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iRICE Decision Support System: Time-Series Forecasting Model for the Risk Management System

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ABSTRACT

The development of a decision support system (DSS) called the Risk Management System aims to empower farmers in making well-informed decisions, ultimately enhancing rice field production. This system focuses on providing a monitoring mechanism that optimizes monitoring and control efforts in paddy plantations. By employing predictive modeling, integrated pest monitoring, and decision support systems for pests, weeds, abiotic variables, and rainfall patterns, it predicts the likelihood and consequences of potential weed infestations, pest outbreaks, and changes in weather patterns like temperature and rainfall. By leveraging precision agriculture technologies and data-driven insights, the Risk Management System keeps a vigilant watch on disease and pest presence in paddy fields. It promptly alerts farmers when specific thresholds are surpassed, enabling them to take immediate action. The system facilitates effective data analysis for extension officers, enabling them to swiftly respond to emergency situations. Overall, this method offers a practical and efficient response to the challenges faced by paddy farmers. It equips them with the ability to make informed decisions, increase production, and effectively manage diseases and pests, ultimately leading to improved agricultural outcomes.

1. Introduction

The art and science of cultivating the soil, growing crops, and raising livestock is known as agriculture [1]. It entails preparing plant and animal goods for human consumption as well as their distribution to markets. Agriculture is a vital sector in Malaysia. For several years, this sector has been the backbone of Malaysian economy by producing agricultural products for domestic consumption, because the earner of exchange. Agriculture also contributes to the national Gross Domestic Products (GDP). There are variety of food crops grown in Malaysia like durian, rice, cocoa, bananas, coconuts, and pineapple. Among them rice is incredibly important in Malaysian society since it promotes agricultural activities and helps to feed a growing population [2].

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Rice is that the second most generally grown cereal crop and the staple food for quite half the world’s population. The people depend upon rice for food calories and protein, especially in developing countries [3,4]. One fifth of the world’s population or over a billion household in Asia, Africa and therefore the America rely on rice systems for his or her main sources of employment and livelihoods. In Malaysia, rice is very crucial among the society since it promotes agricultural activities and helps to feed a growing population. Rice contributes 4.1% of total agricultural value added. Rice accounted for 6.9% of Malaysia's total agricultural land in 1995. By 2005, this percentage had risen to around 9.7%, thanks in part to the introduction of new rice-growing regions. The rice sector is an important source of employment in Malaysia, as it represents a major pillar of the country's agricultural production [5].

Malaysia's rice production faces several challenges to meet national targets [6]. Pests (insects and weeds) and diseases are two of the most serious issues. Farmers has been relying on their own knowledge and technique to combat the pest and disease with pesticide application. However, when there is a fluctuation in time and pest and disease climate-related factors during the input application, these challenges are not totally resolved. There is a risk of potential profits due to an uncontrollable pest, as well as higher production costs caused by unexpected additional input and tasks [7]. Other challenges such as shortfalls in knowledge and skills of farmers about pest and disease management, pesticide selection, and overall handling is limited, and farmers have been misled during the pest and disease identification stage [8].

Decision support systems (DSS), data analysis, and data mining have become more important instruments for enhancing company in the professional sector throughout time [9-11]. A decision support system (DSS) is an information system that participates in and helps human decision-making [12]. It may supply a range of dependable programs and check the decision-makers' requirements and assumptions through a series of human-machine interactions, fulfilling the goal of aiding decision- making [13].

In general, it is an interactive computer information system that may assist decision-makers in making use of data and models and solving the problem of non-structures. It makes extensive use of appropriate computer approaches and, through the interactive human-machine paradigm, aids and improves the efficacy of decision-making concerning semi-structures and non-structures [14]. A little drawback that Decision Support System are insufficient [15]. Fortunately, these errors could overcome with more training data provided which could minimize the errors.

In the development of the Decision Support System (DSS), considering the challenge of complex analysis and the potential limitations of extension workers in interpreting and communicating information to farmers is essential. Several strategies can be implemented to address this issue. Involving extension workers and farmers in the development process can lead to a system that better meets their needs. Engaging them in the design, testing, and feedback stages ensures that the DSS is user-oriented and aligned with their requirements. Besides, it is essential to involve not only extension workers but also other stakeholders, such as agricultural researchers and local leaders, in the DSS implementation. By having support from various levels, the dissemination of information and training can be more widespread. Prioritizing training and capacity building for extension workers is also crucial. They should receive comprehensive training on how to use the DSS effectively, interpret the results, and communicate the recommendations to farmers in a clear and understandable manner. Therefore, to encounter these challenges, the IRICE DSS development should proactively address the challenge of complex analysis and ensure that extension workers can effectively interpret and communicate the information to farmers. By adopting user-friendly interfaces, providing training and localized support, involving stakeholders, and considering the local context, the DSS can overcome these challenges and be a valuable tool in supporting rice cultivation in Malaysia.

The basic components of this decision support system are user interface, database, models of decision making, communication components and software that links users with data and models. This decision support system will help the farmers in decision making regarding their paddy plants. The quantity of pests will be monitored from time to time and the farmers will be warned to take immediate actions if the quantity increases certain level. On the other hand, the diseases of the paddy plants will be also monitored from time to time. The abiotic factors which can cause the increment of pests and disease infections will be also monitored. This will help the extension officers to analyse the data efficiently and to take quick actions during emergency situations.

2. Methodology

This research integrates, the precision agriculture technologies with predictive modelling and integrated pest monitoring and decision support system powered by the Internet of Things (loT) for the pest, weeds, abiotic factors, and rainfall patterns. We built a dashboard which is a web-based system and able to run in Google Chrome, Mozilla Firefox, and Safari browsers.

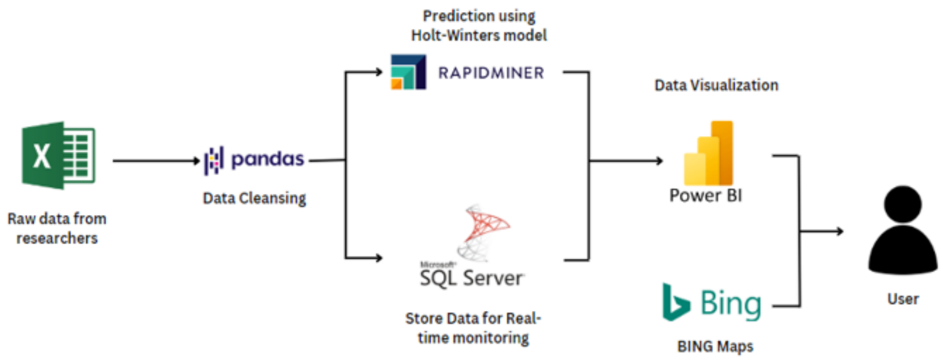

Fig. 1. System Architecture of the iRice Decision Support System

The stakeholders of this research are extension officers, researchers, and system managers. This dashboard will be used by them to monitor the paddy field condition. Then, the extension officers will be able to interpret and analyse the data shown in the dashboard. They will send warnings and steps to be taken to the farmers regarding the analysis report created. We received the researchers' raw data and used Pandas (a Python data analysis library) to clean it up. The cleansed data will be kept on the Microsoft SQL Server so that the real-time monitoring feature can be enabled. Some of the data will be used in RapidMiner for forecasting purposes utilising the Holt-Winters model to forecast future data. Later, all the data will be transferred into PowerBi for data visualisation, where the dashboard is made. The dashboard's heatmap feature will also use Bing Maps. The dashboard will then be given to the extension officers after being published to the server.

Figure 2 represents the specific responsibilities of stakeholders as shown in the use case diagram. Researcher's role in this system is to collect and submit the data of their research in the specific paddy plantation area. This data will be inserted into the database by the system managers. They can also be able to select, update, and delete the data from the database. This system is mainly designed for the extension officers who plays an important role by reviewing and analysing the data shown in the system. The extension officers will be able to view the homepage, data of pests, data of weeds, data of abiotic factors, and the data of rainfall patterns. They can also be able to filter the data according to the days group and years. This will help them to analyse the data more specific.

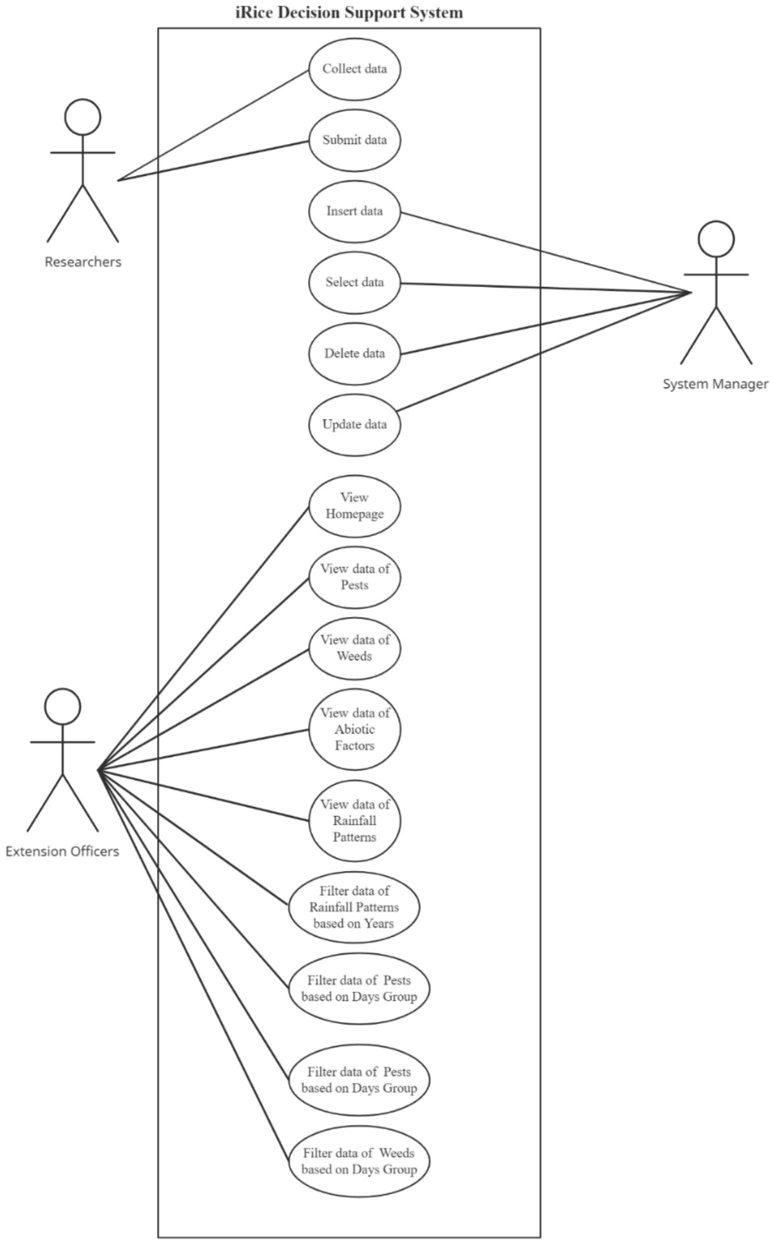

Fig. 2. Use Case Diagram of this iRice Decision Support System

2.1 Software and Hardware Requirement
2.1.1 Power BI

Microsoft Power BI is a business intelligence (BI) platform that provides tools for aggregating, analysing, visualising, and sharing data to nontechnical business users. The user interface of Power BI is intuitive for Excel users, and its deep integration with other Microsoft products makes it a versatile self-service tool that requires little upfront training. This iRice DSS is built in this application because it provides various visualisation tools. This helps to visualize the data easily and more precisely [16]. This application also enables the user to access the system easily via internet.

2.1.2 Pythonic data cleaning

Pythonic Data Cleaning is performed using Pandas. Pandas stands for Python Data Analysis Library. The data cleansing process is performed by importing Pandas library where it contains all the functions for the process. Pandas provides with several fast, flexible, and intuitive ways to clean and prepare the data. This helps with handling the missing and null values in the dataset by checking each column of data. This also ensure our data is clean before proceeding for the next step [17].

2.1.3 Microsoft SQL server

Microsoft SQL Server is a relational database management system (RDBMS) that was created by Microsoft. This product is designed to perform the fundamental function of storing and retrieving data as required by other applications [18]. It can be run on the same computer or on another computer across a network. This iRice DSS is connected with Microsoft SQL Server and programmed with automated updating of data from Excel files where the researchers will enter the research data in it. This enables the real-time monitoring function of the system and the data in the system will be updated daily.

2.1.4 RapidMiner

RapidMiner is a complete data science platform that features visual workflow design and full automation. Coding is not required for data mining tasks when using RapidMiner. It is intended for businesses to analyse the collective impact of their employees, expertise, and data. Rapid Miner's data science platform is designed to support a wide range of analytics users throughout the AI lifecycle and is a widely used data science tool [17]. RapidMiner is used in this project to predict the future data of the Pests and Weeds.

Table 1
Hardware and software requirement for the development of iRice DSS

Hardware	Description
Device	HP Pavilion Laptop-eg2006TX
Processor	12th Gen Intel(R) Core(TM) i7-1255U 1.70 GHz
Random Access Memory (RAM)	16GB
Storage	512GB
Graphics Card	NVIDIA GeForce MX550
Software	**Description**
Power BI	This software is used to visualize the collected data.
Microsoft Excel	The collected data will be saved in .xlsx format in Excel sheets.
Microsoft SQL Server	The collected data will be stored in this local database for real-time monitoring purpose.
Google Collab	This is used to run the Pythonic Data Cleansing process.
RapidMiner	This software is used to predict the future data of the Pests, Weeds, and the Abiotic factors.

2.2 Data Collection

The research of pests conducted for 70 consecutive days [20] and has been focused on the pest called Yellow Stem Borer which can affect the growth of paddy plants. In this research there were four different samplings and each of them were treated different the number of larvae. The number of healthy plants were dead hearts and whiteheads for 70 consecutive days [21]. Later, the percentage of dead hearts were calculated using the given equation 1:

$$\frac{Number\ of\ deadhearts}{Number\ of\ healthy\ plants} \times 100. \tag{1}$$

The data of abiotic factors such as temperature and relative humidity also recorded for the 70 consecutive days in the research location. The recorded the minimum and maximum data of the temperature and relative humidity each day. For the rainfall pattern, we obtained the data from Malaysian Meteorological Department. It contains data of selected meteorological station from all the states, total rainfall, temperature, relative humidity for 22 years as in Table 2.

Table 2
List of data and attributes

Data	Attributes
Pest	Days Group, Treatment, Sample, Healthy, Dead heart, Whitehead, Percentage of Dead heart
Weeds	Days Group, Block, Grass, Sedges, Broadleaved weeds
Abiotics Factor	Days Group. Minimum Temperature, Maximum Temperature, Minimum Relative Humidity, Maximum Relative Humidity
Rainfall Pattern	State, Meteorological Station, Year, Mean temperature-Min (oC), Mean temperature-Max (oC), Rainfall-Total (mm), Rainfall-No. of days, Mean relative humidity (%)

2.3 Implementation
2.3.1 Dashboard

A dashboard is a visual interface that provides users with an overview of various aspects of a system or organization. A dashboard system implementation involves designing, developing, and integrating a dashboard into an existing system or creating a standalone solution. This process typically involves gathering requirements, selecting the right tools and technologies, creating an intuitive user interface, and integrating data sources to present meaningful information to users in real-time. The goal of a dashboard system is to provide stakeholders with relevant and actionable information to make informed decisions and monitor the performance of the system or organization.

2.3.2 Pest and disease

Pest and disease outbreaks can cause substantial yield losses in rice crops. Monitoring pest and disease occurrences and providing early warnings enable farmers to implement timely and targeted pest management strategies. This dashboard (Figure 3) contains the data about the pest called 'Yellow Stem Borer'. All the data were obtained from the research done by the researcher for 70 consecutive days in the paddy field. From this dashboard shows the pie chart for sum of deadhearts by days group. This pie chart shows the total sum of deadheart according to the days group. User who views this dashboard can be able to compare the sum of deadheart with different days group. Here, the highest sum of deadheart is on the 6th Days Group which is 388 and the lowest sum of deadheart is on the 1st Days Group which is 60. Also shows from the dashboard how the data of the pests will be viewed when a particular days group is selected. Here, the 3rd Days Group is selected and it shows the sum of deadheart, sum of healthy plants and the average percentage of deadheart by days group.

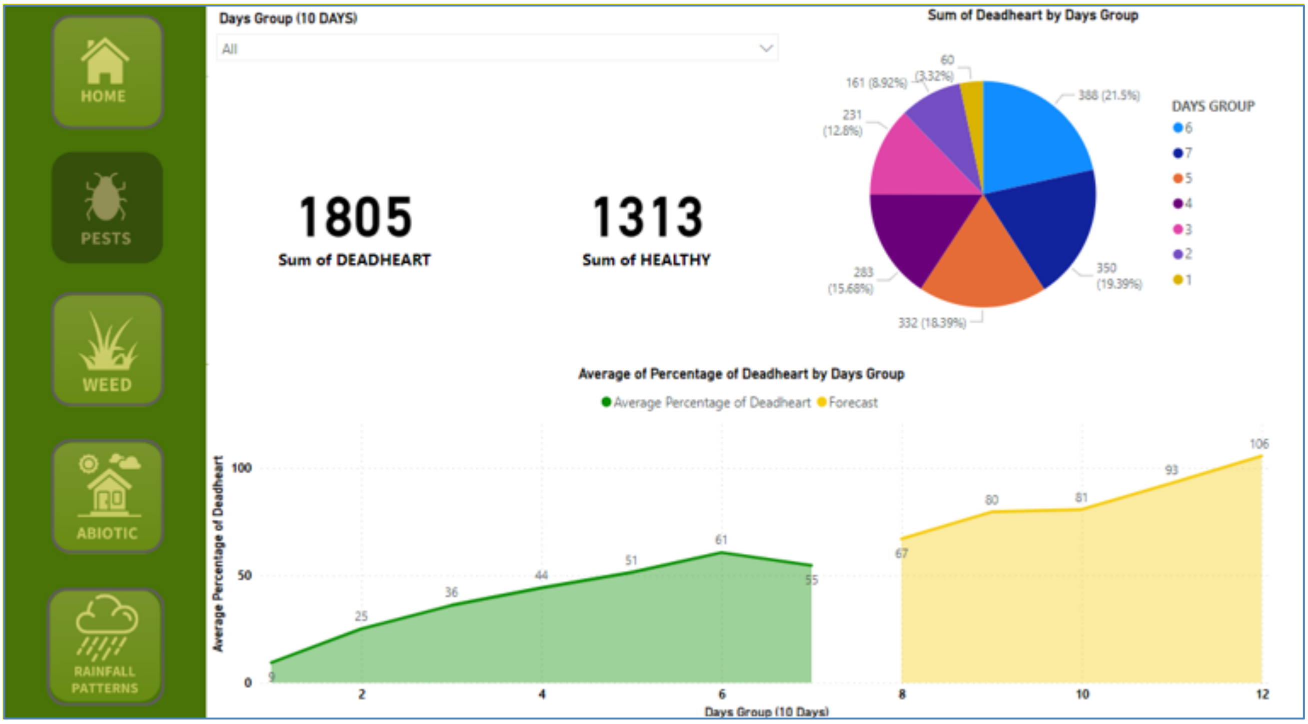

Fig. 3 Data of Pest Based on Percentage and Sum of Deadheart

2.3.3 Weeds

This dashboard contains the visualization of all the data about weeds. The data shown in this page is the number of weeds grown per metre square for 70 consecutive days. There are data of 3 types of weeds (Grass, Sedges and Broadleaved weeds) treated in 3 different types of water treatment (Field Capacity, Saturated and Flooded) in this research. There is also a forecast button which redirect the user to the page where forecasted data is shown.

The slicer function enables the user to select the days group so that the user can view the data of the weeds on that particular days group. Each options represents 10 days. So, there are total of 7 options which represent 70 days. They can also select multiple options to make comparisons between the data. The card function shows the maximum number of weeds (Grass, Sedges and Broadleaved weeds) per metre grown in that water treatment according to the days group.

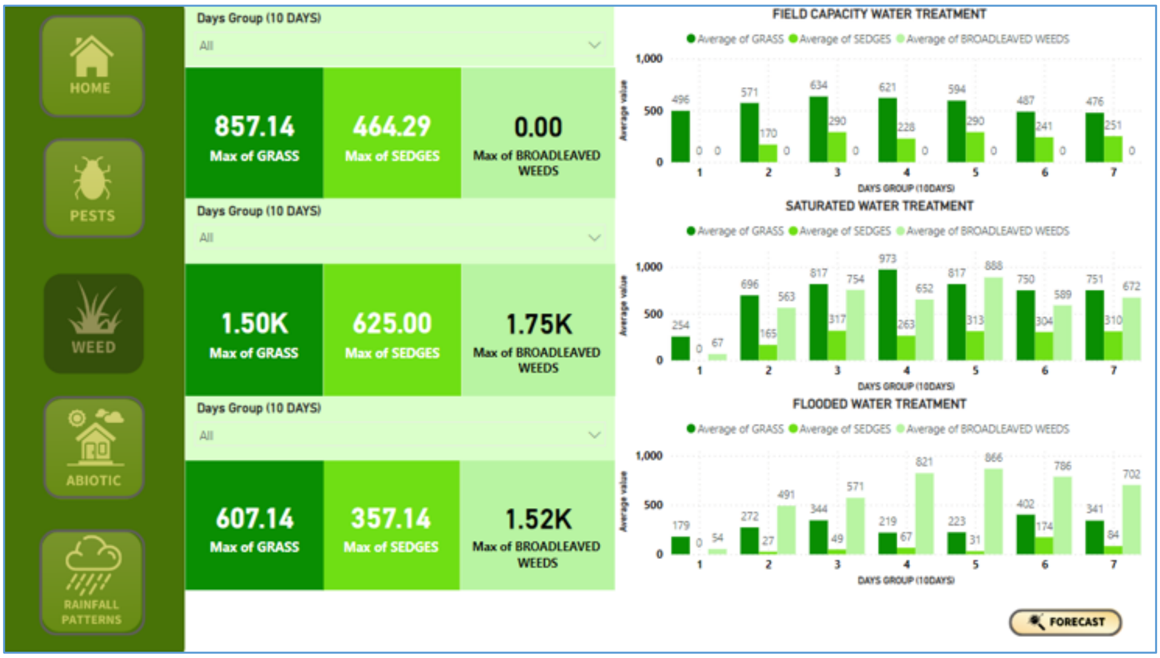

Fig. 4. Data of Weeds in Three Different Water Treatment

2.3.4 Abiotic Factors

Proper monitoring abiotic factor is essential for optimal rice growth and yield. Tailored abiotic factors management recommendations based on soil nutrient analysis and crop nutrient requirements ensure efficient of crop growth. The Abiotic factors page contains all the data of abiotic factors such as relative humidity and temperature that have been recorded during the 70 days of research.

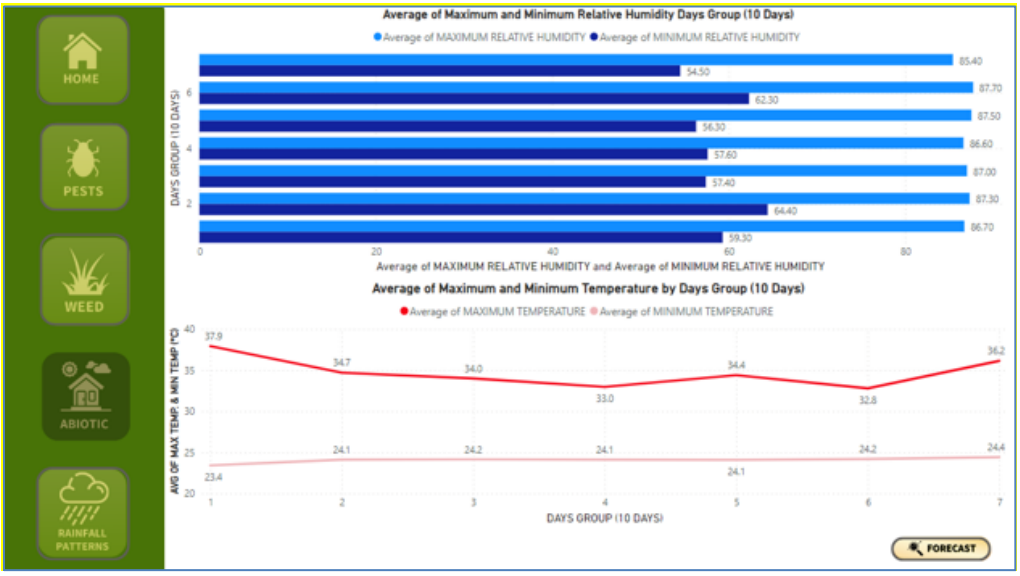

Fig. 5. Data for Abiotic Factors

2.3.5 Rainfall patterns

Weather conditions significantly impact rice cultivation, affecting planting schedules, irrigation, and pest management decisions. Integrating real-time weather forecasts into the DSS allows farmers to plan their activities proactively based on upcoming weather events. By knowing the forecasted weather, farmers can optimize irrigation scheduling, plan for potential heavy rainfall or drought, and take preventive measures against weather-related risks. Rainfall pattern page (Figure 6) contains the data of rainfall pattern for the past 22 years which we obtained from Malaysian Meteorological Department. User can select the year using the slicer function to view the data of rainfall pattern during the particular year. The cards show the average of mean temperature and relative humidity recorded on the particular year. There is a heatmap function which shows the sum of total rainfall all over the country. As we can see the map the red colour is high in Peninsular Malaysia compared to Sabah and Sarawak. This means there are more rainfall in Peninsular Malaysia compared to Sabah and Sarawak.

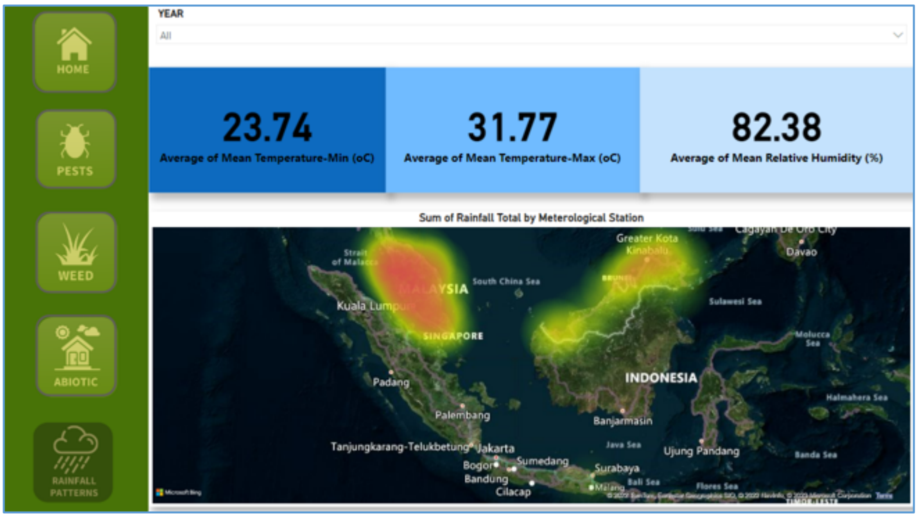

Fig. 6. Rainfall Patterns Page

2.4 Holt-Winter Model

Holt-Winters is a popular method for time series forecasting that combines exponential smoothing with trend and seasonality analysis [22]. It's a type of exponential smoothing that considers both the level and the trend of the time series data, as well as its seasonality. The level model estimates the underlying level of the time series data, considering the recent past values. The trend model estimates the underlying trend of the time series data, considering the recent past values and the level. The seasonality model estimates the underlying seasonality of the time series data, considering the recent past values, the level, and the trend. This method uses three smoothing parameters (α for level, β for trend, and γ for seasonality) to make predictions and adjust the model as new data becomes available. Besides, method is also simple and easy to use, as it does not require a large amount of data to produce accurate forecasts [23].

Holt-Winters can handle multiple seasonal patterns and provide robust forecasts even in the presence of trends and seasonality. The method is widely used in a variety of applications, including sales forecasting, financial forecasting, and demand forecasting. The Holt-Winters operator has several parameters that can adjust to control the behaviour of the forecast for example the number of seasons to use in the calculation, the type of seasonality and the method for initializing the parameters.

The forecasting method mentioned above is implemented using RapidMiner's Holt-Winters method operator. It is included in the Operators panel's "Time & Date" category. A time-series dataset containing a date or time stamp and a numeric value for each observation is required to apply the Holt-Winters operator. The operator will perform a forecast based on the historical data and generate a set of predicted values for a specified forecast horizon.

3. Results and Discussion

Testing and verifying the iRice DSS involves evaluating its performance, accuracy, and usability are required to ensure that it provides reliable and valuable recommendations to users. Besides, as the iRice DSS is deployed and used in the field, continuously monitor its performance, collect feedback from users, and make necessary updates and improvements to enhance its effectiveness over time. The following section discusses the results of weed and abiotic factors for iRice DSS factors.

3.1 Result for Weed

For field capacity water treatment, the maximum number of grasses is 821.43 and the maximum number of sedges is 464.29. The maximum number of broadleaved weeds is 0 because there were no broadleaved weeds grown in the field capacity water treatment during the 70 consecutive days. For the saturated water treatment, the maximum number of grasses is 1500.00 the maximum number of sedges is 625.00 and the maximum number of broadleaved weeds is 1750.00. The highest average of grass grown is during the 4th days group. The highest average of sedges grown is during the 3rd days group and the highest average of broadleaved weeds grown is during the 5th days group. For the flooded water treatment, the maximum number of grasses is 607.14 the maximum number of sedges is 357.14 and the maximum number of broadleaved weeds is 1520.00. The highest average of grass grown is during the 6th days group. The highest average of sedges grown is also during the 6th days group and the highest average of broadleaved weeds grown is during the 5th days group.

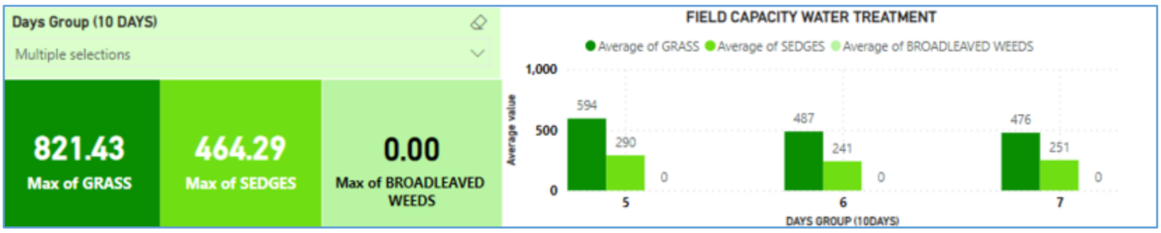

Fig. 7. Comparisons of Weeds in Field Capacity Water Treatment

The predicted weed data for field capacity water treatment, saturated water treatment, and flooded water treatment during the next 50 days are shown in Figures 8 to 10. It shows the predicted average number of weeds for each day's group. To show the difference between the actual data and the forecasted data, they were shown in different colours. Yellow colour indicated the forecast data of grass, blue colour indicated the forecast data of sedges, and the pink colour indicates the forecast data of broadleaved weeds.

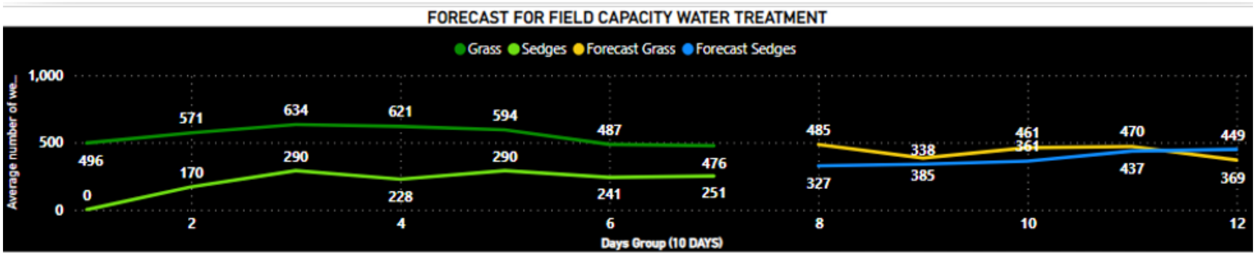

Fig. 8. Forecasted data of weeds in the field capacity water treatment

In Figure 8 shows that the yellow line seems to be decreased in the next 50 days which means the average number of grasses will decrease to 369 whereas the blue line seems to be increased in the next 50 days which means the average number of sedges will increase to 449. There are no broadleaved weeds grown in the field capacity water treatment.

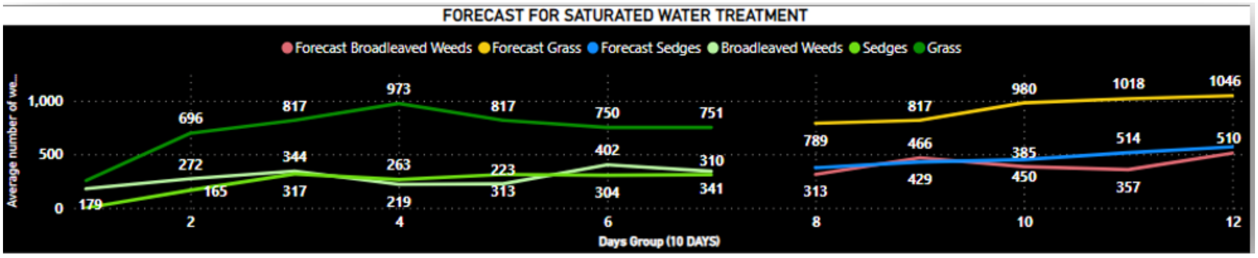

Fig. 9. Forecasted data of weeds in the field saturated water treatment

In Figure 9 shows that the yellow line seems to be increased in the next 50 days which means the average number of grasses will increase to 1046. The blue line also seems to be increased in the next 50 days which means the average number of sedges will increase to 510. The pink line which indicates the broadleaved weeds increases then decreases and increased again to 510 on 12th days group.

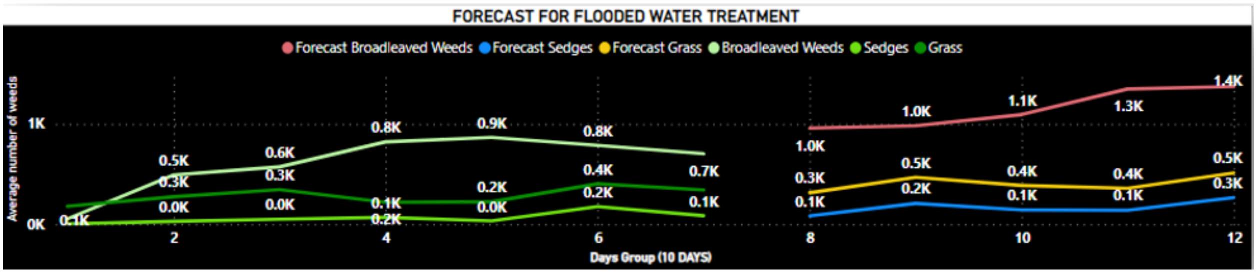

Fig. 10. Forecasted data of weeds in flooded water treatment

Meanwhile in Figure 10 shows that the yellow line seems to be increased in the next 50 days which means the average number of grasses will increase to 510. The blue line also seems to be increased in the next 50 days which means the average number of sedges will increase to 263. The pink line which indicates the broadleaved weeds increases to 1372 on the 12th days group.

3.2 Forecast Result for Abiotic Factors

The highest average minimum relative humidity recorded was 64.40 which is on 2nd days group and the lowest was 54.50 which is on 7th days group. Meanwhile for the data of average maximum and minimum temperature the highest average of maximum temperature recorded was 37.9°C which is during the 1st days group and the lowest was 32.8°C which is on 6th days group. The highest average minimum temperature recorded was 24.4°C which is on 7th days group and the lowest was 23.4°C which is during the 1st days group.

The predicted data for the abiotic factors for the upcoming 50 days are shown in Figures 11 and 12. It shows the predicted data of relative humidity and temperature for each day's group. The actual data and the forecasted data were displayed in various colours to highlight the differences between them.

For average minimum and maximum relative humidity, the actual data were shown in blue colour and the forecasted data were shown in purple colour. The actual data for the average minimum and maximum temperature were displayed in red, whereas the predicted values were displayed in orange. The maximum and minimum data varied as well, with the light colours representing the minimum values and the dark colours the highest values.

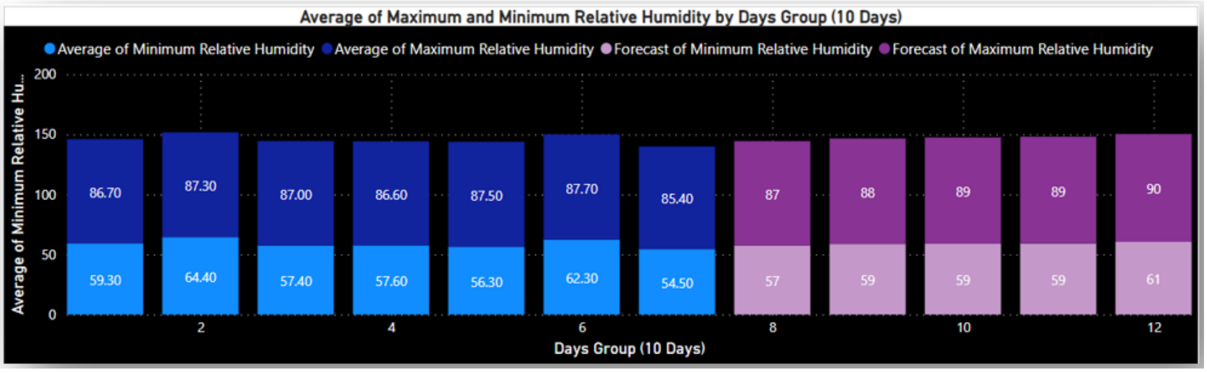

Fig. 11. Forecasted Data of Maximum and Minimum Relative Humidity

The predicted data of average minimum and maximum relative humidity for the next 50 days are displayed in Figure 10. The average maximum relative humidity increases to 90 on the 12th days group and the average minimum relative humidity also increases to 61 on the 12th days group.

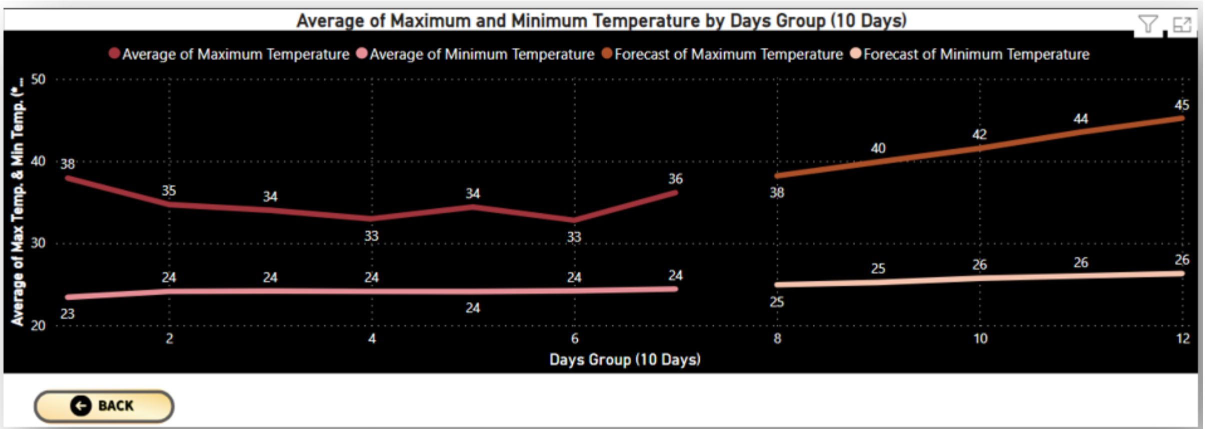

Fig. 12. Forecasted Data of Maximum and Minimum Temperature

The average minimum and maximum temperatures for the next 50 days are shown in Figure 11. On the 12th days group, the average maximum temperature increases to 45°C, and the average minimum relative humidity increases to 26°C as well.

4. Conclusions

Overall, this system is developed for the purpose of monitoring the pests, weeds and abiotic factors in the paddy field by building a simple dashboard named iRice Decision Support System. The system was fully developed and published in website for the use of extension officers. They can view the activity of pests, track the growth of weeds, measure the abiotic factors and they can also keep track of the rainfall pattern with the data of past 22 years provided by Malaysian Meteorological Department. They will examine all the information and advise the farmers on additional steps they should take to boost rice productivity. The extension officers can use the predicted statistics on this dashboard to guide their decisions in the future. This dashboard also contains the forecasted data which can help the extension officers to make decisions for the future. In conclusion, the iRice decision support system will provide an efficient and effective solution to the challenges faced by paddy farmers. It will enhance their decision-making capabilities, increase their yield of production, and help them manage pests and diseases in a timely and effective manner. This system will also help extension officers in analysing data and providing quick solutions during emergency situations. With the implementation of iRice Decision Support System, farmers can look forward to a more productive and profitable future in the paddy cultivation industry.

Acknowledgement
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