DEEP LEARNING APPROACH WITH IMAGE NOISE REDUCTION TO DETERMINE PLANTING DENSITY AND DETECT DEFECTED PADDY SEEDLINGS

By

MOHAMED MARZHAR BIN MOHAMED ANUAR

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Master of Science

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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Master of Science

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Chairman : Alfian Abdul Halin, PhD
Faculty : Computer Science and Information Technology

In recent years food security issues caused by climatic changes, human resources, and production costs require a strategic approach. The emergence of artificial intelligence due to the capability of recent technology in computer processing could become a new alternative to current solutions. Optimal planting density is a crucial factor for paddy cultivation as it will influence the quality and quantity of production. There have been several studies involving planting density using computer vision and remote sensing approach. While most of the studies have shown a good overall performance, they have disadvantages and room for improvement. Among the disadvantages is that the studies aim to detect and count all the paddy seedlings to determine planting density. The defective paddy seedling locations are not pointed out to help farmers in the sowing process. All the previous studies for plant detection used two-stage method object detectors like Faster R-CNN and Mask R-CNN combined with different types of feature extractor architecture such as VGG16, ResNet, Inception and MobileNet. Even though this type of object detector showed high accuracy it has a high inference time. Exploring a one stage method object detector such as Single Shot Detector could solve the high inference time for a real-time defective crop detection and may lead towards the development of an autonomous mobile transplanter. One stage method object detector however tends to show a slightly lower accuracy compared to two stage method. For this work we start with a preliminary study to evaluate the performance difference between machine learning that involve the selection of filters as feature extractor and deep learning technique that eliminates the requirement of hand-crafted features engineering on the classification of paddy fields health as our based line for the classification and detection of defected paddy seedlings. All pre-trained Deep Learning models achieved better accuracy when compared to Machine Learning with filters for feature extraction and custom Deep Learning Model. We then continued our study to find the best method for paddy seedlings

density classification task. All the pre-trained models showed comparable accuracy with the Base Model when trained to classify a new object with hyperparameter tuning and our proposed image pre-processing which reduces noise and enhanced input images features. Transfer Learning also allowed faster training processes by reducing the number of trainable parameters and still capable of achieving good overall performance. The next following study is on the detection of defected paddy seedling using both one stage and two stage method pre-trained object detector model. The objective of the study is to propose a method that can accurately detect and count defective paddy seedlings to determine the sowing location. Four combinations were used, the EfficienDet-D1 EfficientNet that utilizes Bi-directional Feature Pyramid Network and Compound Scaling Constant method outperforming all other models. Our image pre-processing technique managed to enhance the performance of all state-of-the-art pre-trained object detector models. Exploratory research was conducted to propose a robust computer vision approach to classify paddy seedlings density and defected paddy seedlings detection using pre-trained CNN model with transfer learning. Data augmentation, image pre-processing and hyperparameter tuning were applied to achieve the desirable performance. The experiment showed that pre-trained DCNN model works well for classification and detection of a new task with a good overall performance using transfer learning with fine tuning method.

Keywords: Computer Vision, Object Detection, Deep Learning, Convolutional Neural Network, Paddy Seedlings.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

PENDEKATAN PEMBELAJARAN MENDALAM DENGAN PENGURANGAN GANGGUAN IMEJ UNTUK MENENTUKAN KEPADATAN TANAMAN DAN MENGESAN BENIH PADI ROSAK

Oleh

MOHAMED MARZHAR BIN MOHAMED ANUAR

Oktober 2022

Pengerusi : Alfian Abdul Halin, PhD
Fakulti : Sains Komputer dan Teknologi Maklumat

Dalam beberapa tahun kebelakangan ini, isu keselamatan makanan yang disebabkan oleh perubahan iklim, sumber manusia dan kos pengeluaran memerlukan pendekatan strategik. Kemunculan kecerdasan buatan kerana keupayaan teknologi terkini dalam pemprosesan komputer boleh menjadi alternatif baharu kepada penyelesaian semasa. Kepadatan tanaman yang optimum merupakan faktor penting untuk penanaman padi kerana ia akan mempengaruhi kualiti dan kuantiti pengeluaran. Terdapat beberapa kajian yang melibatkan kepadatan penanaman menggunakan pendekatan penglihatan komputer dan penderiaan jauh. Walaupun kebanyakan kajian telah menunjukkan prestasi keseluruhan yang baik, mereka mempunyai kelemahan dan ruang untuk penambahbaikan. Antara kelemahannya ialah kajian bertujuan untuk mengesan dan mengira kesemua anak benih padi bagi menentukan kepadatan tanaman. Lokasi anak benih padi yang rosak tidak ditunjuk untuk membantu petani dalam proses menyemai. Semua kajian terdahulu untuk pengesanan tumbuhan menggunakan pengesan objek kaedah dua peringkat seperti Faster R-CNN dan Mask R-CNN digabungkan dengan pelbagai jenis seni bina pengekstrak ciri seperti VGG16, ResNet, Inception dan MobileNet. Walaupun pengesan objek jenis ini menunjukkan ketepatan yang tinggi, ia mempunyai masa inferens yang tinggi. Meneroka pengesan objek kaedah satu peringkat seperti Single Shot Detector (SSD) boleh menyelesaikan masa inferens yang tinggi untuk pengesanan tanaman rosak masa nyata dan boleh membawa ke arah pembangunan penanam mudah alih automatik. Pengesan objek kaedah satu peringkat bagaimanapun cenderung menunjukkan ketepatan yang lebih rendah sedikit berbanding kaedah dua peringkat. Untuk kerja ini, kami mulakan dengan kajian awal untuk menilai perbezaan prestasi antara pembelajaran mesin yang melibatkan pemilihan penapis sebagai pengekstrak ciri dan teknik pembelajaran mendalam yang menghapuskan keperluan kejuruteraan ciri buatan tangan mengenai klasifikasi kesihatan sawah sebagai asas kami untuk pengelasan dan pengesanan anak benih padi yang rosak. Semua model pra-latihan Pembelajaran Mendalam mencapai ketepatan yang lebih baik jika dibandingkan dengan Pembelajaran Mesin dengan penapis untuk pengekstrakan ciri dan Model Pembelajaran mendalam terubah suai. Kami kemudian meneruskan kajian kami untuk mencari kaedah terbaik untuk tugas pengelasan kepadatan anak benih padi. Semua model pra-latihan menunjukkan ketepatan yang setanding dengan Model Asas apabila dilatih untuk mengklasifikasikan objek baharu dengan pengubahsuaian hiperparameter dan pra-pemprosesan imej cadangan kami yang mengurangkan gangguan dan ciri imej input yang dipertingkatkan. Pembelajaran Pemindahan juga membolehkan proses latihan yang lebih pantas dengan mengurangkan bilangan parameter yang boleh dilatih dan masih mampu mencapai prestasi keseluruhan yang baik. Kajian seterusnya adalah mengenai pengesanan kecacatan anak benih padi menggunakan kaedah satu peringkat dan dua peringkat model pengesan objek terlatih. Objektif kajian adalah untuk mencadangkan kaedah yang dapat mengesan dan mengira dengan tepat anak benih padi yang cacat bagi menentukan lokasi penyemaian. Empat kombinasi telah digunakan, EfficienDet-D1 EfficientNet yang menggunakan Rangkaian Piramid Ciri Dwi-arah dan kaedah Pemalar Skala Kompaun mengatasi semua model lain. Teknik pra-pemprosesan imej kami berjaya meningkatkan prestasi semua model pengesan objek pra-terlatih yg unggul. Penyelidikan penerokaan telah dijalankan untuk mencadangkan pendekatan penglihatan komputer yang mantap untuk mengklasifikasikan kepadatan anak benih padi dan pengesanan anak benih padi yang cacat menggunakan model DCNN terlatih dengan pembelajaran pemindahan. Pengubahsuaian data, pra-pemprosesan imej dan penalaan hiperparameter telah digunakan untuk mencapai prestasi yang diingini. Eksperimen menunjukkan bahawa model DCNN pra-latihan berfungsi dengan baik untuk pengelasan dan pengesanan tugas baharu dengan prestasi keseluruhan yang baik menggunakan pembelajaran pemindahan dengan kaedah pengubahsuaian halus.

Kata kunci: Penglihatan Komputer, Pengesanan Objek, Pembelajaran Dalam, Rangkaian Neural Convolutional, Anak Benih Padi.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

Alfian Abdul Halin, PhD
Senior Lecturer
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Chairman)

Thinagaran Perumal, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

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I hereby confirm that:

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Signature: ______________________

Name of Chairman of Supervisory Committee: Dr. Alfian Abdul Halin

Signature: ______________________

Name of Member of Supervisory Committee: Associate Professor Dr. Thinagaran Perumal

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LIST OF ABBREVIATIONS

Symbol	Definition
AI	Artificial Intelligence
ANN	Artificial Neural Network
AP	Average Precision
API	Application Programmable Interface
BiFPN	Bi-directional Feature Pyramid Network
CNN	Convolutional Neural Network
CUDA	Compute Unified Device Architecture
CUDNN	CUDA Deep Neural Network Library
CV	Computer Vision
DL	Deep Learning
DCNN	Deep Convolutional Neural Network
EVI	Enhanced Vegetation Index
FAIR	Facebook AI Research
FPN	Feature Pyramid Network
GAN	Generative Adversarial Network
GIS	Geographic Information System
GPS	Global Positioning System
GPU	Graphical Processing Unit
GUI	Graphical User Interface
ILSVRC	ImageNet Large Scale Visual Recognition Challenge
IoU	Intersection Over Union
mAP	Mean Average Precision
ML	Machine Learning
MNIST	Modified National Institute of Standards and Technology

MS COCO	Microsoft Common Object in Context
NDVI	Normalized Difference Vegetation Index
PASCAL	Pattern Analysis, Statistic Modelling and Computational Learning
R-CNN	Regional Convolutional Neural Network
RGB	Red, Green, Blue
RS	Remote Sensing
SSD	Single Shot Detector
SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
UPM	Universiti Putra Malaysia
VGG	Vision Geometry Group
VOC	Visual Object Classes

CHAPTER 1

INTRODUCTION

1.1 Background

The biggest challenge in today's agriculture industry is to ensure that the growing population is sufficiently supplied with current food production (Firdaus et al., 2020), (Patel et al., 2019). Rice is the world's second largest, staple food in Asian countries and contributes 90% of the total food production (Firdaus et al., 2020), (Maclean et al., 2013). In recent years food security issues caused by climate changes, human resources, and production costs required a strategic approach (Firdaus et al., 2020), (FAO, 2017). The emergence of artificial intelligence due to the capability of recent technology in computer processing could become a new alternative to current solutions. Deep learning algorithms in computer vision for image classification and object detection can facilitate the agriculture industry especially in paddy cultivation to alleviate human efforts in laborious, burdensome, and repetitive tasks (Kamilaris et al., 2018). We have seen numerous successes in applied deep convolutional neural network (DCNN) algorithms for agricultural research in areas dealing with issues related to pest and disease control, weed management, crop recognition, plant health, and planting density (Kamilaris et al., 2018), (Silva et al., 2020). DCNN has also contributed to the emergence of high spatial remote sensing and temporal remote sensing applications using satellite and unmanned aerial vehicle (UAV) imagery for a wide range of agriculture application as popular and cost-effective solutions. Remote sensing images in RGB (red, green, blue), multispectral, and hyperspectral applications have been widely used for land classification tasks and precision agriculture (Tsouros et al., 2019). Multispectral technologies such as normalized difference vegetation index (NDVI), enhance vegetation index (EVI) and thermal inspection have shown enormous success in measuring vegetation, land use classification, and marine monitoring (Liu et al., 2021) However, due to the characteristics of remote sensing data it has some limitations and practical challenges. Recently, new DCNN approaches that combine remote sensing applications have achieved significant breakthroughs, offering novel opportunities for research and development in remote sensing images on automated image classification and object detection (Li et al., 2018) This new technique can be applied to agricultural industries for solving various issues, especially in precision agriculture.

1.2 Problem Statement

Optimal planting density is a crucial factor for paddy cultivation as it will influence the quality and quantity of production (Hurtado et al., 2021). Thus, it is necessary for the farmers to inspect the paddy fields planting density and to search for defective paddy seedlings at approximately 14 days after planting. Then the defective paddy seedlings are replaced or replanted manually with a new one in its place. This process is called sowing and is known to be labour-intensive as well as being prone to disease outbreaks (Kumar et al., 2021). There have been several studies involving planting density using computer vision and remote sensing approach. While most of the studies have shown a good overall performance, they have disadvantages and room for improvement. Among the disadvantages is that the studies aim to detect and count all the paddy seedlings to determine planting density. The defective paddy seedling locations are not pointed out to help farmers in the sowing process. Counting each and every plant as numerical value to determine planting density required expensive computational resources as it uses two-stage of computational process. First, to determine the object location based bounding boxes with non max suppression algorithm. Second, sending the detected object to feature extractor for a classification task. While image classification is rather a straightforward classification process that only involved feature extractor. Another limitation is the feature engineering task where it requires experts to select or develop filters that capable to extract important of vital features of the input images before feeding it into a machine learning classifier. On the other hand, developing a DCNN with a specific purpose to detect plant and planting density required a large amount of sample or labelled data. Thus, training a pre-trained model via transfer learning involving some hyperparameter tuning to detect a target plant or for classification of planting density is something that is worthwhile to be further explore. All the previous studies for plant detection used two-stage method object detectors like Faster R-CNN and Mask R-CNN combined with different types of feature extractor architecture such as VGG16, ResNet, Inception and MobileNet. Even though this type of object detector showed high accuracy it has a high inference time. Therefore, for real-time object detection it might not be suitable as it has a lower frame per second (FPS) detection. Exploring a one stage method object detector such as Single Shot Detector could solve the high inference time for a real-time defective crop detection and may lead towards the development of an autonomous mobile transplanter. This is another interesting factor why we are exploring into this work. One stage method object detector however tends to show a slightly lower accuracy compared to two stage method. For object detection architecture it uses bounding boxes algorithm with non max suppression technique before sending it into feature extractor for classification task. Thus, noise factor from the background could affect the accuracy of the object detection algorithm. There have been several studies that used multispectral technologies like Normalized Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) associated with high resolution remote sensing imagery combined with object detection to determine plant health. NDVI normalize the image pixel value between the Red Band value and the Near Infrared Value. The normalization factor seems to show a promising result in detecting plant health. To the best of our knowledge with regards to paddy seedlings detection only one study has used a one-stage method object detector. Recently EfficientDet a one stage method object detector used a compound scaling method based on a constant multiplication factor and Bi-Directional Feature Pyramid Network has improved the lower accuracy issue. For this work we decided to accommodate farmers' accessibility constraints in expensive equipment and software to acquire and process multispectral imagery. Thus, we only focus on using RGB as input image for the classification and object detection task. However, we propose of using image pre-processing technique such as image normalization by changing the pixel intensity value of the input image before feeding it into both one stage and two stage object detector with feature extractor as an alternative to multispectral imagery indices such as NDVI and EVI. Training a pre-trained model with small amount of dataset may resulting in lower accuracy. Therefore, we will apply data augmentation to avoid overfitting problem of the model.

1.3 Research Objective

In this work, we aimed to explore several machine learning techniques with filters as feature extractor, custom DCNN models and pre-trained model via transfer learning and hyperparameter tuning on an open public dataset from Kaggle named paddy-distinguisher to determine which one will perform the best for paddy seedlings density classification and defective paddy seedlings detection using aerial imagery. We also explore the effect of some technique to prevent overfitting such as Dropout, Batch Normalization and Kernel Regularizer on our best performance custom DCNN model. We study the performance of pre-trained CNN Network named MobileNetV2 and ResNet50 based on their top-5 performance on the ImageNet Challenge and compared it with our custom Base Model for the classification of paddy seedlings density with our proposed image pre-processing technique which normalize the input image by changing the pixel intensity value to reduce noise factor from the image background illuminance. We also applied data augmentation to overcome the overfitting problem cause by training a pre-trained model with a small number of labelled datasets. Then, we evaluated the accuracy, robustness, and inference latency of one- and two-stage pre-trained object detectors combined with state-of-the-art feature extractors such as EfficientNet, ResNet50 and MobilenetV2 as a backbone in detecting defected paddy seedlings. We also proposed an image pre-processing technique by changing the pixel intensity value to reduce noise and enhance the features and characteristic of defected paddy seedlings. Defected paddy seedlings come in various shape and colour thus it is important to reduce the image noise and enhance the contrast of the defected paddy seedling features before feeding it to the pre-trained object detector model. Furthermore, we also investigated the effect of transfer learning with fine-tuning on the performance of the forementioned pre-trained model. The primary aim is to come out with the best DCNN model with transfer learning and parameter tuning to classify paddy seedlings density and defected paddy seedlings detection using aerial imagery and improve the overall performance with image pre-processing technique and data augmentation. This study also intended to fill the gap by using both one stage and two stage method of pre-trained object detector model incorporating image pre-processing and data augmentation technique in the overall framework to reduce noise and improved the overall performance as an alternative to multispectral imagery indices technique. More specifically the objective can be outlined as follows:

i. To develop automated paddy seedlings density classification and defected paddy seedlings detection using pre-trained DCNN model with transfer learning.

ii. To propose data augmentation and image pre-processing technique for background noise reduction in the overall framework to enhance the performance of the model.

iii. To proposed specifically fined tuned pre-trained DCNN model which efficiently classify paddy seedlings density and detect defected paddy seedlings in aerial images.

1.4 Research Scope

The scope of this study is on the development of automated paddy seedlings density classification and defected paddy seedlings detection using pre-trained DCNN. To be more specific the aim is to comes out with fine tune DCNN model that is capable of interpreting data or digital images with data augmentation and image pre-processing involved to classify paddy seedlings density and detect defected paddy seedlings as an output. The focus of the study is restricted to fine tuning the pre-trained DCNN model to achieved desirable performance in classification and detection task for the new object. The study also explored the effect of transfer learning and pre-processing to reduce image noise, computational cost and parameter of the DCNN model to be more resources efficient. Transfer learning also significantly reduced the training process time because it effectively utilizes the previously learned pattern especially in the middle layer and only re-trained the last layer to differentiate the new object.

1.5 Research Contributions

The following list explain the contribution of the research:

i. Proposed a fine-tuned DCNN model for paddy seedlings density classification and defected paddy seedlings detection.

ii. Proposed an image pre-processing and data augmentation technique to achieved desirable performance.

iii. Proposed a specifically parameter tuning in the pipeline configuration of pre-trained object detector to efficiently detect defected paddy seedlings in real time.

The results showed the comparison of Base Model and pre-trained DCNN to classify paddy seedlings density and four different combination of object detector and feature extractor using both one stage and two stage method to detect defected paddy seedlings. The evaluation on the performance of both methods can help researchers to evaluate the robustness of the model for classification and detecting new object especially for small object detection. It verified the capability of transfer learning as resources efficient method. It also proved the effectiveness of compound scaling method and Bi-Directional Feature Pyramid

Network in one-stage method compared to the conventional one-stage method using anchor boxes with non-max suppression algorithm.

1.6 Thesis Structure

Chapter 1 – The Background, Problem Statement, Research Objective, Research Scope, and Research Contribution of the thesis were discussed in this chapter.

Chapter 2 – Briefly described the Literature Review and Related Works.

Chapter 3 – This chapter described the overall Methodologies used for this study.

Chapter 4 – This chapter is a preliminary study to evaluate the performance of machine learning algorithm using filters as feature extractor, customize DCNN model and pre-trained DCNN Model. We also study the effect of Dropout, Batch Normalization and Kernel Regularizer.

Chapter 5 – This chapter study on the performance of various feature extractor architecture on classification of paddy planting density.

Chapter 6 – This chapter study on different combination of object detector model with feature extractor architecture to detect defected seedlings.

Chapter 7 – This chapter comprehensively summarize the whole study, elaborate the general conclusion, and gave the recommendation for future works.

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