of 150 mm, 1100 rpm cleaning fan speed, and feed rate of 3 kg/s. The predicted grain loss under these conditions was 23.58 kg/ha. The experimental value of grain loss under these conditions was 25.49

kg/ha, which was slightly higher than the predicted value. The difference between the predicted and experimental values is called the residual and can be used to validate and assess the accuracy of the RSM model. In this case, the residual was 1.91 kg/ha, which is relatively small. This suggests that the model is a good fit for the experimental data. Therefore, the results of this study can be used to guide combine harvester operators in optimizing machine settings to minimize grain loss. By minimizing grain loss, farmers can achieve the maximum grain output by utilizing a medium-sized combine harvester.

Table 4.8: RSM optimum conditions, predicted and experimental values of response

Optimum Conditions	Coded Levels	RSM Optimum Values
Forward Speed (km/h)	1.00	2.26
Height of Header (mm)	-1.00	150
Cleaning Fan Speed (rpm)	-1.00	1100
Feed Rate (kg/s)	-1.00	3
Response	RMS Predicted Value	Experimental Value
Grain Loss (kg/ha)	23.58	25.49 ± 2.56

4.3.4 Grain loss prediction using Artificial Neural Network

In this study, an artificial neural network (ANN) was employed to estimate grain loss in a medium-sized combine harvester based on four operational parameters that affect the performance of the machine. The experimental results and corresponding predicted values are presented in Table 4.9.

Table 4.9: Experimental and ANN predicted values of grain loss for different combinations of operation factors

Run	A	B	C	D	Experimental Grain Loss (kg/ha)	ANN Predicted Grain Loss (kg/ha)
1	2.26	350	1500	3	50.72	51.00
2	2.01	250	1300	4.5	69.57	68.45
3	1.76	350	1500	6	43.77	42.41
4	2.26	150	1300	6	36.52	35.65
5	2.26	150	1100	3	22.03	21.68
6	1.76	150	1500	3	26.52	29.05
7	1.76	350	1100	3	43.48	43.51
8	1.76	150	1100	6	31.88	32.48
9	2.01	250	1300	4.5	67.1	68.45
10	2.26	350	1100	6	24.06	41.83
11	1.76	150	1500	6	26.96	27.62
12	2.26	350	1100	3	25.8	26.48
13	2.01	250	1300	4.5	67.83	68.45
14	1.76	150	1100	3	33.48	33.83
15	1.76	350	1500	3	44.93	44.85
16	1.76	350	1100	6	42.9	44.08
17	2.26	350	1500	6	49.42	50.92
18	2.01	250	1300	4.5	68.41	68.45
19	2.26	150	1100	6	23.48	23.66
20	2.26	150	1500	3	35.65	34.28
21	1.51	250	1300	4.5	35.36	36.63
22	2.01	250	1300	1.5	69.71	69.5
23	2.01	250	1300	4.5	68.84	68.45
24	2.51	250	1300	4.5	22.03	17.95
25	2.01	250	1300	7.5	70	63.52
26	2.01	250	900	4.5	24.06	23.53
27	2.01	250	1700	4.5	29.86	28.03
28	2.01	450	1300	4.5	35.07	37.15
29	2.01	50	1300	4.5	17.68	18.73
30	2.01	250	1300	4.5	67.39	68.48

A: Forward speed (km/h); B: Header height (mm); C: Cleaning fan speed (rpm); D: Feed rate (kg/s)

Thirty (30) grain loss datasets obtained from glutinous rice harvesting operations, presented in Table 4.8, were utilized to predict grain loss using ANN. The model was trained using twenty-two (22) datasets, and the remaining eight (8) datasets were used for testing and validation. The performance of the model was evaluated using correlation coefficients (R-values) of 0.9982, 0.9733, and 0.9923 for training, testing, and validation, respectively (Figure 4.6). The fourth graph displays an R-value of 0.9786, which represents the overall performance of the model in predicting grain loss. The dashed line in each graph represents a perfect result, whereas the solid

line represents the best and optimal fits of the linear regression between the predicted and experimental data. The model performed well in predicting grain losses, as indicated by the correlation coefficients and good fit between the dashed and solid lines. Therefore, the developed ANN model was deemed reliable for predicting the outputs of the different sets of input values.

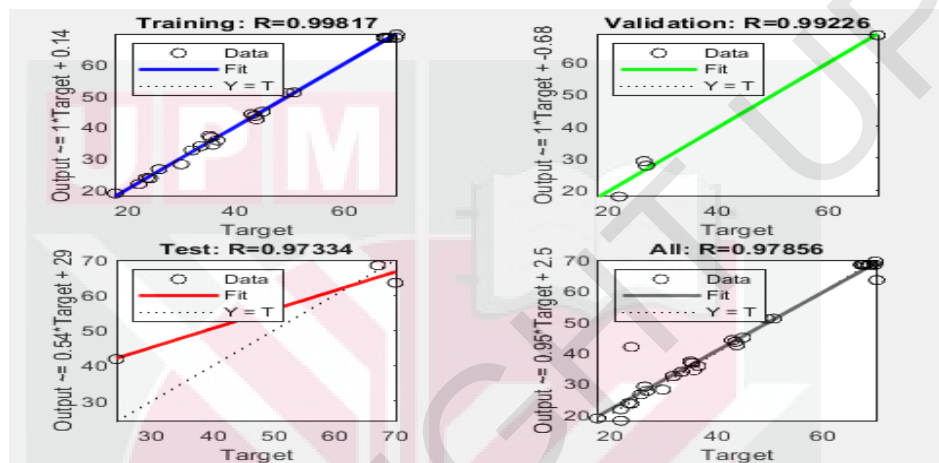


Figure 4.6: Neural network training, prediction, and validation results for grain loss prediction

Figure 4.7 depicts the distribution of errors between the experimental and predicted values after training the neural network. The plot is divided into training, validation, and testing error distributions. A noticeably narrow distribution of errors around zero indicates that the neural network provided accurate predictions (Ma et al., 2023). Both the training and validation error distributions in this plot exhibit a narrow distribution of errors around zero, indicating that the model is likely to produce reliable predictions. In addition, the large number of zero errors in the training and validation data suggests that the neural network can generate predictions for a considerable number of data points.

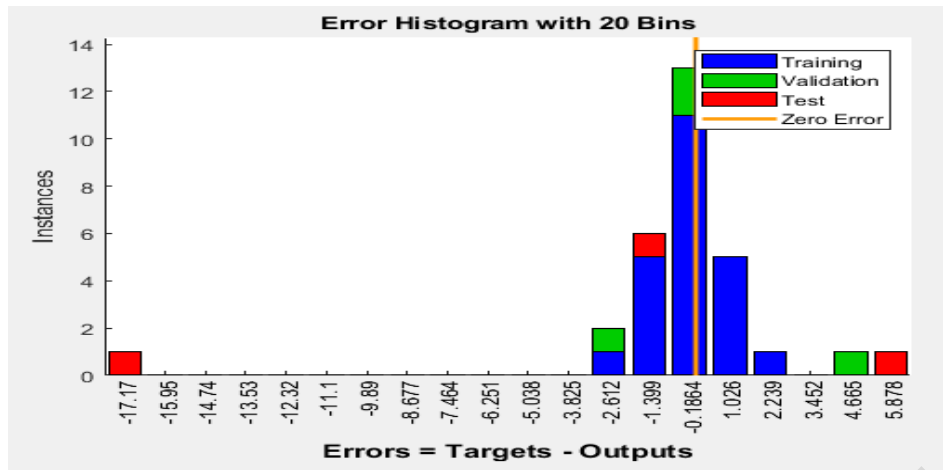


Figure 4.7: Error histogram of the grain loss prediction model

Figure 4.8 shows the performance validation index of the grain-loss prediction model at each epoch. An epoch is the unit of measurement of the number of times the entire training dataset passes through the neural network, whereas the validation performance is the accuracy of the neural network on a hold-out validation dataset (Ma et al., 2023). The graph shows that the best validation performance was achieved at epoch 5 with a mean squared error (MSE) of 5.9061. This implies that the neural network could make the most accurate predictions for the validation dataset. In addition, MSE decreased as the number of epochs increased, indicating that the neural network learned and improved as it was trained.



Figure 4.8: Performance index for the neural network grain loss prediction model

Figure 4.9 displays the training state of the model during the training phase and validation checks at each iteration. The validation check assessed the ability of the neural network to generalize new data. The graph shows that the gradient decreased, whereas mu increased as the number of iterations increased. This is a positive indication that the neural network converges to minimum loss. However, after epoch 9, the number of validation checks increases, suggesting that the neural network overfits the validation data. To avoid this, the number of training datasets can be increased, or a regularization technique can be employed to enhance the performance of the neural network.

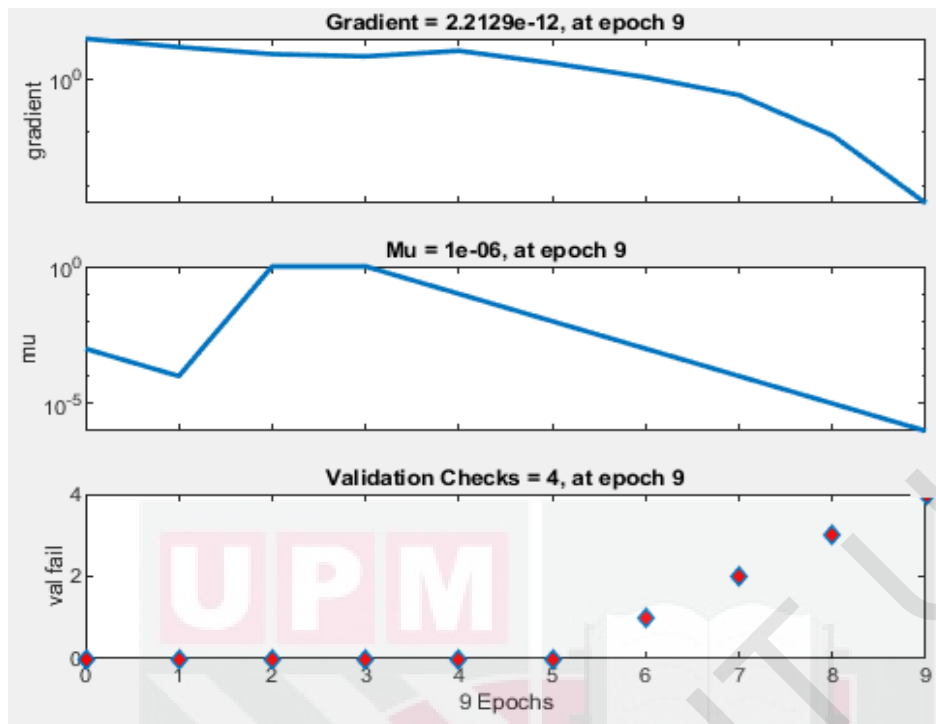


Figure 4.9: Training state of the model training phase for grain loss prediction

4.3.5 Optimization of the combine harvester operational parameters using ANN-GA

The purpose of this study is to utilize the results of artificial neural network (ANN) grain loss prediction to optimize the operational parameters of a combine harvester using genetic algorithms (GA). ANN and GA are important computational techniques that are capable of learning from nonlinear relationships and can be used to adjust the operational parameters of the combine harvester and predict their performance. These approaches provide a comprehensive search for optimal solutions that result in the minimum grain loss from multiple combinations of operational variables.

Based on the results of the genetic algorithm optimization, 63 iterations with different combinations of operational parameters for the combine harvester

and their corresponding grain losses were generated, as presented in the Appendix. The solution with the lowest grain loss was achieved at an optimum combine harvester speed of 2.26 km/h, header height of 252 mm, 1100 rpm cleaning fan speed, and feed rate of 3 kg/s, with a minimum grain loss of 14.70 kg/ha as shown in Table 4.10. The results show that the ANN-GA approach can accurately predict and optimize the operational parameters of the combined harvester, resulting in a significant reduction in grain loss. To minimize grain loss, it is important to operate the combine harvester at an appropriate speed while adjusting the header height to ensure proper cutting and feeding of the crop into the machine, considering the crop and field conditions.

Table 4.10: ANN optimum conditions with predicted value

Optimum Conditions	ANN Optimum Values
Combine Speed (km/h)	2.26
Height of Header (mm)	252
Cleaning Fan Speed (rpm)	1100
Feed Rate (kg/s)	3
Response	ANN Predicted Value
Grain Loss (kg/ha)	14.70

4.3.6 Performance comparison of RMS and ANN prediction models

Table 4.11 presents a comparison of the performance of the prediction models using statistical parameters, such as the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). The results indicated that the R^2 value for the RSM model was 0.9909, higher than 0.9892 for the ANN model. Additionally, the MAE and RMSE values for the RSM model were 1.2537 and 1.7291, respectively, lower than 1.6869 and 3.6794, for the

ANN model. However, the difference in performance metrics between the two models was relatively small, given that both models had R^2 values close to 1, which is one of the most important factors for determining the model accuracy. Therefore, both prediction models showed excellent performance in predicting grain loss.

Table 4.11: Performance results of the RSM and ANN grain loss prediction models

Performance Parameters	Prediction Models	
	RSM	ANN
R^2	0.9909	0.9892
MAE	1.2537	1.7291
RMSE	1.6869	3.6794
Grain Loss (kg/ha)	23.58	14.70

Figure 4.10 shows a comparative plot of the grain loss experimental results plotted against the RSM and ANN predicted results. The plots illustrate that both models exhibit an excellent linear relationship between experimental and predicted values.

According to Pai et al., (2020), the performance of a trained model depends on various parameters, including the number of experiments and the type of process involved in the experiment. RSM, being simpler, sometimes offers accurate predictions when the number of experiments is small, whereas ANN performs well, regardless of the size of the experimental dataset. Thus, the two models can estimate the optimal solution for predicting grain loss in a medium-sized combine harvester.

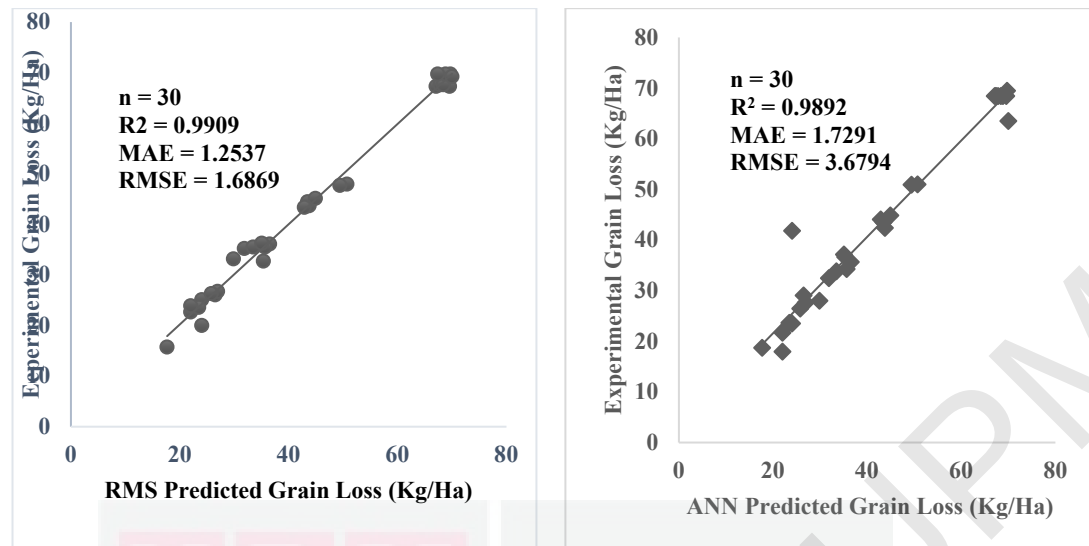


Figure 4.10: Plot of the experimental grain loss against RMS and ANN predicted values

Considering the optimum combine harvester operational parameters obtained from the two optimization methods, the ANN-GA optimization showed a lower grain loss of 14.70 kg/ha (Table 4.10) compared to the RSM-DF optimization of 23.58 kg/ha (Table 4.8), although the difference was relatively small. The difference might be due to the variation in the cutting heights from the optimum operational parameters of the two optimization approaches, with ANN-GA having a higher cutting height than RSM-DF, while the other parameters remain the same. However, both methods can be employed to enhance combine harvester performance, with the minimum amount of grain loss obtained from the two optimization processes being less than 3% of the total crop yield obtained from harvesting (Bhardwaj et al., 2021).

4.3.7 Comparison of the key findings of objective 2 and previous studies

Table 4.12 presents a comparison between the present research and the existing studies. The present research demonstrated a higher predictive accuracy ($R^2 = 0.9909$) with RSM-DF compared to the models used in previous studies. The optimization results show that RSM-DF and ANN-GA models can identify different operational configurations that minimize grain loss more effectively. Specifically, the ANN-GA model achieved a significantly lower minimum grain loss (14.70 kg/ha) compared to RSM-DF (23.58 kg/ha), highlighting the potential of hybrid machine learning models in enhancing combine harvester performance.

The differences in operational parameters utilized in the present research compared to previous studies had a significant impact on the model outcomes. By incorporating a comprehensive set of parameters that affect both intake and threshing/separation processes, the present study was able to achieve a more effective optimization of combine harvester performance, ultimately leading to reduced grain loss.

This study contributes to the existing body of research by providing a robust comparison of RSM and ANN models and showing that combining ANN with genetic algorithms (GA) can yield superior results for optimizing combine harvester settings.

Table 4.12: Comparison between key results of objective 2 and previous studies

Aspect	Present Research	Previous Studies	
		(Nadai, 2020)	(Gundoshmian et al., 2020)
Objective 2	To evaluate the predictive performance of response surface methodology and artificial neural network models in optimizing the combine harvester to minimize grain loss.	Performance Analysis of Combine Harvester using Hybrid Model of Artificial Neural Networks Particle Swarm Optimization.	Prediction of Combine Harvester Performance using Hybrid Machine Learning Modeling and Response Surface Methodology.
Methodology	This study utilized a randomized central composite block design to conduct the experiments using four combine harvester operational parameters which include forward speed, header height, cleaning fan speed, and federate. This study also used RSM and ANN to predict grain loss which provides a basis for optimizing the combine harvester operational parameters using RSM-DF and ANN-GA.	The study utilized a John Deere 1055 Combine Harvester and conducted a factorial experiment to evaluate the effects of operational parameters, such as drum-to-concave distance, fan speed, and sieve opening, on the performance metrics: broken seeds, product loss, and material other than grain. The combine harvester's performance was modeled using an artificial neural network, and the operational settings were optimized with particle swarm optimization (ANN-PSO).	The study used an artificial neural network (ANN) to predict combine harvester performance and applied root mean square (RMS) modeling to optimize the operational parameters. Three key variables—threshing drum and concave distance, fan speed, and sieve opening—were evaluated to minimize product loss, broken seeds, and material other than grain.
Key findings	RSM Model: $R^2 = 0.9909$, $MAE = 1.25$, and $RMSE = 1.69$. The optimal conditions obtained from the RSM-DF model for forward speed, header height, cleaning fan speed, and feeding rate were 2.26 km/h, 150 mm, 1100 rpm, and 3 kg/s, respectively, resulting in a minimum grain loss of 23.58 kg/ha. For the ANN-GA model, the optimal conditions were 2.26 km/h, 252 mm, 1100 rpm, and 3 kg/s, with a minimum grain loss of 14.70 kg/ha.	The ANN-PSO model, with a maximum of 221 iterations and a swarm size of 300, yielded RMSE values of 0.05239, 6.7338, and 0.2059 for BS, PL, and MOG, respectively. The corresponding R^2 values were 0.97, 0.98, and 0.993 for BS, PL, and MOG. The ANN model alone achieved R^2 values of 0.955, 0.899, and 0.73 for BS, PL, and MOG, with RMSE values of 0.06754, 12.1838, and 0.6718, respectively.	R^2 values of 0.9841, 0.9, and 0.87 for BS, MOG, and PL were obtained to model the process. The optimal conditions for the drum-to-concave distance, fan speed, and sieve opening were 7.35 mm, 598.1 rpm, and 16.82 mm, respectively, resulting in minimum values of 0.66, 18.25, and 1.37 for BS, MOG, and PL, respectively.

4.4 Results of experimental modal analysis of sensitive plate for grain loss monitoring system

The first ten (10) natural frequencies (NF) and damping ratios (DR) obtained from the modal experiment on the four stainless steel plate thicknesses, as presented in Table 4.13, were used to evaluate the plate thicknesses.

Table 4.13: Experimental modal analysis data outcome

N	Plate 1 mm		Plate 1.5 mm		Plate 2 mm		Plate 2.5 mm	
	NF (Hz)	DR (%)	NF (Hz)	DR (%)	NF (Hz)	DR (%)	NF (Hz)	DR (%)
1	23.20	21.50	72.10	10	24.30	5.94	24.10	8.06
2	39.30	15.30	133	6.42	33.20	5.11	41.70	2.58
3	37.20	5.29	191	3.44	58.30	10.3	41	3.63
4	74.80	2.12	206	2.37	86.70	0.04	196	0.51
5	121	3.52	245	1.01	90.30	0.008	24.10	8.06
6	128	0.21	296	2.33	115	6.64	41.70	2.58
7	145	0.60	341	3.42	125	0.55	41	3.63
8	169	2.32	406	1.72	131	1.02	196	0.51
9	231	1.18	442	1.98	138	1.16	24.10	8.06
10	250	4.56	469	1.57	238	0.96	41.70	2.58

N = number of impacts, NF = natural frequency, DR = damping ratio

Table 4.14 presents the results of the polynomial model fitting of the four stainless-steel plate thicknesses. The fitted polynomial model equation shown in Table 4.12, outlines how the model describes the performance of the plate's natural frequency and damping ratio in the experimental modal analysis. A higher y value indicates a better performance when comparing different parameters in a dataset, whereas a lower y value indicates a poor performance. To obtain an ideal plate thickness for a grain-loss monitoring system, a higher natural frequency and damping ratio are required. From the polynomial model equation in Table 4.14, it can be observed that when the predictors (X1 and X2) are constant, a 1.5 mm plate thickness has a better baseline for the intercept, indicating the best model fitting that minimizes the

difference between the predicted model and actual observed values. However, in the case of the damping ratio, the 1 mm plate thickness has a higher intercept value than the 1.5 mm plate thickness, but the difference is insignificant. This suggests that the thicknesses of the two plates are the most significant.



Table 4.14: Polynomial Model Fit Statistical Analysis of the plate natural frequency and damping ratio

Equation Plot	y = Intercept + B1*x^1 + B2*x^2									
	Plate 1 NF (Hz)	Plate 1.5 NF (Hz)	Plate 2 NF(Hz)	Plate 2.5 NF (Hz)	Plate1 Damping (%)	Plate1.5 Damping (%)	Plate 2 Damping (%)	Plate 2.5 Damping (%)		
Intercept	6.38 ± 16.07	37.46 ± 15.92	21.20 ± 26.41	-2.02 ± 86.80	28.01 ± 2.46	11.32 ± 1.55	8.05 ± 3.87	6.94 ± 3.81		
B1	12.56 ± 6.71	44.26 ± 6.65	7.88 ± 11.03	30.73 ± 36.25	-8.27 ± 1.03	-2.77 ± 0.65	-1.27 ± 1.62	-1.22 ± 1.59		
B2	1.20 ± 0.59	-0.02 ± 0.59	1.03 ± 0.98	-2.59 ± 3.21	0.60 ± 0.091	0.19 ± 0.057	0.054 ± 0.14	0.10 ± 0.14		
Residual Sum of Squares	1307.35	1282.56	3529.07	38123.78	30.66	12.2	75.86	73.45		
R ² (COD)	0.98	0.99	0.90	0.09	0.93	0.82	0.34	0.08		
Adj. R ²	0.97	0.99	0.87	-0.16	0.91	0.77	0.15	-0.18		
F-Value	149.26	436.6	30.56	0.36	47.74	16.23	1.79	0.32		
P-Value	<0.0001	<0.0001	0.00035	0.71	<0.0001	0.0024	0.24	0.74		

The coefficient of determination (R^2), F-value, and P-value were used to evaluate the performance of the plates based on the dataset using a statistical analysis. The R^2 measures the adequacy and goodness of fit of the model, which indicates that the model explains the variation in the plate parameters. An R^2 value closer to 1 indicated an excellent fit. The F-value evaluates the overall significance of the polynomial model, with higher F-values indicating the effectiveness of comparative data. P-values facilitate the determination of the statistical significance of the data.

Table 4.14 presents the performance results of the four stainless-steel plate thicknesses. The results of the natural frequencies of the four plate thicknesses show R^2 values of 0.98, 0.99, 0.90, and 0.09, for plate thicknesses of 1, 1.5, 2-, and 2.5-mm plate thicknesses, respectively. The 1.5 mm plate thickness demonstrated the highest R^2 value, indicating better performance than the other plate thicknesses. The residual sum of squares for the 1.5 mm plate was the lowest, indicating a better fit to the model. The F-value of 436.60 obtained for the 1.5 mm plate was also higher than the other plate thicknesses. In terms of P-values, the 1, 1.5, and 2-mm plate thicknesses were found to be highly significant, while the 2.5 mm plate was not significant. These results suggest that a 1.5 mm plate thickness exhibits better performance in the model analysis based on the natural frequency.

The R^2 values for the damping ratio of the four plate thicknesses were 0.93, 0.82, 0.34, and 0.08, with the 1 mm plate thickness having the highest value. However, in terms of the residual sum of squares 1.5 mm plate had the lowest

value compared with the other plate thicknesses. Furthermore, the 1 mm plate thickness has the highest F-value as well, followed by a 1.5 mm plate thickness, whereas the 2 mm and 2.5 mm plate thicknesses have relatively low F-values. Compared with plate thicknesses of 2 mm and 2.5 mm, the P-values of the 1 mm and 1.5 mm plates were significantly higher.

The results of the Bode graphs in Figure (4.11 - 4.14) are presented in Table 4.15. The values of the phase responses of the plate thickness 1.0 mm, 1.5 mm, 2.0 mm, and 2.5 mm were 55 °, 55 °, 58 °, and 37 °, respectively. This indicates that the plate thickness of 2.0 mm had the highest phase response. However, plate thickness 1.5 mm has the maximum and rapid frequency response of 1200 Hz compared to 500 Hz, and 260 Hz for plates 1.0 and 2.0 mm respectively as shown in the graphs, indicating excellent vibration and noise-resistant capabilities.

Table 4.15: Frequency response performance of the plates

Plots	Bandwidth	Phase Response (degrees)	Ability to withstand high vibration and noise
Plate 1.0 mm	Narrow	53	Good
Plate 1.5 mm	Very narrow	55	Excellent
Plate 2.0 mm	Narrow	58	Good
Plate 2.5 mm	Wide	37	Poor

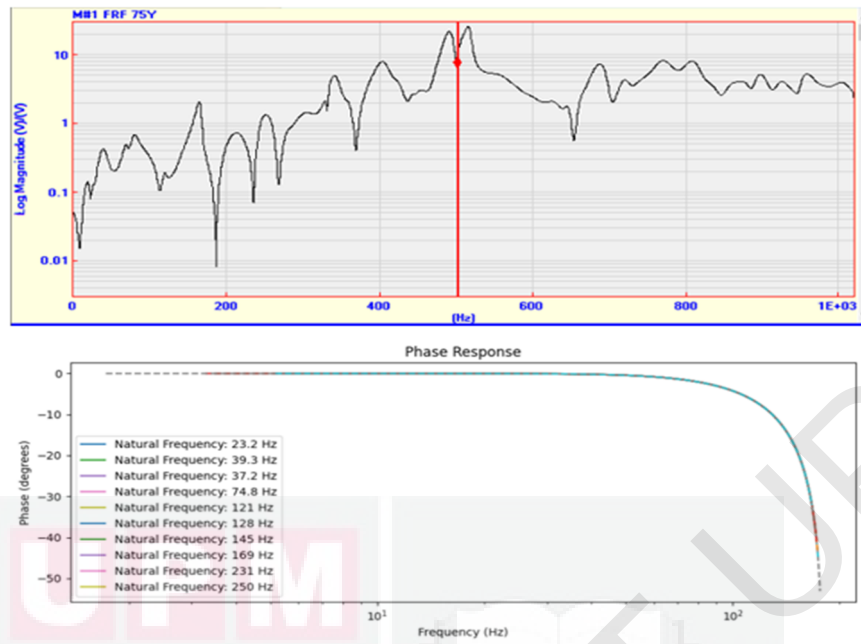


Figure 4.11: Bode plots showing the frequency response of 1 mm plate thickness

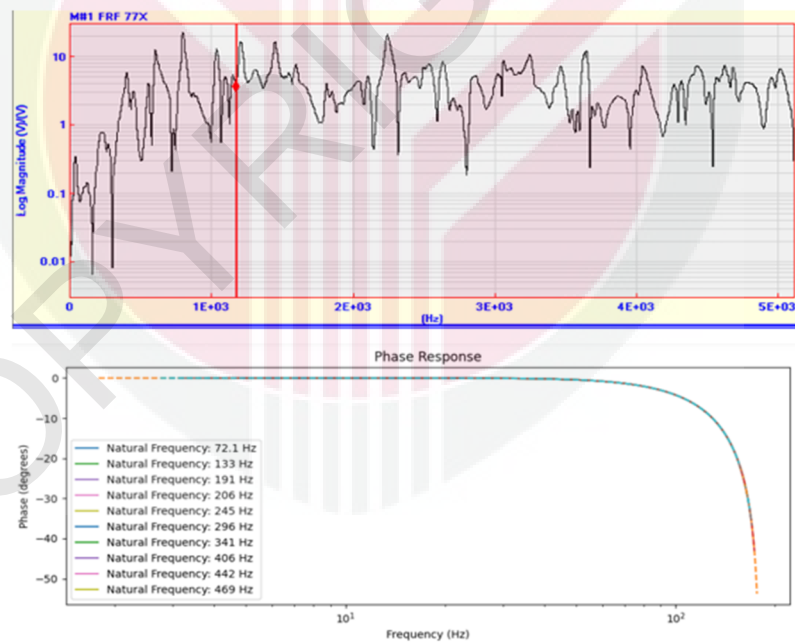


Figure 4.12: Bode plots showing the frequency response of 1.5 mm plate thickness

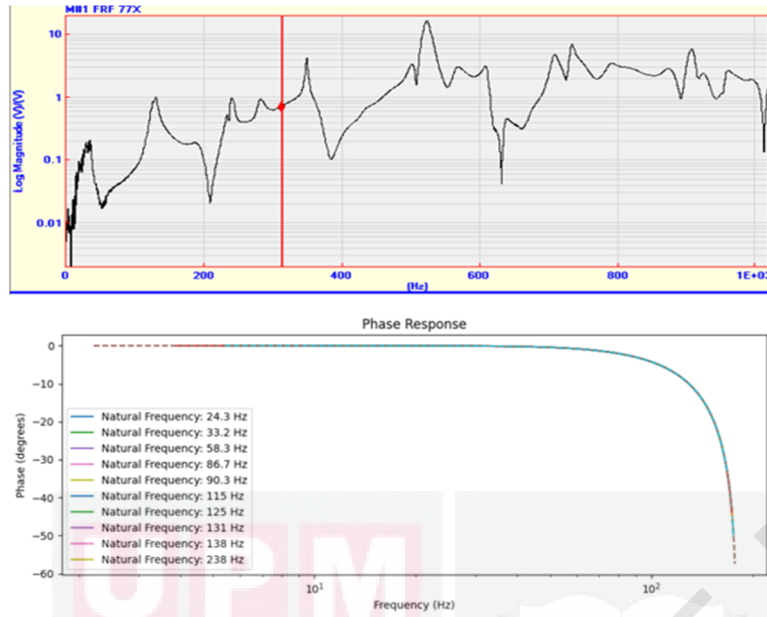


Figure 4.13: Bode plots showing the frequency response of 2 mm plate thickness

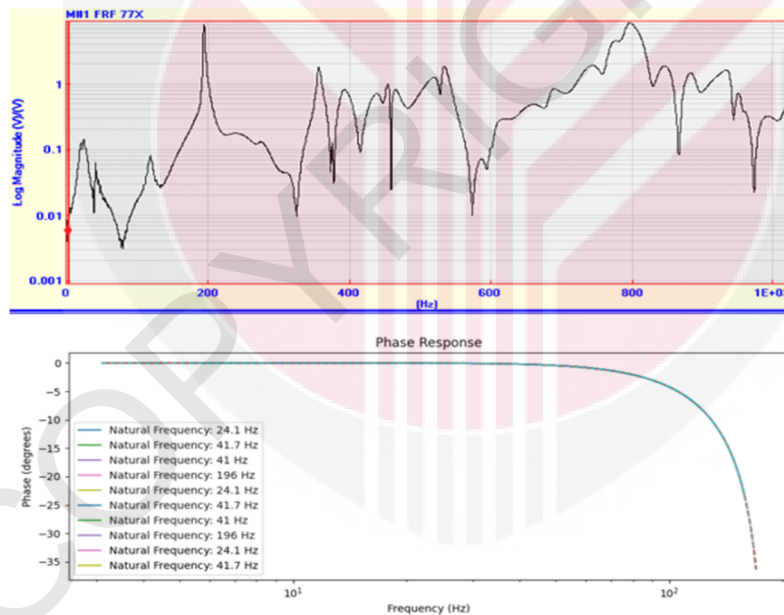


Figure 4.14: Bode plots showing the frequency response of 2.5 mm plate thickness

Based on the analysis of the peak bandwidths, plates with narrow bandwidths, specifically plate thicknesses of 1, 1.5, and 2 mm, were found to be suitable for filtering specific frequencies. However, plates with wider bandwidths, such

as a 2.5 mm plate thickness, are suitable for amplifying all frequencies. In this case, a 1.5 mm stainless steel plate was selected due to its better performance compared to the other thicknesses. This plate was chosen because it has a higher natural frequency and damping ratio, which are suitable for its size geometry, and it can withstand high vibrations and noise due to its narrowest bandwidth and high-frequency response, making it a better option for grain-loss-sensitive plates. This aligns with the findings of Xu et al., (2019), which states that the lower the plate thickness, the greater the relative deformation of the sensitive monitoring plate surface, and consequently, the higher the charge it produces.

4.5 Grain loss monitoring system calibration

The calibration of the grain loss monitoring system is crucial for ensuring the accuracy and reliability of the output data of the system. It enhances the system's monitoring accuracy and provides quality data for analysis, reporting, and decision making, leading to a more reliable system. The calibration identifies areas for improvement to increase the efficiency and performance of the system. In this study, one of the most significant aspects of the calibration was to determine the optimum impact voltage of grains and materials other than grains on the sensitive plate to develop a thresholding algorithm that can identify the impact of grains from paddy straw.

The results of the grain loss monitoring system calibration experiment are presented in Table 4.16. This experiment involved using a variable-speed table

belt conveyor and varying the drop height of the materials to measure the impact voltage of both grain and non-grain materials at different speeds and material drop heights obtained from the design metrics. The aim was to analyze the impact voltage of grains, short straws, long straws, and a mixture of grains and straws to determine the optimum impact voltage for grains, which is essential for coding the grain-impact-voltage detection logic for the monitoring system. The voltage range obtained for each material category is shown in Figure 4.15. The minimum and maximum values were used as the lower and upper limit optimization criteria, respectively, in the Design-Expert software to obtain the optimum values for the materials.

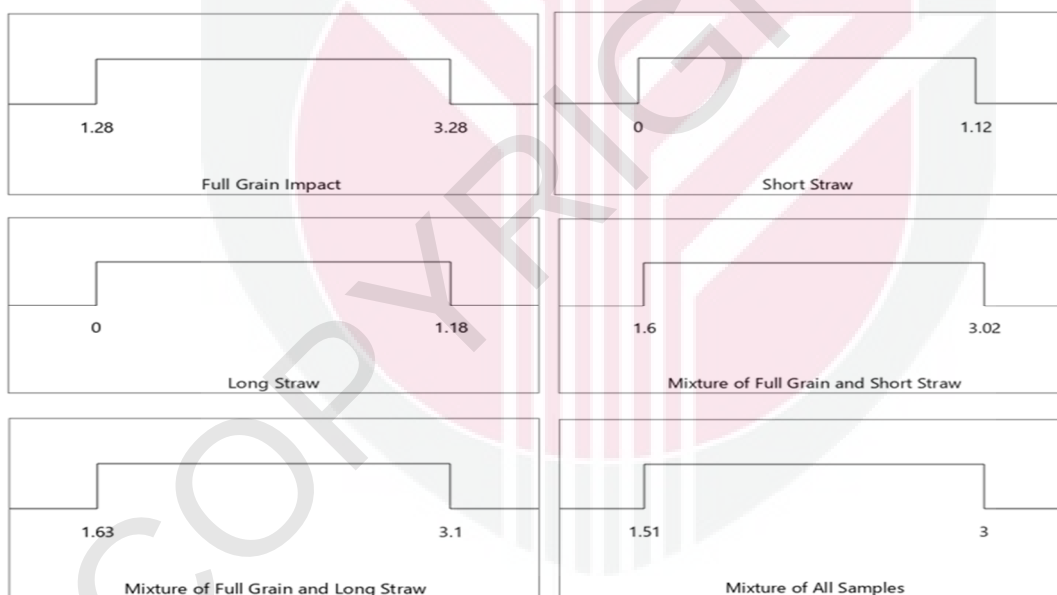


Figure 4.15: Impact voltage range of grain and materials other than grain

Table 4.16: Experimental results of grain loss monitoring system calibration

Run	Conveyor Belt Speed (m/s)	Drop Height (mm)	Full Grain Impact (v)	Short Straw Impact (v)	Long Straw Impact (v)	Full Grain & Short Straw (v)	Full Grain & Long Straw (v)	Full Grain, Short & Long Straw (v)
1	1.53	168.93	1.96	0.00	0.00	1.85	1.88	1.80
2	0.57	275	1.28	0.00	0.00	1.73	1.80	1.76
3	1.53	275	2.53	1.02	1.06	2.40	2.45	2.38
4	2.48	275	3.11	1.08	1.14	2.83	2.90	2.80
5	1.53	275	2.61	1.03	1.05	2.42	2.47	2.40
6	1.53	275	2.60	1.02	1.05	2.41	2.47	2.40
7	0.85	200	1.55	0.00	0.50	1.60	1.63	1.51
8	2.20	350	3.28	1.12	1.18	3.02	3.10	3.00
9	2.20	200	3.05	1.05	1.10	2.98	3.04	2.95
10	1.53	381.07	2.84	1.00	1.03	2.77	2.80	2.74
11	1.53	275	2.62	1.02	1.07	2.44	2.48	2.41
12	1.53	275	2.61	1.02	1.08	2.45	2.47	2.42
13	0.85	350	1.67	0.85	1.00	2.14	2.19	2.10

4.5.1 Relationship between conveyor belt speed and drop height on grain impact voltage

Figure 4.16 visualizes the relationship between conveyor belt speed (m/s) and material drop height (mm) to optimize these factors in assessing the voltage impact of grain and non-grain materials on a sensitive plate. The conveyor belt speed ranges from 0.85 to 2.2 m/s; this parameter influences the speed at which materials are transported, thereby impacting the sensitive plate. The drop height of materials from the conveyor onto the sensitive plate varies between 200 and 350 mm, with a higher drop height potentially leading to a greater impact on the plate.

The plot reveals a positive correlation between conveyor belt speed and the impact strength of the grains. A higher conveyor belt speed means the grains have less time to deform upon hitting the sensitive plate surface. However, the impact strength decreases as the drop height is reduced, attributed to the lower energy imparted to the grains falling from a shorter height onto the plate's surface.

A large portion of the plot is covered by a yellow region, representing the optimal area where the system operates efficiently, yielding high grain impact at higher belt speeds and moderate drop heights. The gray area denotes less optimal conditions, suggesting that certain combinations of conveyor speed and drop height within this area should be avoided.

The red points at the four corners represent boundary conditions, while the central red point marked "5" indicates an optimal test point within the efficient region. The labels on the plot show the impact voltage of different materials: full grain impact at 3.2726V; short straw at 1.12V; long straw at 1.3932V; a mixture of full grain and short straw at 2.9449V; a mixture of full grain and long straw at 3.0105V; and a mixture of all samples at 2.9157V, under optimal conditions of 2.2 m/s conveyor belt speed and a 342.20 mm drop height.

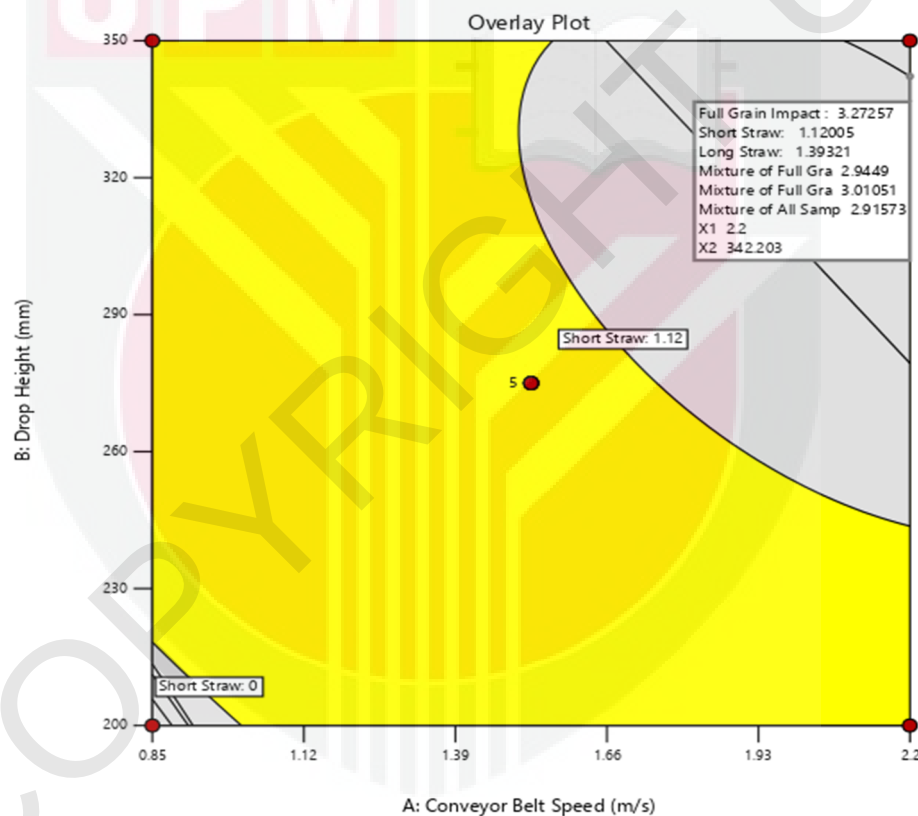


Figure 4.16: Graphical optimization plot of the conveyor belt speed and material drop height

The optimal grain impact voltage obtained in this study corresponds to the findings of previous research by Liang et al., (2016) and Liang (2020), that reported a grain impact voltage range of 2–5 V. Similarly, according to Liang et

al., (2015) and Liang et al., (2016), the impact voltage of the straws should be less than 1.5 V. This finding was consistent with the results of the present study. This indicates that the optimal grain impact voltage achieved in this study can be utilized to establish a threshold value for the grain-impact detection logic in the monitoring system.

Therefore, considering the grain impact voltage values presented above, the monitoring system was programmed using a threshold logic conditional statement included in the code uploaded to the system to determine the impact of the grains on the surface of the sensitive plates. The statement was written as "if (voltage > 2.40 && voltage <= 4.3) read the impact as grain". It was applied to all the 15 sensors used in the system. The complete coding is presented in the methodology.

4.6 Performance analysis of the grain loss monitoring system

The accuracy of the grain loss monitoring system is a performance metric that determines the correctness and efficiency of the system when subjected to real combine harvester operation. The optimal performance of the monitoring system was indicated by the maximum percentage accuracy of the system obtained during harvesting.

The results of the experiment indicated that the maximum accuracy of the monitoring system was 88.45%, whereas the minimum accuracy was 69.57%.

The average accuracy of the system, as determined from the range of experimental metrics, was 86%.

The accuracy of the monitoring system was analyzed using an analysis of variance (ANOVA), as presented in Table 4.17. The results indicate that the grain loss monitoring system is directly related to the linear and quadratic effects of the operational variables of the combine harvester. The F-value of 29.42 indicates that there is only a 0.01% chance that an F-value of this large could occur due to noise. The monitoring system had satisfactory goodness of fit, which was confirmed by a p-value of 0.0001, indicating that the performance of the system was highly significant. The p-value was further used to evaluate the significance of the different operational parameters of the combine harvester, which provided the information required to understand the performance of the monitoring system with respect to the experimental variables. P-values <0.0001 indicate the high significance of the respective parameters. The coefficient estimates and their respective values show that the combine harvester speed, header height, and cleaning fan speed significantly affect the accuracy of the grain-loss monitoring system.

The accuracy of the monitoring system was evaluated using coefficient of determination (R^2), coefficient of variation (CV), and adequate precision (AP). An R^2 value close to 1 indicates that the system can accurately measure grain loss, a lower CV indicates consistent measurements, and a higher AP indicates the reliability of the system. The results of the analysis (Table 4.17) show that the monitoring system has an R^2 value of 0.9636, CV of 1.73, and AP of

18.9017. These results indicate that the experimental data agree with the performance of the system, and that the monitoring system is a reliable tool for measuring grain loss in combine harvesters. These results can be used in further analyses and applications.

Table 4.17: ANOVA of grain loss monitoring system performance accuracy

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	530.50	9	58.94	29.42	0.0001	< significant
A-Combine Harvester Speed	166.68	1	166.68	83.19	0.0001	<
B-Height of Header	67.27	1	67.27	33.58	0.0002	
C-Cleaning Fan Speed	35.76	1	35.76	17.85	0.0018	
AB	1.61	1	1.61	0.8041	0.3910	
AC	4.16	1	4.16	2.08	0.1801	
BC	0.6328	1	0.6328	0.3158	0.5865	
A ²	222.98	1	222.98	111.29	0.0001	<
B ²	25.68	1	25.68	12.82	0.0050	
C ²	36.73	1	36.73	18.33	0.0016	
Residual	20.04	10	2.00			
Pure Error	2.52	5	0.5035			
Cor Total	550.53	19				
R²	0.9636					
CV	1.76					
Adequate Precision	18.9017					

4.7 Prediction of grain loss monitoring system performance parameters using machine learning algorithms

Machine learning algorithms offer the potential for advanced modeling to accurately predict the highest level of machine performance (Gundoshmian et al., 2020). In this study, decision tree and random forest regression algorithms were used to predict the performance of a grain loss monitoring system in terms of the accuracy of the system and grain losses. Three datasets were used for the predictions: the monitoring system accuracy, grain loss recorded by the monitoring system, and grain loss determined using the conventional method for system validation.

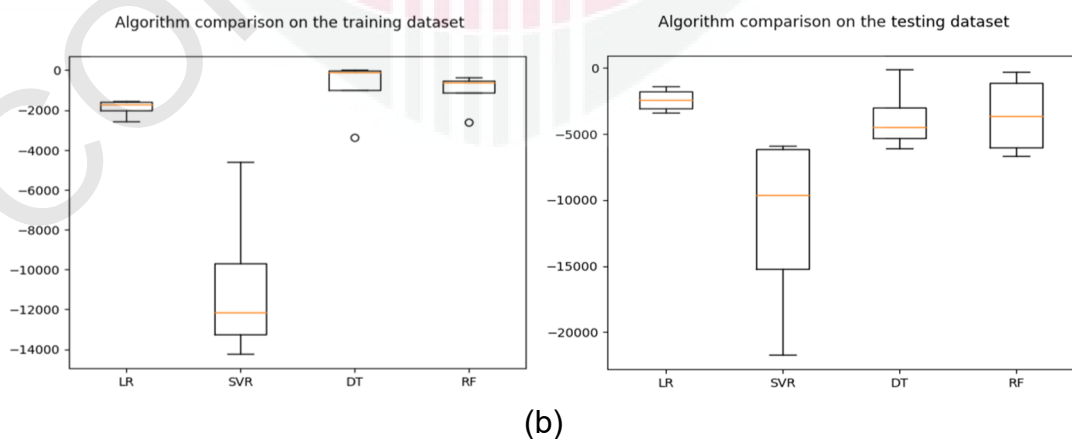
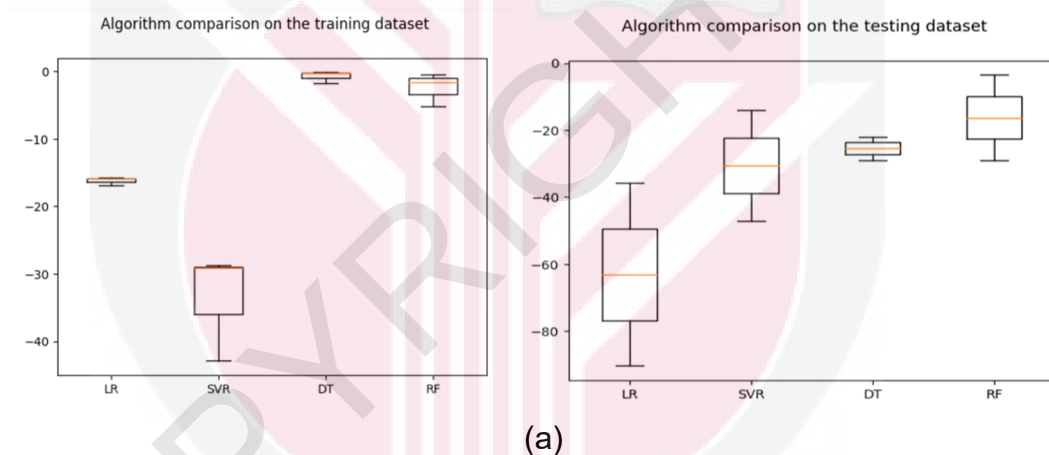
4.7.1 Selection of machine learning algorithms

The process of comparing machine learning algorithms is crucial for selecting the most appropriate algorithm for a given problem or dataset to make a well-informed decision that is not influenced by bias (Benos et al., 2021). In this study, four machine-learning algorithms were compared using datasets obtained from the field evaluation of the grain loss monitoring system (Table 4.18).

Table 4.18: Experimental datasets for grain loss monitoring system

Randomized runs	Forward Speed (km/h)	Height of Header (mm)	Cleaning Fan Speed (rpm)	Grain Loss Measured (Monitoring System)	Grain Loss Counted (Conventional)	Monitoring Accuracy (%)
17	2.26	200	1500	615	735	83.67
20	1.76	200	1500	475	620	76.61
16	2.43	275	1300	440	544	80.88
14	2.01	149	1300	432	563	76.73
12	2.26	200	1100	422	527	80.08
9	1.76	200	1100	408	547	74.59
4	2.01	275	1636	357	423	84.4
18	2.01	275	1300	322	373	86.33
1	2.01	275	1300	318	365	87.12
2	2.26	350	1500	314	355	88.45
19	2.01	275	1300	312	361	86.43
10	2.01	275	1300	310	359	86.35
8	2.01	275	1300	309	359	86.07
11	2.01	275	1300	307	349	87.97
15	2.26	350	1100	272	330	82.42
3	1.59	275	1300	256	368	69.57
6	1.76	350	1500	227	290	78.28
13	2.01	275	963	218	275	79.27
5	1.76	350	1100	211	276	76.45
7	2.01	401	1300	168	190	88.42

The datasets were divided into 80 % training and 20 % testing sets, and the performance of the training and testing sets was evaluated using linear regression, support vector regression, decision tree regression, and random forest regression algorithms. The aim was to determine the best algorithms for predicting the performance variables of the grain loss monitoring system. A comparison of the performance of the algorithms is presented in Figure 4.17, using box-and-whisker plots of the absolute mean squared errors of the algorithms. Therefore, the algorithm with the lowest absolute mean squared error was selected as the best prediction algorithm for this dataset.



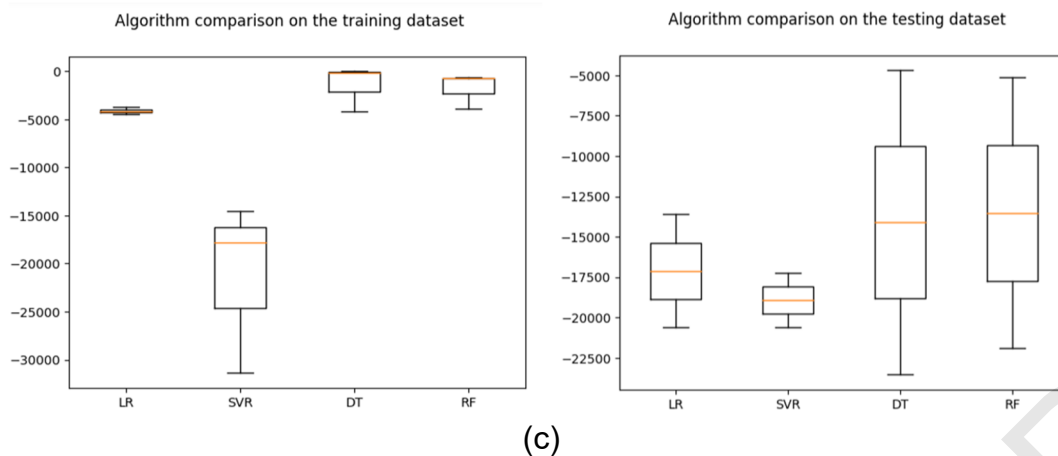


Figure 4.17: Box plots for machine learning algorithms comparison for grain loss monitoring system prediction datasets (a: monitoring accuracy, b: monitoring grain loss, c: conventional grain loss)

Figure 4.17a shows a box-plot algorithm comparison of the monitoring system accuracy datasets obtained using the four algorithms. The box plot for the training dataset shows that the decision tree regression had a minimum absolute mean squared error (MSE) value of 0.73, followed by random forest with 2.46, linear regression with 16.19, and support vector regression with the highest MSE value of 33.59. This suggests that decision tree regression is the most effective algorithm for training the data. However, in the testing set evaluation, the random forest regression had the lowest MSE of 16.30, followed by decision tree regression at 25.54, support vector regression at 30.66, and linear regression with the highest MSE value of 63.23. This indicates that random forest regression is the best testing algorithm.

Figure 4.17b shows a box-plot algorithm comparison of the monitoring system grain loss datasets. The training box plot showed a minimum absolute mean squared error (MSE) of 0.91 for decision tree regression, followed by random forest regression with 1.05, linear regression with 1.89, and support vector

regression with the highest MSE value of 10.79. This indicates that the decision tree regression is the best prediction algorithm for the training set. In contrast, the testing set algorithm comparison showed that linear regression had the lowest absolute MSE value of 3.17, followed by random forest with 3.82, decision tree regression with 4.06, and support vector regression with the highest MSE of 12.82. This implies that the random forest was the best prediction algorithm for the testing set because of its better performance in the training set.

Figure 4.17c shows a box-plot algorithm comparison of the conventional grain loss datasets. The training set algorithm comparison showed a minimum absolute mean squared error (MSE) of 1.41 for decision tree regression, followed by random forest regression with 1.75, linear regression with 4.10, and support vector regression with the highest MSE value of 21.25. This suggests that the decision tree regression is the optimal algorithm for evaluating the training set. However, the testing set algorithm comparison shows that random forest had the lowest absolute mean squared error of 13.53, followed by decision tree with 14.12, linear regression with 17.11, and support vector regression with the highest negative mean squared error value of 18.93. This suggests that a random forest regression is the best algorithm for evaluating the testing set.

Based on the evaluation of the three datasets of the grain loss monitoring system performance parameters, decision tree, and random forest regression emerged as the top performing algorithms, exceeding linear regression and

support vector regression. Therefore, these two algorithms were selected for further analysis to predict the monitoring system grain loss, conventional grain loss, and the accuracy of the monitoring system.

4.7.2 Performance comparison of Random Forest and Decision Tree prediction models

The accuracy of the models was evaluated using a coefficient of variation (R^2), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). R^2 measures the proportion of variance in the output variables that explain the model. The stronger the relationship between the input and output variables, the higher the value of R^2 . MAE measures the average difference between the predicted and experimental values. A lower MAE indicates a better model fit. The MSE and RMSE measure the squared difference between the predicted and experimental values. Lower MSE and RMSE values indicate better model performance. The results of the Random Forest and Decision Tree model performance for the three performance variables of the grain-loss monitoring system are presented in Table 4.19 – 4.21.

Table 4.19 shows the performance results of random forest (RF) and decision tree (DT) for the training and testing models of the monitoring system grain loss with the following values: The RF model had 0.9962 R^2 , 4.9791 MAE, 44.5893 MSE, and 6.6800 RMSE for the training set, and 0.98965 R^2 , 6.2927 MAE, 62.3651 MSE, and 7.900 RMSE for the testing set, respectively, while the DT model had 0.9992 R^2 , 1.3626 MAE, 8.1832 MSE, and 2.8606 RMSE

for the training set, and 0.9987 R^2 , 1.4359 MAE, 8.9297 MSE, and 2.9900 RMSE, respectively. The results showed that the DT model had slightly higher R^2 values for both the training and testing sets, indicating a better data fit. The model also had relatively lower MAE, MSE, and RMSE values for both the training and testing sets, indicating that it is more accurate than the RF model.



Table 4.19: Random Forest and Decision Tree Models performance metrics for monitoring system grain loss prediction

Performance Metrics	Random Forest Regression Algorithm				Decision Tree Regression Algorithm			
	R ²	MAE	MSE	RMSE	R ²	MAE	MSE	RMSE
Training Model	0.9962	4.9791	44.5893	6.68	0.9992	1.3626	8.1832	2.8606
Testing Model	0.9865	6.2927	62.3651	7.9	0.9987	1.4359	8.9297	2.99
Input Variables Feature Importance								
Combine Harvester Speed		0.6421				0.6765		
Height of Header		0.1909				0.1944		
Cleaning Fan Speed		0.1670				0.1391		

The performance results of the Random Forest (RF) and Decision Tree (DT) models for predicting conventional grain loss are presented in Table 4.20. The results indicate that the RF model achieved 0.9889 R^2 , 7.9387 MAE, 189.3390 MSE, and 13.6900 RMSE values for the training set, and 0.9500 R^2 , 17.4774 MAE, 900.0840 MSE, and 30.0000 RMSE values for the testing set, respectively. Similarly, the DT model obtained 0.9992 R^2 , 1.6508 MAE, 17.3333 MSE, and 4.1633 RMSE values for the training set, and 0.9979 R^2 , 1.9259 MAE, 13.3333 MSE, and 3.6500 RMSE values for the testing set, respectively. The results suggest a significant difference in MAE, MSE, and RMSE between the RF and DT models for both the training and testing datasets, with the DT model having the lowest errors, indicating that it has a better predictive accuracy than the RF model.

Table 4.20: Random Forest and Decision Tree model performance metrics for conventional grain loss prediction

Performance Metrics	Random Forest Regression Algorithm				Decision Tree Regression Algorithm			
	R ²	MAE	MSE	RMSE	R ²	MAE	MSE	RMSE
Training Model	0.9889	7.9387	187.339	13.6900	0.9992	1.6508	17.3333	4.1633
Testing Model	0.9500	17.4774	900.084	30.0000	0.9979	1.9259	13.3333	3.6500
Input Variables Feature Importance								
Combine Harvester Speed			0.7297				0.7101	
Height of Header			0.1673				0.2050	
Cleaning Fan Speed			0.1030				0.0849	

The monitoring system accuracy prediction performance results for the Random Forest (RF) and Decision Tree (DT) models are presented in Table 4.21. The results showed that the RF model had 0.9962 R^2 , 4.9791 MAE, 44.5893 MSE, and 6.6800 RMSE values for the training sets and 0.9865 R^2 , 6.2927 MAE, 62.3651 MSE, and 7.9000 RMSE values for the testing sets. Similarly, the DT model has 0.9992 R^2 , 1.3626 MAE, 8.1832 MSE, and RMSE 2.8606 values for the training set and 0.9987 R^2 , 1.4359 MAE, 8.9297 MSE, and 2.9900 RMSE values for the testing set respectively. The prediction model accuracy was measured based on the level of prediction errors. The lower the errors, the better the prediction accuracy. The results show a significant difference in MAE, MSE, and RMSE between the RF and DT models for both the training and testing datasets, with the DT model having the lowest errors, indicating that it has a better predictive accuracy than the RF model.

Table 4.21: Random Forest and Decision Tree Model Performance metrics for monitoring system accuracy prediction

Performance Metrics	Random Forest Regression Algorithm				Decision Tree Regression Algorithm			
	R ²	MAE	MSE	RMSE	R ²	MAE	MSE	RMSE
Training Model	0.9853	0.4799	0.4174	0.65	0.9948	0.1857	0.1386	0.3723
Testing Model	0.9637	0.7743	0.8519	0.92	0.9961	0.1683	0.1153	0.34
Input Variables Feature Importance								
Combine Harvester Speed		0.7166				0.7059		
Height of Header		0.1662				0.1895		
Cleaning Fan Speed		0.1172				0.1046		

Based on the residual differences between the actual and predicted values. An ideal model should have a random scatter point forming an approximately constant width around the identity line. Figures 4.18 – 4.20 show the RF and DT residual plots for the monitoring system grain loss, conventional grain loss, and monitoring system accuracy. The residual plots for the decision tree (DT) models across all prediction variables had a random scatter point around the identity lines, indicating that the model was unbiased and had a constant variance. However, the residual plots for the random forest models (RF) showed that the majority of the points deviated significantly from the identity line, suggesting a higher error, as reflected by the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) values. This suggests the presence of outliers in the RF model due to misidentification.

Based on the evaluation of the prediction performance metrics of the random forest and decision tree models on the three datasets of the grain loss monitoring system, the decision tree algorithm emerged as a superior model for all datasets in terms of prediction accuracy, outperforming the random forest algorithm. This is because the decision tree is generally faster to train the data than the random forest, especially on small datasets, such as the data for the grain loss monitoring system. In addition, the decision tree is less sensitive to noise than the RF, which is advantageous when there is a possibility of noise and outliers in the process. Therefore, the aim of comparing different machine learning models was achieved because the performance of machine learning algorithms can vary depending on the specific dataset and evaluation metrics used.

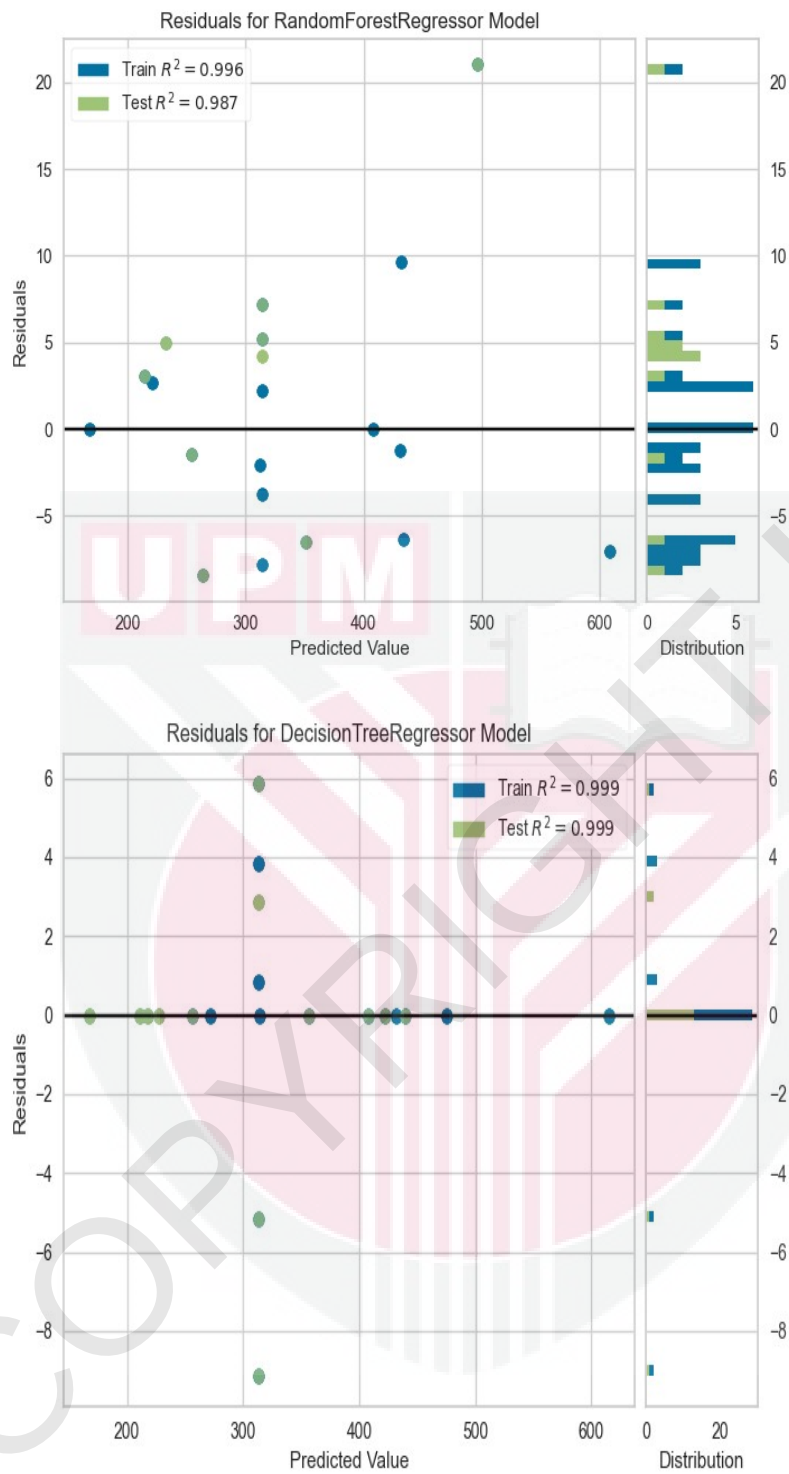


Figure 4.18: RF and DT residual plots for monitoring system grain loss prediction

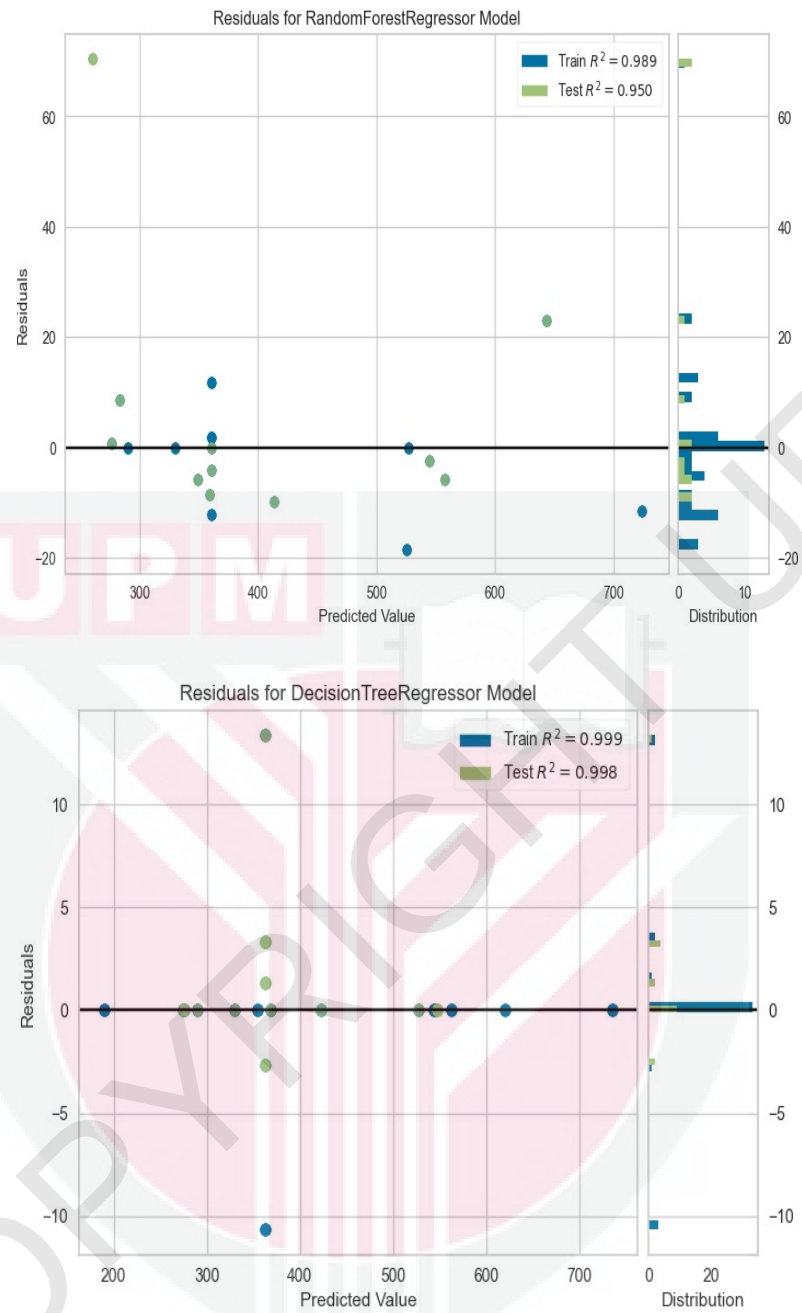


Figure 4.19: RF and DT residual plots for conventional grain loss prediction



Figure 4.20: RF and DT residual plots for monitoring system accuracy prediction

4.7.3 Feature importance of combine harvester operational factors on prediction models

The input variable feature importance results highlight the operational factors of the combine harvester that have the most significant impact on prediction

models. It measures the percentage increase in the mean squared error of the predicted values as a result of permutation of the input variables. The higher the percentage, the more important is the variable to the predictive ability of the model.

Table 4.19 presents the feature importance of the input variables for predicting the grain loss of the monitoring system. The results indicate that Random Forest (RF) attributes 64.21% importance to combine harvester speed, 19.09% to header height, and 16.70% to cleaning fan speed. In contrast, the Decision Tree (DT) assigned 67.65% importance to combine harvester speed, 19.44% to header height, and 13.91% to cleaning fan speed.

The input variable importance features for predicting the conventional grain losses are listed in Table 4.20. The results indicate that Random Forest (RF) attributes 72.97% importance to combine harvester speed, 16.73% to header height, and 10.30% to cleaning fan speed. In contrast, the Decision Tree (DT) assigned 71.01% importance to combine harvester speed, 20.50% to header height, and 8.49% to cleaning fan speed.

Table 4.21 presents the input variable feature importance for the prediction of the monitoring system accuracy. The results show that RF attributes 71.66% importance to combine harvester speed, 16.62% to header height, and 11.72% to cleaning fan speed, whereas DT assigns 70.59% importance to combine harvester speed, 18.95% to header height, and 10.46% to cleaning fan speed.

Based on the input feature importance variables for both the Random Forest (RF) and Decision Tree (DT) models, all three input features—combine harvester speed, header height, and cleaning fan speed—were considered important according to their respective percentage levels and ability to improve the predictive capabilities of the models. However, in terms of monitoring system performance variables, such as grain loss and accuracy, the random forest (RF) and decision tree (DT) models yielded similar results, with the combine harvester speed being the most significant feature, followed by the header height and cleaning fan speed. However, the RF model gives slightly more weight to the combine harvester speed, whereas the DT model gives slightly more weight to the height of the header. This is likely due to the fact that both models can learn the importance of the different features from the data. These findings can help improve the performance of both the grain loss monitoring system and the combine harvester in terms of monitoring and minimizing grain loss. It also highlights that the combine harvester forward speed is the most significant factor affecting the performance of the machine. It therefore needs to be optimized to get the best working speed during harvesting.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

This thesis elaborates on the potential of sensing technologies to provide useful information for monitoring grain loss in combine harvesters. This chapter provides an overall conclusion to the research findings and their main contributions. The limitations and recommendations for future research are also presented.

5.1 Conclusions

This study reviewed various grain loss measurement methods, highlighting the labor-intensive nature and limitations of the conventional approaches. Existing methods are time-consuming, rely heavily on operator skills for combine harvester adjustments, and are not suitable for real-time monitoring. The application of sensing technology in combine harvesters is limited, resulting in suboptimal machine performance. These findings served as the basis for developing a real-time grain loss monitoring system to assist operators in optimizing machine parameters. The system aims to enhance combine harvester efficiency and reduce grain loss during harvesting.

In this study, the performance evaluation of the combine harvester and its energy utilization in glutinous rice harvesting were determined. The grain loss results obtained from the system evaluation were used to optimize the

operational parameters of the combine harvester to minimize grain loss. Finally, the developed monitoring system was calibrated and evaluated in a real field harvesting operation.

The findings from Objective One show that the medium-sized combine harvester performed relatively well in glutinous rice harvesting, with a field speed of 2.42 km/h, field efficiency of 59.78%, theoretical field capacity of 0.56 ha/h, effective field capacity of 0.33 ha/h, and fuel consumption of 14.89 l/ha. The grain throughput capacity was 1,796.91 kg/h at an effective operational rate of 0.33 ha/h, with a total energy consumption of 1,020.66 MJ/ha, indicating that the combine harvester is technically suitable for use in glutinous rice fields under the tested machine operational conditions.

Based on the findings from Objective Two, the optimization of combine harvester operational parameters using RSM-DF and ANN-GA shows that ANN-GA resulted in lower grain loss than RSM-DF. The optimized values of forward speed, header height, cleaning fan speed, and feed rate obtained from the RSM-DF model were 2.26 km/h, 150 mm, 1,100 rpm, and 3 kg/s, respectively, while for the ANN-GA model, the values were 2.26 km/h, 252 mm, 1,100 rpm, and 3 kg/s. The minimum grain loss values achieved were 23.58 kg/ha using the RSM-DF model and 14.70 kg/ha using the ANN-GA model. The optimal results from both optimization approaches demonstrated that the minimum grain loss was less than 3% of the total grain throughput capacity, which is within the acceptable limit for grain loss.

The results from the third objective revealed that a plate thickness of 1.5 mm was selected due to its superior performance in the experimental modal analysis. This thickness exhibited a higher natural frequency and damping ratio, making it well-suited for the plate's size and geometry. The plate thickness can withstand high vibration and noise due to its narrow bandwidth and high-frequency response, making it an ideal choice for developing grain loss sensing plates.

Furthermore, the grain loss monitoring system was developed including three sensitive plates and a monitoring circuit integrated to form a complete system. The grain loss monitoring system was calibrated using a variable-speed table belt conveyor under different combinations of material drop heights and conveyor speed to determine the optimal grain impact voltage. The results showed a positive relationship between the conveyor belt speed and the strength of the grain impacts. The optimal voltage for grain impact obtained was 3.27 V, with the optimal conveyor belt speed and drop height of 2.20 m/s and 342.20 mm, respectively. Subsequently, the grain impact voltage was used to formulate a threshold logic statement for detecting grain impacts from materials other than grain on the sensitive plate.

The monitoring system was evaluated based on three combine harvester parameters: forward speed, header height, and cleaning fan speed. The system achieved a maximum accuracy of 88.45% and a minimum of 69.57%, with an average accuracy of 82%. The system showed a strong fit, with a highly significant p-value of 0.0001. This p-value assessed the importance of each

operational parameter, offering insights into the monitoring system's overall performance. These findings confirm the reliability of the monitoring system as a tool for measuring grain loss in combine harvesters.

The datasets obtained from the field evaluation were used to predict system performance using machine learning algorithms. The accuracy of the prediction models was assessed by evaluating the prediction error, where lower error values indicate better accuracy. The results showed a significant difference in MAE, MSE, and RMSE between the RF and DT models for the training and testing datasets. The DT model outperformed the RF model, displaying lower error rates and suggesting superior prediction accuracy. The prediction model is key in validating system performance, identifying the best model, and ensuring the system's accuracy for future use.

5.2 Recommendations for future research

Based on the development and evaluation of the grain loss monitoring system in this study, the following recommendations are made for future research. These recommendations aim to address the identified limitations and enhance the overall performance and reliability of the sensing system for monitoring grain loss during harvesting.

- It is recommended to explore alternative materials or protective coatings that can withstand the harsh operating environment of the combine harvester.
- Future improvement of the sensing system should incorporate a flexible mounting mechanism that allows adjustable positioning of the sensing plates.

- A calibration routine for each sensing plate should be carried out before the operation, this can provide uniform sensitivity across all plates.
- The monitoring circuit should be designed and printed on a printed circuit board (PCB) to provide a unique circuit structure and wiring.
- For mass production and further improvement of the monitoring system an industrial-grade microcontroller should be used. Arduino microcontroller was utilized only for prototyping.

5.3 Summary

This study was conducted to improve the performance of medium-sized combine harvesters. The performance of the combine harvester was evaluated in a glutinous rice field. The results of the grain loss were utilized to optimize the operational parameters of the combine harvester using response surface methodology and artificial neural network prediction models. A grain loss monitoring system with three sensitive plates was developed, installed, and evaluated to monitor and measure real-time grain loss from the combine harvester. Machine learning algorithms were used to predict the performance variables of the grain loss monitoring system.

5.4 Research contributions

- This study introduces a real-time grain loss monitoring system specifically designed for medium-sized combine harvesters, which has not been extensively studied in previous research.
- The system enables instant adjustments to the combine harvester's operational parameters to minimize grain loss during harvesting.
- The study offers improved solutions with higher accuracy than conventional methods of determining grain loss.

- A comprehensive field evaluation of the developed grain loss monitoring system was performed under real harvesting conditions, validating its effectiveness and reliability.
- The application of this system in real-field conditions helps bridge the gap between laboratory research and field performance, demonstrating its practical application.



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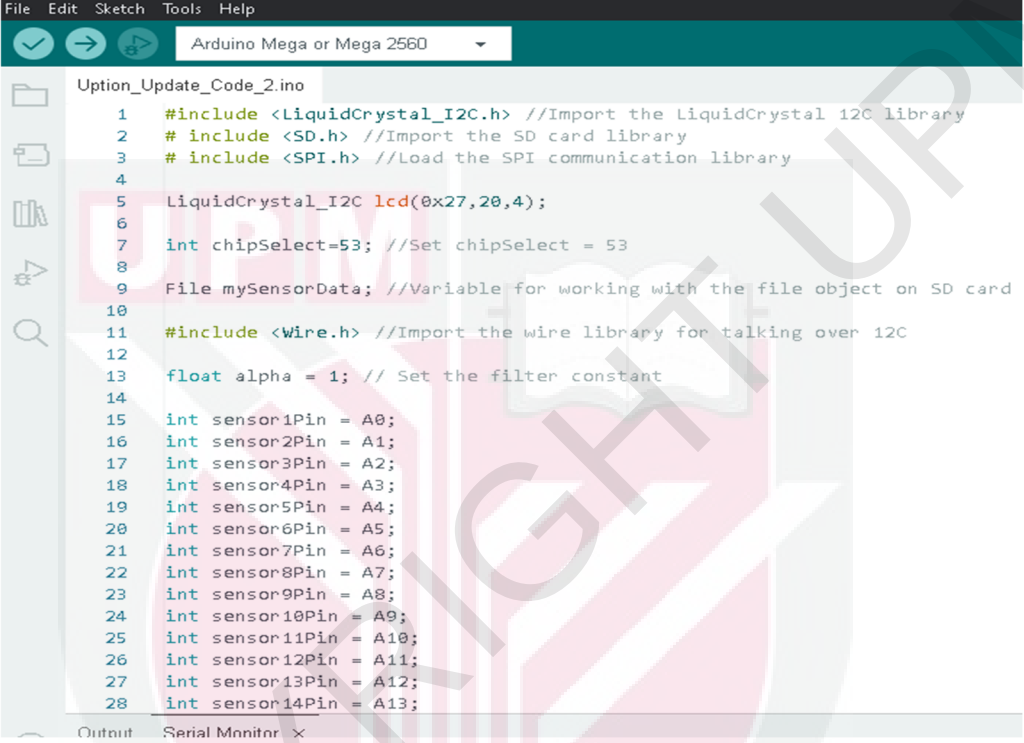
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APPENDICES

Appendix A

Arduino Integrated Development Interface



The screenshot displays the Arduino IDE interface. The top menu bar includes File, Edit, Sketch, Tools, and Help. Below the menu is a toolbar with icons for saving, running, and other functions. A dropdown menu shows 'Arduino Mega or Mega 2560'. The main workspace shows a sketch named 'Uption_Update_Code_2.ino'. The code is as follows:

```
1  #include <LiquidCrystal_I2C.h> //Import the LiquidCrystal 12C library
2  #include <SD.h> //Import the SD card library
3  #include <SPI.h> //Load the SPI communication library
4
5  LiquidCrystal_I2C lcd(0x27,20,4);
6
7  int chipSelect=53; //Set chipSelect = 53
8
9  File mySensorData; //Variable for working with the file object on SD card
10
11 #include <Wire.h> //Import the wire library for talking over 12C
12
13 float alpha = 1; // Set the filter constant
14
15 int sensor1Pin = A0;
16 int sensor2Pin = A1;
17 int sensor3Pin = A2;
18 int sensor4Pin = A3;
19 int sensor5Pin = A4;
20 int sensor6Pin = A5;
21 int sensor7Pin = A6;
22 int sensor8Pin = A7;
23 int sensor9Pin = A8;
24 int sensor10Pin = A9;
25 int sensor11Pin = A10;
26 int sensor12Pin = A11;
27 int sensor13Pin = A12;
28 int sensor14Pin = A13;
```

At the bottom, there is a tab for 'Serial Monitor'.

Appendix B

Appendix B1: Coding for reading the impact of grain from the sensors

```
// Read the raw sensor values
sensorRead1 = analogRead(sensor1Pin);
sensorRead2 = analogRead(sensor2Pin);
sensorRead3 = analogRead(sensor3Pin);
sensorRead4 = analogRead(sensor4Pin);
sensorRead5 = analogRead(sensor5Pin);
sensorRead6 = analogRead(sensor6Pin);
sensorRead7 = analogRead(sensor7Pin);
sensorRead8 = analogRead(sensor8Pin);
sensorRead9 = analogRead(sensor9Pin);
sensorRead10 = analogRead(sensor10Pin);
sensorRead11 = analogRead(sensor11Pin);
sensorRead12 = analogRead(sensor12Pin);
sensorRead13 = analogRead(sensor13Pin);
sensorRead14 = analogRead(sensor14Pin);
sensorRead15 = analogRead(sensor15Pin);
```

Appendix B2: Coding for filtering the sensor reading

```
// Apply the high-pass filter to each sensor reading
filtered1 = alpha * (prevFiltered1 + sensorRead1 - prevFiltered1);
filtered2 = alpha * (prevFiltered2 + sensorRead2 - prevFiltered2);
filtered3 = alpha * (prevFiltered3 + sensorRead3 - prevFiltered3);
filtered4 = alpha * (prevFiltered4 + sensorRead4 - prevFiltered4);
filtered5 = alpha * (prevFiltered5 + sensorRead5 - prevFiltered5);
filtered6 = alpha * (prevFiltered6 + sensorRead6 - prevFiltered6);
filtered7 = alpha * (prevFiltered7 + sensorRead7 - prevFiltered7);
filtered8 = alpha * (prevFiltered8 + sensorRead8 - prevFiltered8);
filtered9 = alpha * (prevFiltered9 + sensorRead9 - prevFiltered9);
filtered10 = alpha * (prevFiltered10 + sensorRead10 - prevFiltered10);
filtered11 = alpha * (prevFiltered11 + sensorRead11 - prevFiltered11);
filtered12 = alpha * (prevFiltered12 + sensorRead12 - prevFiltered12);
filtered13 = alpha * (prevFiltered13 + sensorRead13 - prevFiltered13);
filtered14 = alpha * (prevFiltered14 + sensorRead14 - prevFiltered14);
filtered15 = alpha * (prevFiltered15 + sensorRead15 - prevFiltered15);
```

Appendix B3: Coding for converting filtered sensor reading to voltage reading

```
// Convert the filtered sensor readings to voltages
voltage1 = (5. / 1023.) * filtered1;
voltage2 = (5. / 1023.) * filtered2;
voltage3 = (5. / 1023.) * filtered3;
voltage4 = (5. / 1023.) * filtered4;
voltage5 = (5. / 1023.) * filtered5;
voltage6 = (5. / 1023.) * filtered6;
voltage7 = (5. / 1023.) * filtered7;
voltage8 = (5. / 1023.) * filtered8;
voltage9 = (5. / 1023.) * filtered9;
voltage10 = (5. / 1023.) * filtered10;
voltage11 = (5. / 1023.) * filtered11;
voltage12 = (5. / 1023.) * filtered12;
voltage13 = (5. / 1023.) * filtered13;
voltage14 = (5. / 1023.) * filtered14;
voltage15 = (5. / 1023.) * filtered15;
```

Appendix B4: Coding for applying grain impact detection logic for reading the impact of grain from non-grain materials and sending notification to the buzzer module

```
// Apply the impact detection logic to each filtered sensor reading
if (voltage1 > 2.40 && voltage1 <= 4.3) {
  digitalWrite(buzzerPin, HIGH);
}
else {
  digitalWrite(buzzerPin, LOW);
}
if (voltage1 > 2.40 && voltage1 <= 4.3) {
  impact1 = count1++;
}

Serial.println(sensorRead1);
Serial.println(voltage1);
Serial.println(impact1);
delay(delayTime);

if (voltage2 > 2.40 && voltage2 <= 4.3) {
  digitalWrite(buzzerPin, HIGH);
}
else {
  digitalWrite(buzzerPin, LOW);
}
if (voltage2 > 2.40 && voltage2 <= 4.3) {
  impact2 = count2++;
}
}
```

Appendix B5: Coding for counting the impact of grain detected for the three sensitive plates

```
// Sum up the impacts detected by each sensor
int subimpacts1[5] = {impact1, impact2, impact3, impact4, impact5};
int subtotal1 = 0;
for (int i = 0; i < 6; i++) {
    subtotal1 += subimpacts1[i];
}
int subimpacts2[5] = {impact6, impact7, impact8, impact9, impact10};
int subtotal2 = 0;
for (int i = 0; i < 6; i++) {
    subtotal2 += subimpacts2[i];
}
int subimpacts3[5] = {impact11, impact12, impact13, impact14, impact15};
int subtotal3 = 0;
for (int i = 0; i < 6; i++) {
    subtotal3 += subimpacts3[i];
}
```

Appendix B6: Coding for printing the total impact of grain from each sensitive plate on the LCD screen

```
// Print the total impact count on the LCD
lcd.setCursor(0, 1);
lcd.print("Sensitive PLT1: ");
lcd.print(subtotal1);
lcd.setCursor(0, 2);
lcd.print("Sensitive PLT2: ");
lcd.print(subtotal2);
lcd.setCursor(0, 3);
lcd.print("Sensitive PLT3: ");
lcd.print(subtotal3);
|
```

Appendix B7: Coding for saving data on microSD card

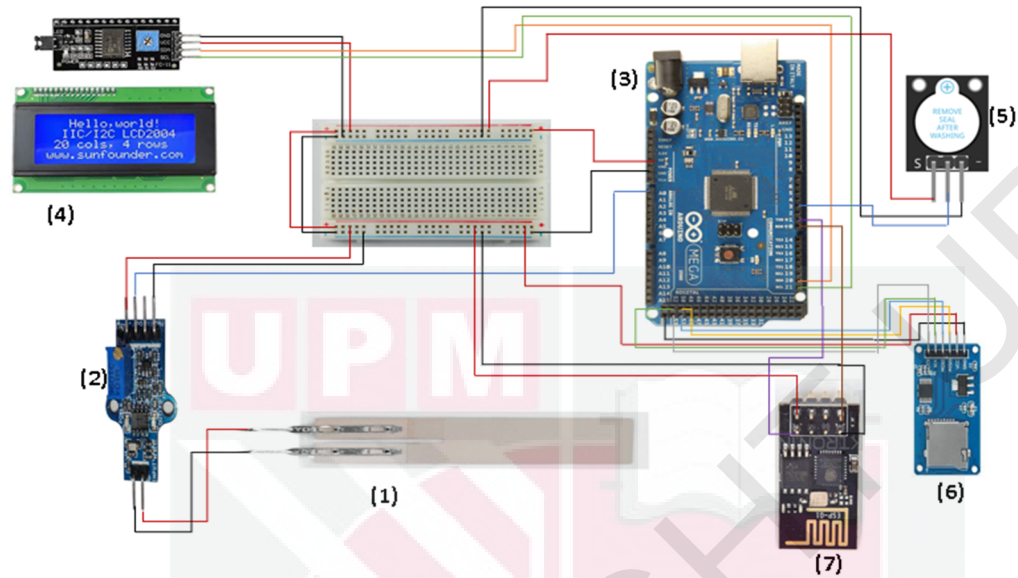
```
mySensorData= SD.open("PTData.txt", FILE_WRITE); //Open PTData.txt on the SD card

if (mySensorData) { //Only do this thing if the data open successfully
}

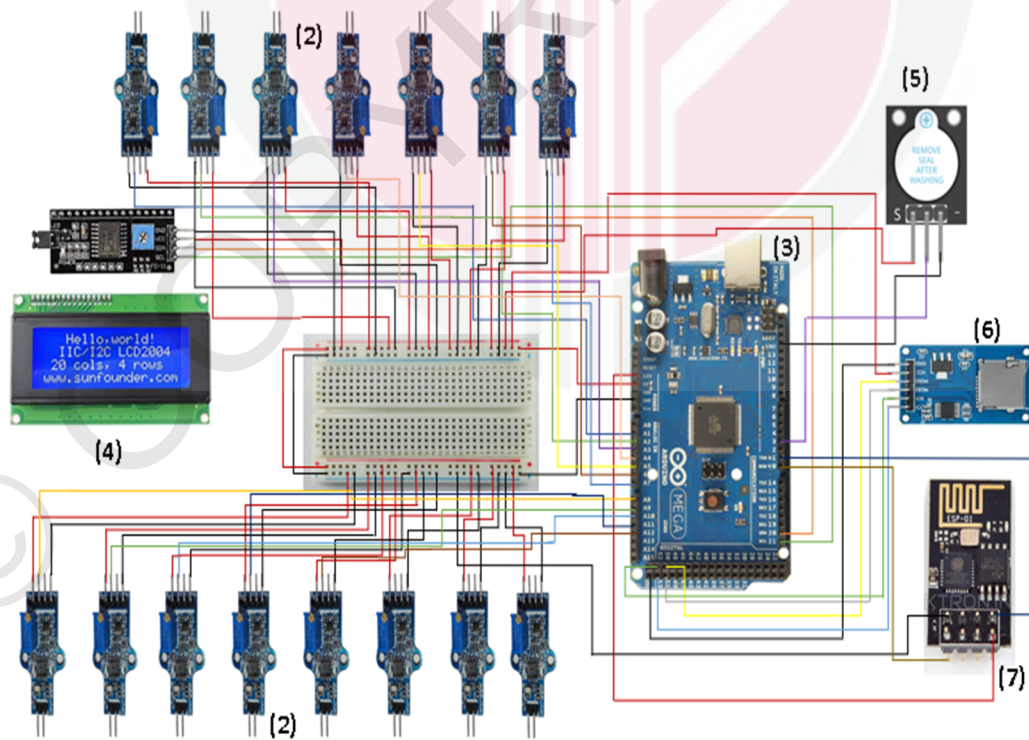
mySensorData.print(impact1); //Write impact1 value to the SD card
mySensorData.print(","); //Write comma
mySensorData.print(impact2); //Write impact2 value to the SD card
mySensorData.print(","); //Write comma
mySensorData.print(impact3);
mySensorData.print(",");
mySensorData.print(impact4);
mySensorData.print(",");
mySensorData.print(impact5);
mySensorData.print(",");
mySensorData.print(impact6);
mySensorData.print(",");
mySensorData.print(impact7);
mySensorData.print(",");
mySensorData.print(impact8);
mySensorData.print(",");
mySensorData.print(impact9);
mySensorData.print(",");
mySensorData.print(impact10);
```

Appendix C

Appendix C1: Monitoring circuit using single sensor and amplifier module



Appendix C2: Grain loss monitoring circuit with complete component connections.



LIST OF PUBLICATIONS

Journal article:

Bomoi, M. I., Nawi, N. M., Aziz, S. A., Saufi, M., & Kassim, M. (2022). Sensing Technologies for Measuring Grain Loss during Harvest in Paddy Field : A Review. *AgriEngineering*, 4, 292–310.

Bomoi, M. I., Nawi, N. M., Aziz, S. A., Saufi, M., & Kassim, M. (2023). Experimental Analysis of a Sensitive Plate for Grain Loss Monitoring System. *Kongzhi Yu Juece/Control and Decision*, 38(06), 2345–2354.

Nawi, N. M., Bomoi, M. I., Aziz, S. A., & Kassim, M. S. M. (2024). Evaluation of Field Performance and Energy Consumption of a Medium-sized Combine Harvester for Harvesting Glutinous Rice in Malaysia. *Pertanika Journal of Science and Technology*, 32(3), 1385–1399. <https://doi.org/10.47836/pjst.32.3.22>