Precision Agriculture Through Weather Forecasting

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***Abstract*—Weather plays a significant role in both agriculture and farming. Accurate weather predictions allow farmers to make informed decisions and manage their resources effectively in terms of yield and costs. Precision agriculture is an approach that uses information technology to manage farming operations. The main aim of this research is to achieve precision agriculture by selecting suitable data analytics techniques, such as autoregressive integrated moving average, linear regression, artificial neural networks, and decision tree. A prediction model is trained to forecast weather behaviors such as rainfall, humidity, and temperature. The projected results are correlated to determine which weather factors have the most significant impact on the paddy yield while opening possibilities for farming decision support and insights into productivity.**

***Index Terms*—weather parameters, ARIMA, ANN, decision tree, linear regression**

I. Introduction

Having a good understanding of weather forecasting is very important as inaccurate weather prediction can cause the loss of agricultural products and waste resources. Precision agriculture exploits information technology to increase farm effectiveness and efficiency. Authors in [1] stated that weather forecasting in agriculture helps decide the best time to irrigate and apply fertilizers to crops. Therefore, accurate weather predictions are necessary to allow farmers to make informed decisions and proper planning to maximize yields as well as minimize costs and losses in their products.

Incorrect weather assumptions make farmers not informed of any weather changes. As a result, they perform inefficient farming operations. Unfavorable weather conditions can affect irrigation. Fields located far from the pipe often do not get sufficient water supply consistently. Crops cannot get enough water if the weather is too hot or there is too much water during the rain. Excess rainwater can also cause less concentration of fertilizers for paddy. The use of pesticides raises food safety issues for its residues in the rice. Crop loss is sensitive to severe wind conditions that can damage crops especially when near maturity. Soil quality data is needed to avoid acidic soil because the iron leaves rusty residue on the water's surface. Bird and pest problems arise because crops are inappropriately protected.

Data analytics can distinguish unperceived regularities and patterns from data sets. Authors in [2] mentioned that data analytics combined with internet of things is the main innovation for agriculture, as also identified in [3] for a smart city. Therefore, this research proposes the trial and error approach of prominent data analytics techniques on paddy production in Brunei where rice self-sufficiency should be obtained through the use of modern technology. The main aim is to investigate the requirements of the stakeholders, perform data analytics, and produce a result that can help them make informed decisions and save resources. In detail, the objectives of this research are: effectively choose data analytics techniques to achieve precision agriculture, better predict the optimal period to plant, and harvest paddy from weather forecasting data.

II. Related Works

In recent studies, weather forecasting is arguably considered a crucial process as it plays a vital role in the daily life of people. Hence, the meteorological field is expected to have large databases. Over the last century, the accuracy of weather predictions has been one of the most challenging concerns of meteorologists working on science and technology [4]. According to [5], traditional weather forecasting uses massive computing power consumption to build a mathematical model. It roughly took ten days for a maximum period of accurate weather forecasting. Hence, due to the abundance of sufficiently available weather data, a data analytics model can be beneficial due to its computational efficiency.

Several works on data analytics for weather forecasting are available publicly. Authors in [6] explored the effects of artificial neural networks (ANN) on predicting weather conditions developed in the TensorFlow framework and Python to read the weather data. In [7], rainfall weather data is predicted using seven data analytics models which are evaluated comprehensively. Similarly, authors in [8] also predicted rainfall data using a regression-based statistical model by using five years of weather data. However, it showed an approximate value instead of an accuracy test. There is research on other variables of weather data using various techniques. Authors in [4] stated that the temperature is lenient to forecast. They found that autoregressive integrated moving average (ARIMA) performed better than other models.

From another perspective, authors in [5] explored the most common data analytics techniques to develop a reliable weather forecast for a long-term use. It includes classification and regression reports. Despite their incredible work, our research is not in line with their research that predicted specific weather conditions, such as sunny, hot, or mild. To predict

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the temperature, the ARIMA model is an advantage because of the data requirement. It requires data on the time series that particularly caters to a sequence of standard structures and provides a simple yet powerful method for time series predictions. Furthermore, authors in [4] found that the model performs better in predicting maximum temperature than six other models. Another study [9] concluded that ARIMA models could efficiently capture the air temperature by producing the smallest mean squared error (MSE) compared to other models.

Wind direction and speed can be predicted by using ANN. The Keras library is used as a mixture of deep learning and machine learning because it is simpler and easier to apply compared to others. Moreover, the library integrates deeply Tensorflow to produce a better workflow and functionality. Another study [10] implemented three data analytics algorithms to predict the wind speed, direction, and output power of wind turbines. The research found that all three models perform significantly well in predicting wind speed in a short interval. However, the generated models in predicting the wind direction had less accuracy than wind speed prediction.

Linear regression is initially used to predict rainfall amount; however, other weather factors influence the result. Hence, linear regression is required to examine the strength of relationships between these weather variables. Authors in [11] applied a modified linear regression model to analyse the rainfall in India, especially in different southern areas. It concluded that the proposed model has a small error percentage compared to other techniques such as clustering. All parameters except rainfall use one algorithm technique. This is due to the complication encountered in developing the prediction model on rainfall data.

III. Methodology

A conceptual framework as shown in Fig. 1 is required as a methodology for this work. The research phase enunciates the requirements of the work. The interview phase includes data collection from the agencies involved in paddy cultivation. The parameter setting phase defines the weather variables that are configured in the prediction model. The data understanding phase discovers initial insights, such as the relationship between the variables. The data preparation phase finalizes the data set that involves the data cleaning. The modeling phase selects, applies, and calibrates the appropriate techniques to produce a quintessential result. The performance evaluation phase delivers one or more models that have been evaluated for quality and effectiveness.

In detail, the research phase satisfies several requirements before starting the research, such as defining the objectives, surface-level research on weather and paddy, and others. An online interview was conducted with supervising officer from the Department of Agricultural and Agrifood. The purpose of this interview is to gather more information regarding paddy and identify any potential problems related to its production. The parameter setting phase involves weather data and paddy yield data.

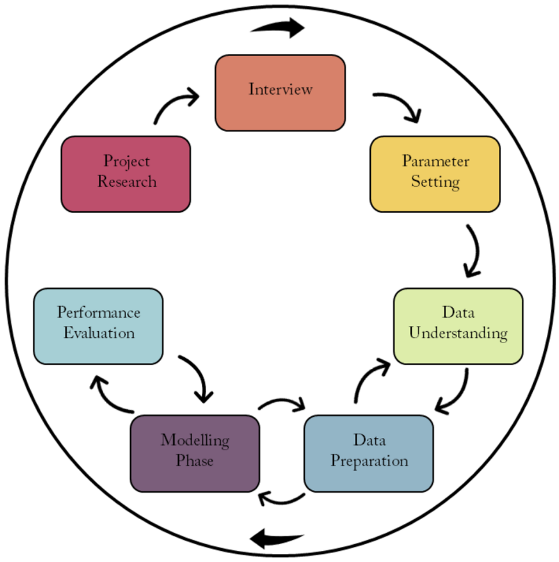

Fig. 1. Cross-industry standard process for data mining-based framework.

Weather datasets are obtained from Brunei Darussalam Meteorological Department (BDMD) and the weather station at the Imang Dam reservoir area. The data includes wind speed in knots around Brunei international airport, relative humidity in percentage, temperature (minimum, maximum, mean) in degrees Celsius, rainfall in millimeters (mm), and wind direction in degrees true north. Temperature and relative humidity were recorded daily, rainfall was collected daily and monthly, and wind direction and speed were captured on an hourly and daily basis. Rainfall, temperature, and relative humidity were recorded from July 2020 to July 2021, but wind direction and speed were collected from January to July 2021.

The data understanding phase examines how to capture the weather data. Meteorological thermometers are used in measuring the temperature of the air. Since all datasets are portable and text documents, additional processing is required to convert them into a spreadsheet format for easier analysis. It is important to note that the wind speed and direction are an hourly basis. All variables except rainfall have no missing values that need to be pre-processed to have more reliable analyses. Rainfall data needs imputation because it contains ’Nil’ and ’Trace’ values. ’Nil’ is used to indicate no rain occurring on the day, and ’Trace’ represents an amount less than 0.1mm.

Because there are two datasets available from BDMD and Imang Dam reservoir, it is essential to compare the features and identify how they affect the prediction model. In terms of data collection, Imang Dam reservoir data is more favorable because it retrieves data more frequently that can provide more accurate results. Weather factors are more prevalent during the daytime, such as ambient light and wind speed. A Python program is developed to accomplish this data cleaning.

In the modeling phase, appropriate modeling techniques are chosen for each weather parameter. Subsequently, further calibration is required to optimize the results. Should there be a need to bring the data into specific requirements of the prediction technique, it returns to the data preparation phase. This approach is similar to the multi-level analysis in [12]. In detail, decision tree is used to classify the classes of high and low/normal humidity. The humidity prediction is merely a classification problem rather than a regression. Since the unit used for relative humidity is in percentage, it is not practical to predict the humidity based on those values. Values larger than 85% are marked as one for high humidity, or else zero for low/normal humidity.

Five ARIMA models for rainfall and temperature with their respective p, d, and q values are evaluated with Akaike Information Criterion (AIC). AIC is a prediction error estimator that tells the quality of a statistical model for a given set of data. Models with lower AIC perform better predictions. Both wind direction and wind speed models use ANN, however, there is a need for rescaling the data between zero and one as has been done in [13]. After fitting the data, the prediction can be executed.

The predicted paddy yield is compared with the predicted weather variables to measure the linear correlation between the datasets. To investigate the impact of weather factors on paddy yield, correlation analysis is conducted to see the presence of a relationship between the two variables and measure the degree of the relationship. Pearson correlation coefficient is used to measure the linear correlation between two sets of interval data. It is implemented by taking the weather data and paddy yield within a given period to model the overall relationship. It is calculated on both historical data and predicted values. The coefficients are observed for any discrepancies or irregularities. The historical data is analyzed from July to December 2020 to maximize the full range of known values, and the prediction is from January to July 2021.

IV. Results and Discussion

The predicted temperature follows a peculiar pattern. It is almost identical to a damped sine wave in that the amplitude decreases as time goes by. Fig. 2 shows the test set error range. There are uncertainties in measuring the temperature of the day. In the dataset, these temperature uncertainties are not included. Therefore, it is assumed that the daily temperature has a sensitivity of ±0.05 °C.

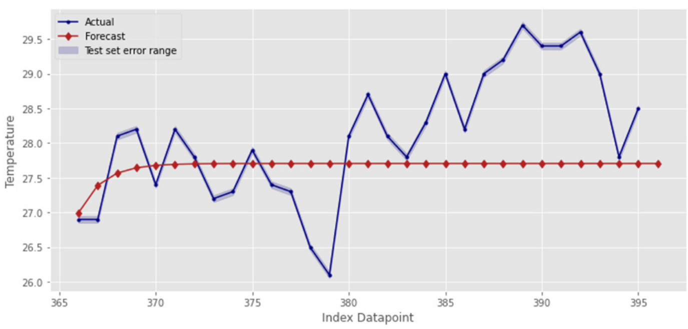

Fig. 2. Close-up view of predicted temperature in July 2021.

In the first ten entries on the predicted humidity label, the model predicted six entries correctly. This shows promising results, but more analysis is needed to assess its true performance. Both wind speed and direction are predicted sequentially. It uses TensorFlow at the back end to develop the ANN model. Wind direction is predicted at noon because predicting other time provides inaccurate results. However, the wind speed is predicted at the average value of the day. The prediction is important because the wind carries moisture and affects temperatures from one area to another. The wind travels from high-pressure areas to low-pressure areas, at the same time the direction shift is affected by heat and pressure. This is the reason why ANN is unable to accurately predict the high and low of the shift. On particular days, the predicted direction of the wind is the opposite of the actual wind direction. It happens when the predicted wind degree increases. Similar to wind direction, wind speed is also affected greatly by air pressure, especially between two pressure areas. The prediction model is accurate when the predicted wind speed follows almost the same pattern as the actual wind speed. However, the difference between the predicted and the actual wind speed is just about 2km/h.

In Fig. 3, the difference between the predicted and actual rainfall for most of the index datapoint is around 10mm. On several days, the predicted rainfall amount is high, but the actual amount is much lower than the predicted one. On other days, the predicted rainfall amount is much lower than the actual one. Although linear regression is a straightforward model, its behavior is almost similar to that of ANN in the prediction of the wind albeit with a larger difference in the predicted and actual values. Unfortunately, linear regression cannot handle the vast jump in the value, as there can be a huge difference in the amount of rainfall between the current and the previous day.

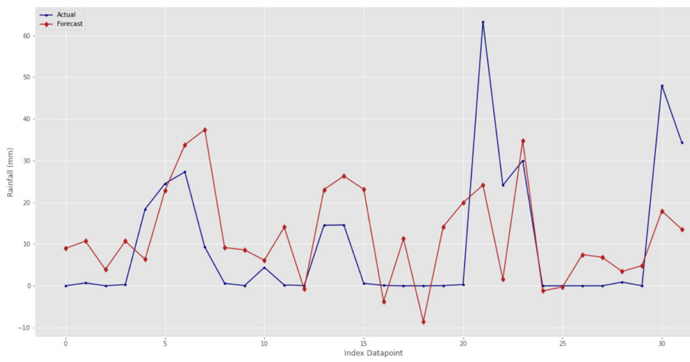

Fig. 3. Close-up view of predicted rainfall amount.

Fig. 4 shows that the ARIMA model could not predict a high rainfall amount of more than 20mm. For days where the rainfall amount is less than 3mm, the predicted value is around 10mm which reflects an inaccuracy of the ARIMA model. There are no reliable resources that specify the sensitivity of the instrument for measuring rainfall. Hence, the error range is set to zero. Two models that predict rainfall does not provide satisfactory results. Decision tree is required, although it cannot classify continuous data. If the rainfall amount is expected to be greater than 5mm, then it is rain. Otherwise, it is no/little rain. The decision tree classifies 6 out of 10 predictions correctly. The behavior is identical to the decision tree for predicting humidity. The spreadsheet prediction can recognize the seasonality of the data. For example, the forecasted total yield in April and October 2021 is above one million kilograms, similar to the actual total yield. However, the problem persists when several predicted total yields are negative. Hence, the values are converted to absolute numbers.

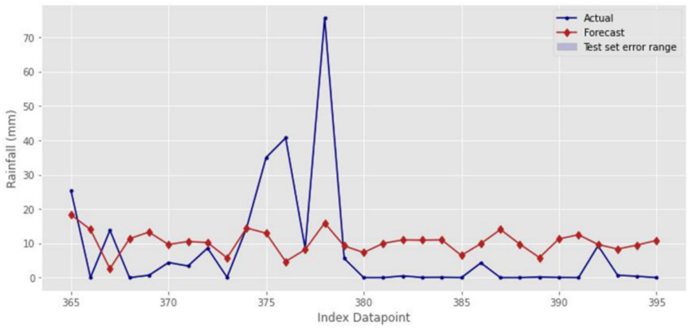

Fig. 4. Close-up view of rainfall amount in July 2021.

Performance analysis is used to select the best algorithm to reach the objectives. The ARIMA model in predicting temperature has an MSE score of 1.01. The lower MSE score the better the model. Although the result is not perfect, the ARIMA model performs significantly well in predicting the average temperature. There are three performance analyses made for predicting humidity. First, the accuracy score of the decision tree in classifying between high humidity and low/normal humidity is 68.75%. It means that out of ten observations, the prediction model can correctly classify almost seven times. Second, the MSE score of decision tree is 0.34. In this case, the MSE score cannot be used to show the true performance of classification models. Hence, it needs alternative performance analysis, such as accuracy score and confusion matrix. Third, the area under the curve(AUC)-receiver operating characteristic (ROC) curve in Fig. 5 is used to show the trade-off between sensitivity and specificity. The classifier performs well with false positive rate (FPR) between 0.4 and 1.0. For FPR between 0 and 0.35, the model is unable to predict correctly.

The confusion matrix gives a clear representation of how the model performs in classifying the data. The model correctly predicts low/normal humidity 16 out of 32, and high humidity six out of 32. However, it incorrectly predicts that the data is high humidity when it is low/normal humidity three out of 32 times, and low/normal humidity when it is high humidity seven out of 32 times. The model has an MSE score of 1.61 in predicting the wind direction, which is considered good as the direction of the wind can quickly change within air pressure. The R2 score is -0.47 which shows that the model cannot follow the trend of the data because the closer the R2 score to one the better prediction. The model has a satisfactory MSE score of 0.35 in predicting wind speed. Even though wind direction and speed use the same technique, the difference in MSE score demonstrates that there could be other factors involved in predicting wind behaviors. With an R2 score of 0.564, the ANN model is a good model to predict wind speed.

Fig. 5. ROC curve with AUC score of humidity.

The ARIMA model for predicting rainfall has a horrendous MSE score of 244. This is because the model cannot precisely predict the time when there is a surge in rainfall due to heavy rain on several days. For example, the rainfall amount almost reaches 80mm on day 378 but the predicted rainfall is 15mm. All these days contribute to a large MSE score. Linear regression is also applied to predict rainfall. However, it shows that the model has an MSE score above 200 similar to ARIMA Model. Additionally, the R2 score is 0.170 which indicates a very low correlation between rainfall and other variables. This can be explained that there lacks of atmospheric pressure data.

ARIMA and linear regression models are unable to achieve MSE scores lower than 200. Hence, the focus is on classification values. The decision tree model achieved an accuracy score of 65.62% and the MSE score of 0.34. Although the MSE score is low, it does not fully reflect the performance of the model. Hence, the AUC-ROC curve and confusion matrix are used to assess it. In Fig. 6, the AUC-ROC curve of decision tree in predicting rainfall does not show big improvements. The curve is far from the top left corner between 0 and 0.8 FPR which shows standard performance and a 0.6 AUC score is considered poor performance. In the confusion matrix, 16 out of 32 times the model correctly predicts little/no rain, and 5 out of 32 times rain. However, 3 out of 32 times it incorrectly predicts that the day is raining when in fact it has little/no rain, and 8 out of 32 times it incorrectly predicts that the day has low/no rain when it is raining.

The overall performance analysis is listed in Table I. The best-performing model is the prediction of wind speed using ANN. However, the performance of the other models can be calibrated to better predict the weather variables. All results are used to decide whether the algorithm can be utilized to correlate the predicted weather variables and the predicted

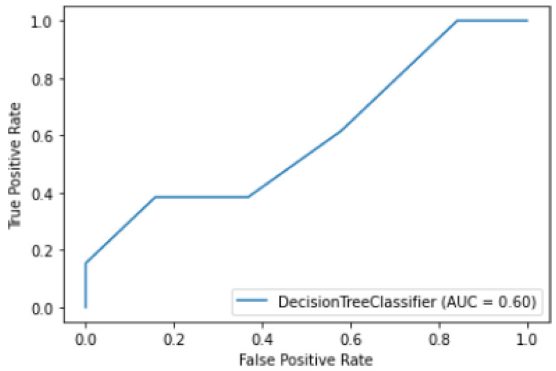

Fig. 6. ROC curve with AUC score of rainfall.

paddy yield.

TABLE I
SUMMARY OF PREDICTION MODEL PERFORMANCE.

Parameter	Model	MSE	Accuracy	AUC-ROC	R2
Temperature	ARIMA	1.01	-	-	-
Humidity	DT	0.31	68.75%	0.82	-
Wind Speed	ANN	0.43	-	-	0.56
Wind Direction	ANN	1.74	-	-	-0.47
Rainfall	ARIMA	244	-	-	-
	LR	209	-	-	0.17
	DT	0.34	65.62%	0.60	-

Fig. 7 shows that the predicted total paddy in 2021 has a similar pattern to that of the actual total paddy in 2020. This prediction can recognize the seasonality of the dataset. However, the predicted values are below zero, hence, readjustment to the model is needed. The predicted total paddy yield is converted to absolute value to achieve a better result as illustrated in Fig. 8. After all predictions have been accomplished, it proceeds to investigate the correlation between the predicted weather variables and the forecasted total paddy yield.

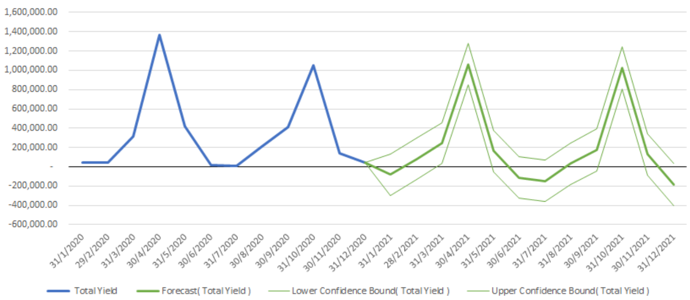

Fig. 7. Forecast of total paddy yield.

Pearson correlation coefficient is computed to find the degree of correlation between certain weather factors and paddy yield. Table II compiles how monthly temperature, relative humidity, wind speed, and average rainfall are correlated with paddy yield. The investigation is separated by the weather dataset from BDMD and Imang Dam dataset, and divided into historical and predicted values. There appears to be the strongest degree of correlation between monthly average rainfall using Imang Dam data and historical paddy yield. It means that the increase in monthly average rainfall is accompanied by the increase in monthly paddy yield and the other way around. However, the monthly average rainfall from BDMD data shows an opposite correlation. This anomaly can be further investigated by comparing the correlation between predicted values and historical values. Monthly average relative humidity does not appear to have a significant correlation with monthly paddy yield with most values near zero. The correlation values for monthly average temperature and monthly average wind speed appear to be consistent between the two datasets.

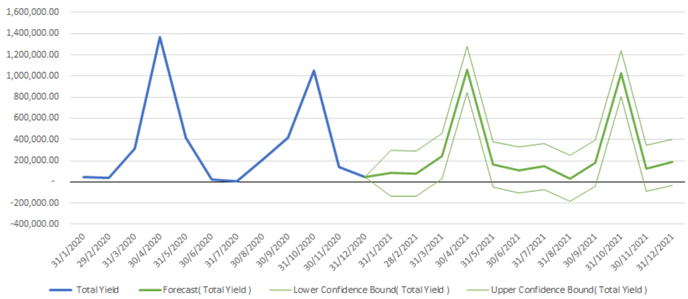

Fig. 8. Adjusted forecast of total paddy yield.

TABLE II
CORRELATION BETWEEN WEATHER PARAMETERS AND PADDY YIELD.

Monthly Weather Parameter Average	BDMD value		Imang Dam value	
	Historical	*Predicted*	*Historical*	*Predicted*
Rainfall	-0.12	-0.57	0.71	-0.38
Temperature	-0.28	0.27	-0.36	0.12
Humidity	0.09	-0.05	0.11	-0.61
Wind Speed	0.33	-0.35	0.36	-0.32

The highest correlation on the predicted values exists for monthly average relative humidity from Imang Dam dataset. However, it is significantly different from BDMD data. Moreover, it can be assumed as an outlier compared to all other correlations that could occur from coincidence or skewed data. In detail, the monthly average relative humidity in Imang Dam dips in value for April 2021 which coincides with the increase of paddy yield due to the harvesting period, which leads to a skew in the correlation coefficient. Similar to the other weather parameters, higher accuracy could be attained with more historical weather data. The second biggest correlation is for monthly average rainfall in the BDMD dataset, which has a magnitude greater than 0.5. The correlation of predicted weather data appears to agree with the two datasets, except for the predicted monthly average relative humidity. An insight exists on the relative usefulness of the datasets based on the highest correlation values with the paddy yield data. An observation can be made on the Pearson coefficient values using BDMD data which are negative for both historical and predicted values, despite the significant differences in their magnitude.

Overall, there appears to be no definitive trend of the correlation between monthly average rainfall and monthly paddy yield. Furthermore, the Pearson coefficient for predicted values appears to be similar between datasets but differs in magnitude. Monthly average rainfall for Imang Dam data appears to have a score lower than from the BDMD dataset. This can be further discovered using interpolation methods for the two stations to fill the gaps in meteorological data [14]. Moreover, the gridded surface meteorological data can be obtained through an extensive network of weather stations to provide spatially and temporally complete coverage [15]. There is an interesting observation for the Pearson coefficient of monthly average temperature and wind speed correlated to monthly paddy yield, in which the correlation of the historical values is in the opposite direction to the correlation of the predicted values. This is due to the seasonality patterns of temperature and wind speed in Brunei affected by the monsoon seasons that are different from the paddy yield pattern.

It is important to examine the monthly paddy yield data. Paddy harvesting seasons occur during relatively the same periods every year regardless of weather or climate conditions, which follow the paddy lifecycle and planting guidelines. It is expected that harvesting periods record high yields. Although the weather has an impact, it is not significantly reflected in the total monthly paddy yield. There is a possibility of other factors that affect paddy yields, such as post-harvest losses, pests, and diseases. To address this, crop simulation is expected to model the impact of weather on paddy yield better with the help of visual inspection as previously done in the factory [16]. Overall, the weather parameters of rainfall, temperature, and wind speed indicate a true correlation with paddy yield, although magnitude and direction are inconsistent. The result is aligned with the research in European agriculture [17].

The correlation between wind speed and paddy yield appears to be the most consistent between datasets, hence, it can imply the similarity between the geographical condition of the two areas. Relative humidity seems to have an insignificant correlation to paddy yield due to the relatively unchanging humid climate of Brunei. Moreover, other factors affect paddy production, such as the paddy type, environmental conditions, and the influence of humans.

V. Conclusion

Brunei aims to achieve rice self-sufficiency shortly, where the aid of modern technology is expected to play a part in accelerating the production of total yield. The weather is the dominant factor that decides the outcome of agriculture. An accurate weather prediction is critical to obtaining full growth efficiency. Data analytics is non-trivial to predict weather and climate behaviors as a step towards achieving precision agriculture. This research proposed the selection of data analytics techniques in paddy cultivation and tested their performance. The selected techniques are ARIMA, linear regression, ANN, and decision tree. It also measured the impact between weather conditions and paddy yield using correlation analysis within the geographical context of Brunei. This was achieved by calculating the Pearson correlation coefficients for the BDMD and Imang Dam weather stations as well as for the historical and predicted values. Overall, the results show that rainfall, temperature, and wind speed significantly correlate with paddy yield. This coincides with existing literature that confirmed the impact of weather conditions on crop yield. The main constraint is an inadequate amount of weather and paddy yield data. In the future, reliable and consistent weather data is necessary for producing highly accurate results in agricultural applications, with sufficient spatial and temporal coverage.

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