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APPLICATION OF ARTIFICIAL NEURAL NETWORK TECHNIQUES FOR RICE YIELD PREDICTION

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Abstract

Rice is a key agricultural product in Thailand because of their geographic location and climate, which are both well-suited to rice production. The agriculture sector needs to adopt innovative technologies to enhance efficiency in the way they produce rice and obtain greater economic return. Machine Learning and Artificial Neural Networks (ANN) can assist in forecasting rice yield. This study aimed to forecast rice yield using ANN based on historical data obtained from five governmental agencies: Department of Agricultural Extension, Office of Agricultural Economics, Thai Meteorological Department, Department of Alternative Energy Development and Efficiency, and Hydro-Informatics Institute. Data used in the study covered the period 2013-2022 and encompassed 34 different variables. The data was split into training, validation and testing data sets (80:10:10). Results showed that the ANN model produced good results in predicting rice yield with respect to: 1) Predictive Accuracy (94.00%), 2) Precision (94.92%), 3) Recall (92.56%), 4) Specificity (95.35%), and 5) F1-Score (94.00%). In conclusion, this study shows evidence of the suitability of ANNs for forecasting rice yield and can assist farmers as they make cultivation plans and manage their enterprise in the marketplace. Future improvements to the input data will allow for improved accuracy in forecasting yield.

Keywords: Artificial Neural Network Techniques; Prediction; Rice yield.

1. Introduction

Rice is the staple food of the world's population. [1-3]. Climate change [4-5] has a direct impact on both rice yields - both in terms of quantity and quality; thus, resource management and crop planning are critical for farmers to combat this problem. Also, although water is not the only limitation on rice growing areas across the globe, it is still a major limiting factor for growing rice as it is the number one cash crop in many countries globally [6]. These issues can be addressed using innovations and modern technology to mitigate the negative effects of rice cultivation on the environment. Global market price fluctuations, as well as outbreaks

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of pests and disease [7] may also have a major impact on rice yields if they are not properly managed.

Thailand ranks as the sixth largest producer of rice globally by producing approximately 4.0% of total world production; behind the People's Republic of China (29.0%) and the Republic of India (25.2%). Thailand produces rice as well as being the second largest exporter of rice globally. In 2022 Thailand exported 7.69 million metric tons of rice valued at 138 billion THB (13.5% of total global rice market share) after India (38.8%), but ahead of Vietnam (12.4%). The Thai government has set an export target of 8.5 million metric tons in 2023 due to the increased demand for rice from countries like the Philippines and Indonesia, as they have very low domestic supply of rice [8]. The Thai Government is also continuing to improve the rice industry to further increase their global competitiveness by developing high yield, disease resistant rice varieties, and investing in biotechnology. Recent research has also highlighted opportunities in digital agriculture, such as the use of drones in the monitoring and fertilization of crops and the application of Artificial Intelligence (AI) in predicting weather conditions and anticipating the occurrence of pest and disease outbreaks.

Artificial Neural Networks (ANNs) (i.e., Machine Learning techniques) are rapidly growing in popularity, and are being used in many areas, including agriculture [9-11] due to their ability to adequately model complex, non-linear relationships that exist between many input variables. In agriculture ANNs can assist in analyzing factors contributing to yields; including but not limited to; impacts of weather, climate, soil characteristics, accurate records of water use and resource management; and to provide more accurate forecasts for increased farm sustainability. AI [12-13] and Big Data Analysis [14-15] techniques will also assist farmers with utilizing predictive weather forecasting tools, tracking market activity and managing resources effectively.

Numerous studies demonstrate the benefits of using ANNs in agricultural forecasts. For example, traditional Multiple-Linear Regression (MLR) vs. ANNs as a predictor of early harvested potato yields; Preferably, ANNs yielded much greater accuracy based on the compounding influences of many variables associated with plant growth, soil properties, and weather conditions [16]. Agricultural yield studies using corn and sugar beans throughout the United States Corn Belt demonstrated the significant reduction in prediction error associated with using ANNs compared to traditional techniques [17]. Thus, it is reasonable to expect that ANNs will significantly improve yield forecast accuracy and provide maximum efficiency in using agricultural resources.

The use of Machine Learning in predicting rice crop yields is the goal of this research study. Specifically, this study utilizes Artificial Neural Networks (ANN) to model rice yield prediction. The study's authors obtained data for this study from numerous different government sources, containing data regarding thirty-four (34) different attributes that may be related to rice yield, including weather, soil, water source, and management practices. The total data set is then divided into three (3) subsets for the purpose of training the ANN model: Training Set (80%); Validation Set (10%); Testing Set (10%) [18-20]. This division of

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the overall dataset is very important for assessing how well the ANN model can perform with complex data structures. The ANN model was created to identify relationships between independent variables (or predictors) that may be associated with rice yield producing dependent variables (or results). Performance was assessed using common statistical measurement conventions: Accuracy, Precision, Recall, and F1- Measure. Based on the results of the study, it was determined that ANN is a powerful method for analyzing complex datasets and providing accurate predictions of rice yields, therefore making it a useful tool for future agricultural research and development. The conceptual framework for the research is represented in Figure 1 [21].

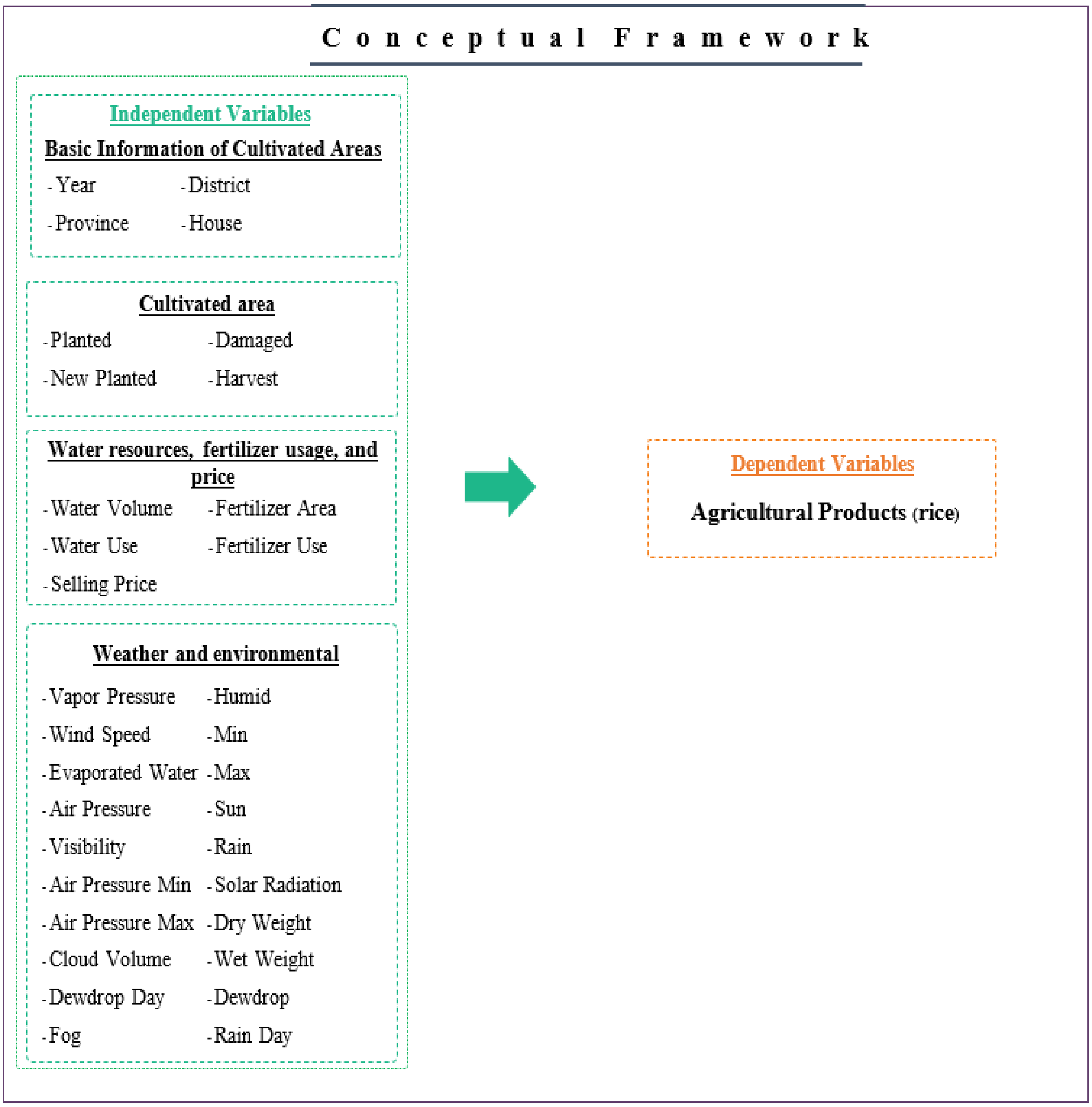

Fig. 1. Conceptual framework of the research.

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2. Materials and Methods

2.1 Research Methodology and Tools

2.1.1 Datasets and Data Pre-processing

This study makes use of publicly available data sets collected by the government of Thailand for use in research and academic purposes. The dataset covers a ten-year period from 2013 until 2022 and was carefully processed before being utilized in the development of the model. The pre-processing included outlier detection and removal, noise reduction (removing any noise that could negatively affect the outcome of the models created), and transformation of data into the numerical or categorical formats required by the architecture of the models used. The completed data cleaning process is presented in Figure 2.

In addition to the data cleaning, the researcher performed a skewness analysis on the data in order to assess the level of distribution of the dataset's values. The results of the skewness analysis are summarized in Figure 3. Skewness is a measure of normality of a dataset, where an extremely low value (0) represents a normal distribution that will improve the effectiveness of the models. By understanding the distribution of the values in the data set, the researcher was able to select processing methods that will increase the accuracy of the forecasting model's results.

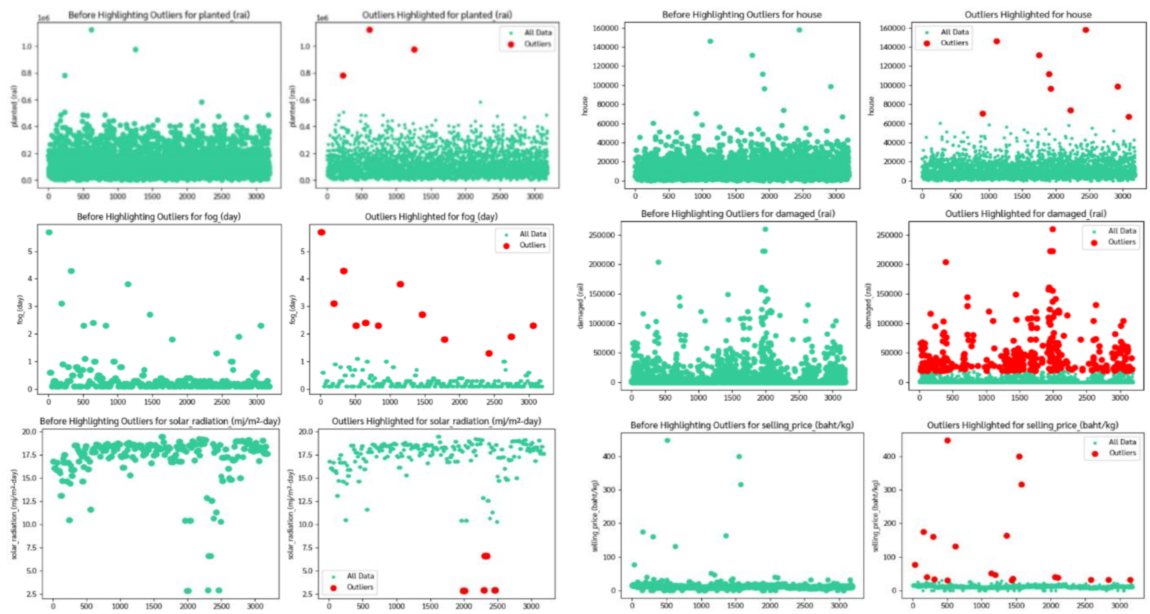

Fig. 2. Outlier detection of datasets.

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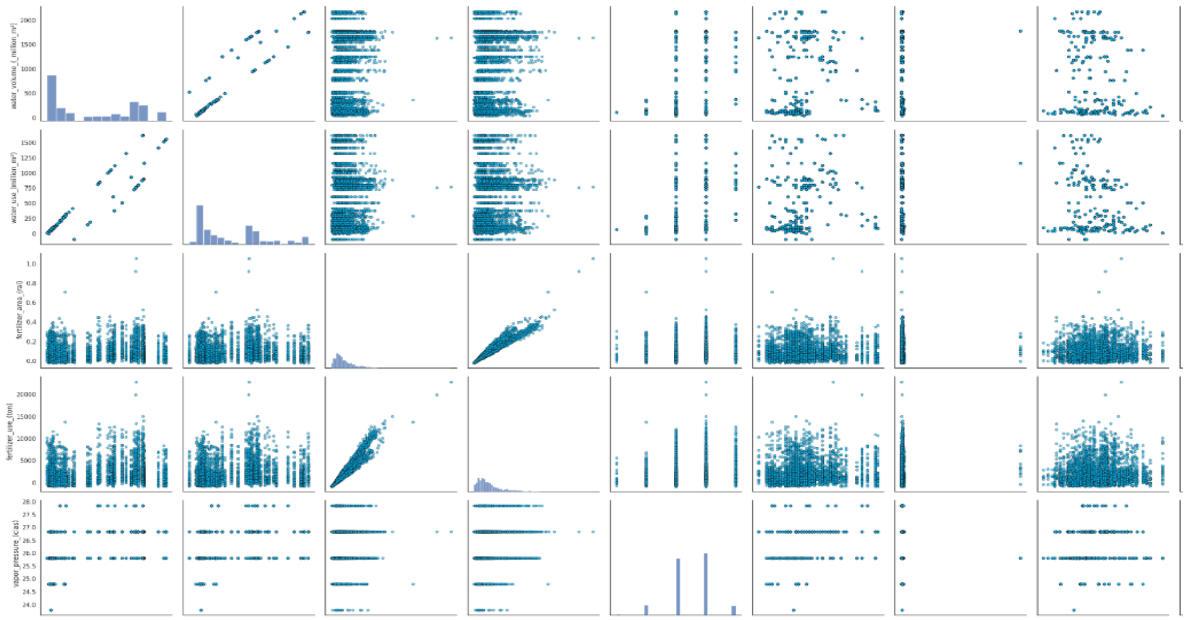

Fig. 3. Analyzing the relationship between variables with Pairs Plot.

2.1.2 Data Validation

The rice farming dataset was compiled as part of a project to synthesize all available rice crop statistics into a single dataset for all areas and periods covered by the research. Using the info () method, the structure of the dataset was verified to ensure that there are no structural errors (or other errors) and that it contains all (but broken down) data, which provides a good base for building predictive models. Table 1 identifies all the variables included in the rice farming dataset, gives the number of observations in the dataset for each variable, and includes the data type for each variable. There was a total of 3,192 observations in the dataset without any missing values. The observations fall into three types of data types, int64 (integer), float64 (floating-point), and object.

Table 1. shows the details of important data sets related to rice cultivation.

Column	Non-Null Count	Data type
year	3192 non-null	int64
province	3192 non-null	object
district	3192 non-null	object
house	3192 non-null	int64
planted (rai)	3192 non-null	float64
new planted (rai)	3192 non-null	float64
damaged (rai)	3192 non-null	float64
harvest (rai)	3192 non-null	float64

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Column	Non-Null Count	Data type
selling price (baht / kg)	3192 non-null	float64
water volume (million_m³)	3192 non-null	float64
water use (million_m³)	3192 non-null	float64
fertilizer area (rai)	3192 non-null	float64
fertilizer use (ton)	3192 non-null	float64
vasopressor (class)	3192 non-null	int64
windspeeds (knot)	3192 non-null	float64
evaporated water (mm)	3192 non-null	float64
air pressure (hpa)	3192 non-null	float64
visibility (km)	3192 non-null	float64
Air pressure min (hpa)	3192 non-null	float64
Air pressure max (hpa)	3192 non-null	float64
Cloud volume (deka)	3192 non-null	float64
Dewdrop day (day)	3192 non-null	int64
fog (day)	3192 non-null	float64
Rain day (day)	3192 non-null	float64
dewdrop (°c)	3192 non-null	float64
Wet weight (°c)	3192 non-null	float64
Dry weight (°c)	3192 non-null	float64
Solar radiation (mj/m²-dat)	3192 non-null	float64
humid (%)	3192 non-null	float64
rain (mm)	3192 non-null	float64
sun (h)	3192 non-null	float64
maxt (°c)	3192 non-null	float64
mint (°c)	3192 non-null	float64

2.1.3 Data Improvements

After the dataset was processed through screenings and removing outliers, it was prepared for use in constructing the ANN model. The steps taken to refine the dataset for use in the ANN model are shown in Table 2. and summarized as follows:

1. The Original dataset had 3,192 records and 34 variables.

2. 697 outliers were removed from the Original dataset prior to the model building so that we do not have any errant predictions due to inaccuracies from outliers. All 34 variables were kept.

3. The Final dataset used to build the ANN consists of 2,495 records and 34 variables.

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Table 2. Summary of the number of data sets and variables after outlier screening.

Description	Amount	
	Data	Variable
Data Frame	3,192	34
Subtract out-of-threshold datasets (cut out the entire dataset)	697	0
The data available for neural network modelling	2,495	34

The dataset refinement will provide the ANN with high-quality and consistent data, which will lead to increased confidence in the results from a data analysis perspective.

2.1.4 Exploratory Data Analysis (EDA)

Pearson Correlation Coefficient was used to assess the linear relationship between all the variable pairs so that each pair could be represented by a value from -1 to 1. The results of that correlation were summarized in a Correlation Matrix shown in Figure 4. The lighter the color in the cell, the more closely related (higher correlations) the two variable pairs are, while the darker the cell, the less closely related (lower or no correlations) the two variable pairs are.

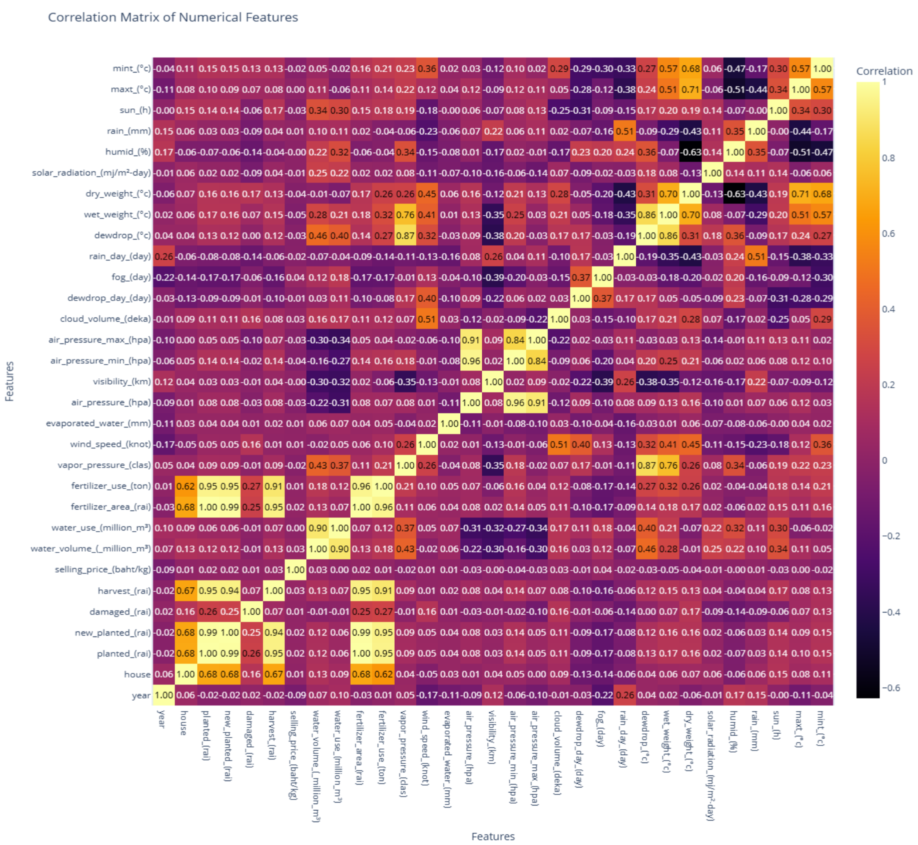

Fig. 4. Correlation between variables.

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Correlations of the pairs of variables that had coefficients of greater than 0.80 indicated that these pairs have a very high positive linear relationship with each other. An example of that is with minimum sea-level pressure and its correlation with mean and maximum air pressure, or new planting areas and their correlation with total planting area or total harvested area; the implication is that the larger the number of areas being planted, the greater the amount of yield. Another example of this study is through the use of fertilizers and their correlations with fertilized area and total yield. Another example of this study is through the use of fertilizers and their correlations with either fertilized area or total yield. There was also significant positive correlations found between different meteorological variables including dew point, wet-bulb temperature, or vapor pressure which once again confirms known relationships among physical principles. These correlations are critical in our understanding of how changing one variable (in this example, increasing the amount of fertilizer used) will have an effect on the entire agricultural sector.

2.1.5 Data Partitioning: Training, Validation, and Testing

The 2,495-entry dataset is split into three subsets at an 80:10:10 ratio for testing and validation of the model and to limit the overfitting of the model. The distribution of the dataset is displayed as follows, outlined in Table 3:

1. Training Set (80% / 1,996): Used for training the ANN by adjusting weights and parameters according to the independent variables (33).

2. Validation Set (10% / 249): Used as part of the training phase to evaluate how well the ANN generalizes to new data and to identify overfitting.

3. Testing Set (10% / 250): Used to evaluate the accuracy of the model as it would be run in a hypothetically simulated environment after training.

Table 3. Data Breakdown for Practice Examine and test neural network models.

Size of ...	Type of Data Frame	
	row	columns
- data	2,495	34
- X_train	1,996	34
- X_val	249	34
- X_test	250	34

2.1.6 Artificial Neural Network

The ANN model developed to forecast yields for rice features a multi-layered architecture with three (3) types of layers: an input layer, hidden layers, and an output layer. Each of these layers processes complex relationships among environmental and agricultural variables.

Hyperparameter Adjustment: During hyperparameter tuning of the ANN model, various activation functions (e.g., relu or sigmoid) were experimented with to achieve optimal results. Additionally, dropout layers were added to assist in reducing the occurrence of overfitting (i.e., training on only the training dataset). Lastly, values for both learning rate and batch size were optimized to minimize the value for loss.

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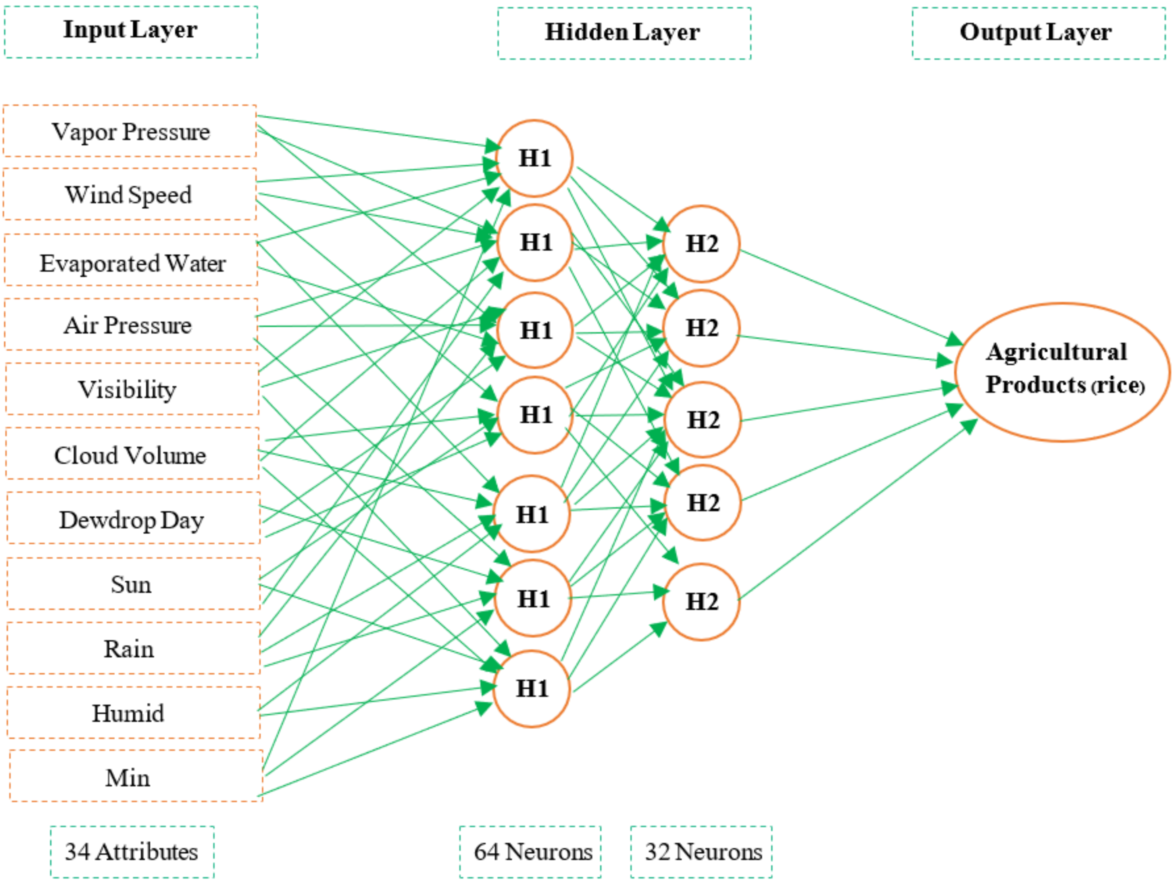

Fig. 5. Structure of a neural network for predicting agricultural yield (rice).

Model Architecture (refer to figure 5)

1. Input Layer, which consists of 34 features such as vapor pressure, wind speed, air pressure, rainfall and humidity.

2. Hidden Layers which contain two (2) layers; the first hidden layer has 64 nodes and provides input to the second hidden layer which contains 32 nodes that creates deeper features of the data.

3. Output Layer consists of a sole node and represents the rice yield prediction.

2.2 Methodology

The operational framework for this research consists of four primary steps: Data Pre-processing, Data Partitioning, Model Training, and Performance Evaluation, as shown in Figure 6. In the workflow, Data Collection and Pre-Processing are the starting points for the research and the goal is to have a clean dataset that is fully prepared for analysis. The pre-

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processing section of the research includes a full audit of the data quality, identifying missing values, and normalizing the data so that all of the data values are on the same scale. This process ensures that the dataset will be compatible with the architecture of an Artificial Neural Network.

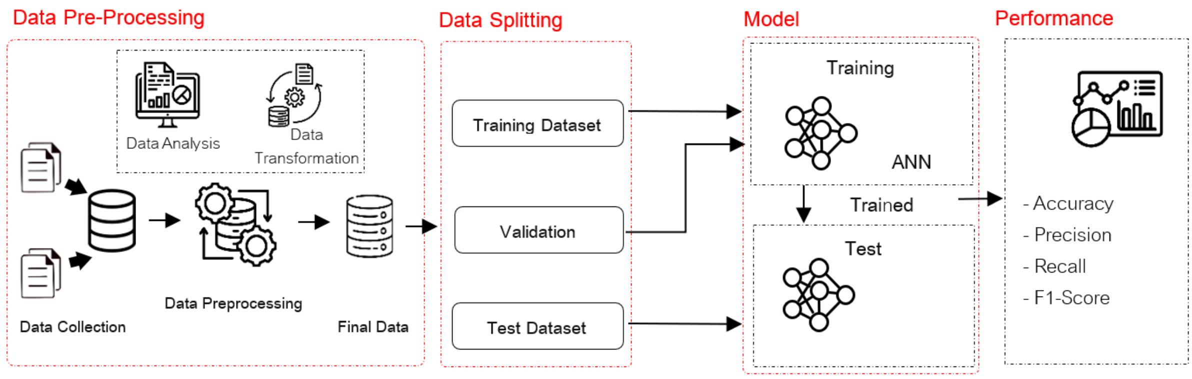

Fig. 6. Shows the working process of creating and evaluating an artificial neural network (ANN) model.

After completing the pre-processing step, the dataset will be separated into three different subsets: a Training Set, a Validation Set, and a Test Set. These three subsets of data are critical to the development and testing of the reliability of the final model.

The main focus of this research is the Artificial Neural Network (ANN) which is a very effective way to analyze complex patterns within a dataset. Once the model has been developed, the performances of the model will be evaluated using a variety of evaluation criteria, including Accuracy, Precision, Recall, Specificity, and F1-Scores. These evaluation criteria will provide a quantitative measure of how well the model produces accurate and reliable predictive results.

3. Results and Discussion

3.1 Performance Evaluation of the Artificial Neural Network (ANN) Model

Utilizing a detailed hyperparameter tuning process to obtain the optimal performance for an Artificial Neural Network (ANN) requires determining the specific configuration of the ANN according to the following criteria: Number of Layers, Number of Neurons, Learning Rate, Batch Size, and Epochs (to produce the highest predictive accuracy). The ANN's performance was evaluated based on a variety of metrics including Accuracy (the number of correct predictions), Loss (the difference between predicted and actual values), and F1-score

(to evaluate the balance of Precision to Recall; a multi-dimensional approach for evaluating reliable and consistent prediction capabilities for agricultural yield forecasting).

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3.1.1 Hyperparameter Optimization

The hyperparameter tuning process is a critical phase that directly influences the model's predictive capabilities. The primary parameters adjusted included the Activation Function, Batch Size, Dropout Rate, and Learning Rate. The goal was to identify the "Best Hyperparameters" that allow the model to achieve maximum efficiency. The final optimized parameters used in this study are summarized in Table 4.

Table 4. Summary of Optimized Hyperparameters for the ANN Model

Parameter	Score
Activation	ReLU / Softmax
Batch Size	16
Dropout Rate	0.40
Epochs	300
Learning Rate	0.0001
Optimizer	Adam
Hidden Layers	2
Neurons	(64, 32)

1. **Activation Function:** ReLU was implemented in the hidden layers to mitigate the Gradient Vanishing problem, while SoftMax was used in the output layer for classification.
2. **Batch Size:** Set at 16 for efficient parameter updates.
3. **Dropout Rate:** Established at 0.40 to prevent overfitting by randomly deactivating 40% of neurons during each training cycle.
4. **Epochs:** Conducted over 300 cycles to ensure thorough learning without incurring overfitting.
5. **Learning Rate:** Configured at 0.0001 to ensure stable and precise convergence.
6. **Optimizer:** The Adam algorithm was selected for its fast and stable convergence properties.
7. **Hidden Layers:** Two hidden layers were utilized to process complex data relationships.
8. **Neurons:** The architecture featured 64 neurons in the first hidden layer and 32 neurons in the second hidden layer.

3.1.2 Confusion Matrix Analysis

The implementation of a confusion matrix (see Figure. 7) enabled further exploration of how well the ANN model can predict classification results based on client segmented support vector machine approaches. The confusion matrix classifies classification results into four classifications: true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

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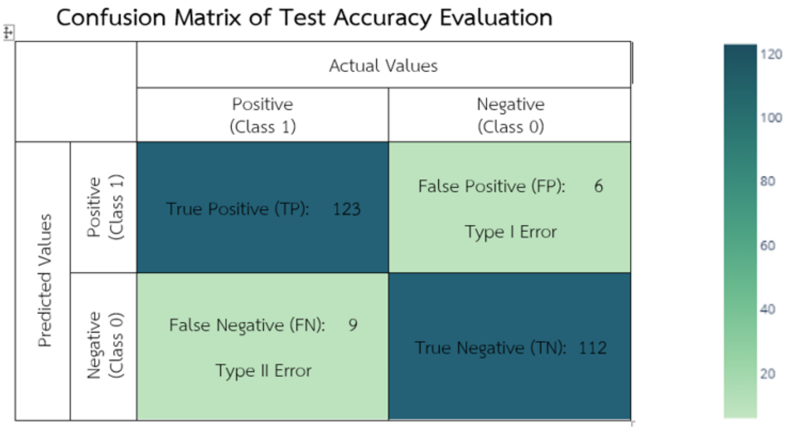

Fig. 7. Confusion matrix of the neural network model.

As seen in Figure 6, there was a high degree of classifier accuracy for the ANN model, given the large number of observed TP and TN classifications. The relatively few classifieds as errors are indicative of a low rate of incorrect predictions in the model.

3.1.3 Performance Metrics Results

The model was evaluated using four primary metrics: Accuracy, Precision, Recall, and Specificity, as detailed in Table 5.

Table 5: Summary of Performance Metrics

Metrics	Score	Formula
Accuracy	0.9400	$\frac{TP + TN}{Total}$
Precision	0.9492	$\frac{TP}{TP + FP}$
Recall (Sensitivity)	0.9256	$\frac{TP}{TP + FN}$
Specificity	0.9535	$\frac{TN}{TN + FP}$

- Accuracy (94.00%): Reflects the overall correctness of the model.
- Precision (94.92%): Indicates high accuracy in positive predictions with a low false-positive rate.
- Recall (92.56%): Demonstrates the model's ability to identify positive instances comprehensively.
- Specificity (95.35%): Shows precision in correctly identifying negative instances.

With all metrics exceeding 0.92 (92%), the results confirm that the ANN model possesses high predictive power and reliability.

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3.1.4 Evaluation through F1-Score and Macro Average

As shown in Table 6, accuracy can be a poor choice for model validation on unbalanced datasets; thus, to validate model performance on the positive/negative classes, both F1-score and macro-averaged metrics are used along with accuracy.

Table 6. Results of model performance measurement using F1-Score and Macro Average.

Metrics	Score	Formula
F1-Score	0.9400	$2\text{x}\dfrac{\text{Precision x Recall}}{\text{Precision} + \text{Recall}}$
Macro Average	0.9400	$\dfrac{\text{F1} - \text{Score}(0) + \text{F1} - \text{Score}(1)}{2}$

1. F1 Score (0.9400), in conjunction with precision and recall, serves as an indicator of how well the algorithm has been designed as compared to precision and recall for both negative and positive classes; therefore, we can conclude from the above F1 score that the algorithm can perform highly regardless of class.
2. Macro Average (0.9400) is simply the average of both precision and recall over all classes; thus, a macro average of 0.9400 indicates good performance in general for all classes.

3.1.5 Model Performance via Learning Curves

The Learning Curve is an important tool used to assess the training of the network model, by showing how the accuracy and loss of the network will change as a function of the number of Epochs. Therefore, using the learning curve helps in understanding whether the model is learning properly and identifying potential problems such as either overfitting or underfitting.

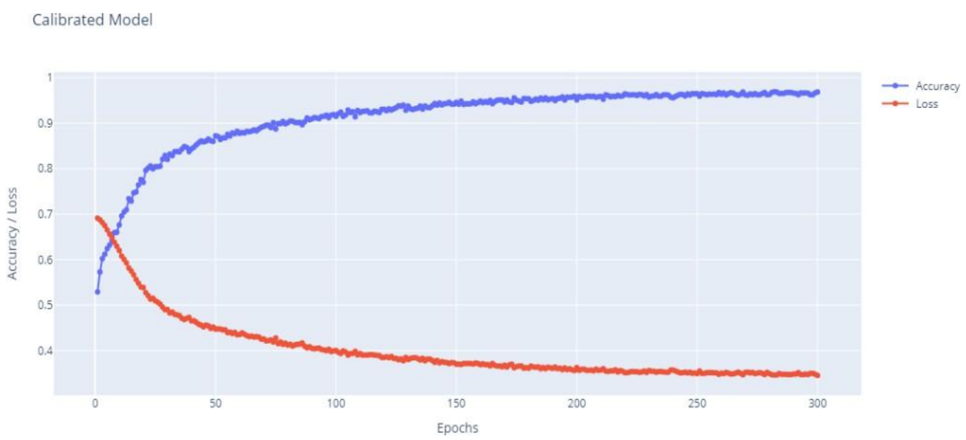

Fig. 8. The learning graph shows the relationship between the accuracy and loss value of the model.

Below is the analysis of findings of the Learning Curve shown in Figure 8:

- Accuracy (in blue): The blue line for accuracy increased dramatically while the network was being trained and has concluded to a plateau around 200 epochs. This indicates that the model has learned the underlying patterns of the data.

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- Loss (in red): The initial decline in the red line indicates that the loss has fallen significantly during the beginning stages of training, thus the prediction accuracy was increasing at a rapid rate. The loss line has now reached a stable level or has converged to an average.

As such, the increase in accuracy along with a decrease in loss without diverging (continuing to increase or decrease) confirm that the ANN model trained properly and performed at a high level without overfitting.

4. Conclusions

The current research demonstrates the application of Artificial Neural Network (ANN) forecasting models to successfully predict the yield of rice. The experimental results indicate that the predictive ability of the ANN exceeded 9 4 % relative to the concept of Precision (94.92%), Recall (92.56%), Specificity (95.35%), and F1 (94.00%).

The study presents some key findings based on the results obtained during experimentation:

1 . Systematic Development: The ANN's achievement of high performance has come as a result of processes involving systematic application of hyperparameter tuning. Hyperparameter tuning was accomplished by optimizing model characteristics such as activation function, batch size, dropout rate, and epochs. As the training process continued, both loss values consistently decreased while accuracy continued to improve, indicating that the ANNs yield predictions would be reliable.

2 . Balanced Evaluation of Performance: The use of the F1 score and Macro Average to evaluate model performance indicates that the developed ANN model consistently produces high Precision measures regardless of high or low yields per rai. The use of the F1 score confirms that there is a positive relationship between Precision and Recall, which is critical in the deployment of the ANN model in practical applications throughout the agricultural sector.

3 . Data Pre-processing as a Vital Component of Model Learning: This research emphasizes that the need for effective Data preprocessing methods (e.g., data balancing, outlier prevention and management, and the selection of strategic features) has a substantial impact on the capability of any model to learn effectively. Data pre-processing techniques not only improved predictive accuracy but also increased the ability of the ANN model to adapt to complex environments.

4 . Agricultural Management Practicalities: The ANN model represents a valuable resource for farm-level yield management and agricultural planning. Reliable harvest forecasts allow farmers and stakeholders to make informed decisions about how to allocate resources such as water and fertilizers and where to site farm operations. In addition, the potential for using satellite-based spatial information through the incorporation of high-resolution environmental analysis into the ANN model should change the overall purpose of the research toward resulting in Precision Agriculture through more effective micro-scale resource allocation.

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5 . Limitations Associated with Data and Geographical Area of Application: A primary limitation of this research is the geospatial limitations of rice producing regions being investigated and may not represent the total geospatial diversity of all rice-producing areas. Researchers should investigate alternative sources of research data, such as Satellite Imagery or Real-time IoT data collection, in order to expand the capabilities of the ANN model. Researchers should also pursue greater understanding and application of multiple methods for selecting features that will improve model adaptability in diverse climates

6 . Continued Hyperparameter Refinement: Even though the current hyperparameter tuning techniques yielded strong results, additional refinements exist. Future studies should consider experimentation with a broader range of hyperparameters including layer size, number of nodes, and learning rate; under diverse conditions for the purpose of maximizing predictive accuracy and increasing flexibility of the ANN model.

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