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Research Article

Optimization of Rice Yield Prediction for Hyper Parameters of Artificial Neural Network

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ABSTRACT

Introduction: Development of neural network models An effective Artificial Neural Network (ANN) requires proper structural design and tuning of hyperparameters. Research in agricultural forecasting shows that ANNs have great potential to manage complex nonlinear relationships between variables. Climate, Hydrology and Environment. Accurate rice yield forecasting is extremely important for Thailand as rice is a major economic crop that plays a role in the country's food security and economic stability.

Objectives: The objectives of this research is to develop a neural network model. An Artificial Neural Network (ANN) that has been optimized for forecasting Thailand's annual rice yield. It focuses on tuning hyperparameters to increase model accuracy and stability, thereby enhancing forecasting efficiency to support agricultural planning and resource management.

Methods: The study uses annual data collected over 12 years (2013–2024), data on 5 government organizations and determined 34 predictor series, under various climate parameters, water resources, solar energy influences – rainfall and temperature, relative humidity, and solar radiation, as well as reservoir sizes. All the data was scaled with Min–Max Scaler which is used to make up the model stable and reduce variation with the range of the data. Testing involved analyzing the ANN structures with 1-2 hidden layers, and tuning the important hyperparameters ie. number of nodes, batch size, dropout rate, learning rate, activation function, optimiser, number of training epochs to reach the structure of the model which produces the best forecasting results.

Results: The optimized ANN model demonstrated excellent predictive performance, achieving an R^2 value of 0.9757, RMSE of 0.0780, MRAE of 0.0121, MASE of 0.0128, and MAE of 0.0061, with an overall prediction accuracy of 98.40%. These results confirm that appropriate hyperparameter tuning substantially improves ANN forecasting capability for annual rice yield estimation.

Conclusions: The findings indicate that a well-configured and properly tuned ANN model can significantly enhance the accuracy of rice yield forecasting in Thailand. The superior performance achieved using optimizers such as Adam and RMSProp highlights the effectiveness of advanced optimization techniques in ANN training. This modeling approach provides valuable insights for monitoring rice production, supporting water resource planning, and accelerating the development of smart agriculture systems in Thailand.

Keywords: Artificial Neural Network (ANN), Hyperparameter Optimization, Rice Yield Prediction

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INTRODUCTION

Rigorous Rice crops' forecasting is mechanism for stability of food and economic in manufacturer countries. Thailand is main manufacturer and exporter [1]–[4] . However, Climate Change Impacts on Water and Extreme weather events from global warming cause uncertainty in rice crop, increase risk long-term of production. [5]–[7] In this case have complexity, then forecasting have to use nonlinearity and multidimensional model, which deep learning and hybrid machine learning technique is better than traditional linear model. [8]–[10]

In traditional forecasting model use static model or linear equations. that have issue when process non-linear and complexity data, which have relationship between climate, water and natural resource. That are characteristic of Farming systems. [11], [12] Previous research of last decade has focused on application of artificial intelligence and machine learning technique. Especially Artificial Neural Networks (ANNs) are technique which learning complexity patterns, effective spatial and temporal data in farming systems. [13]

However, the effectiveness of ANNs in predicting agricultural production does not rely simply on the structure of the model, but equally crucially on its choice and optimization of hyperparameters which are important in the process of learning and model output. Underfitting or overfitting, both of which can directly affect predictive accuracy, due to erroneous hyperparameter settings, have been observed extensively in experimental studies [14], [15]. For this reason, modern research is beginning to apply automatic parameter optimization techniques such as metaheuristic optimization to ANNs to improve the learning efficiency and predictive capabilities of the models [16], [17].

Hyperparameters are critical parameters for effective implementation of ANNs. The optimization and prediction accuracy, stability, and the overall capability of the model are directly influenced by tuning the architecture and learning parameters including the number of nodes in each layer (nodes), batch size, dropout rate, learning rate, optimizer, activation function, and number of training epochs [18]–[20]. Specifically, the number of nodes in hidden layers is important to learn nonlinear connections for the data. With an improper setup, overfitting or insufficient learning problems can occur. Conversely, balanced tuning of the number of nodes was shown to markedly improve the performance and stability of ANNs in earlier work [21], [22].

This research sets out to provide models for forecasting the annual rice yield for Thailand using a hyperparametric neural network integrating data of Thai government departments (the Department of Agricultural Extension, the Office of Agricultural Economics, the Meteorological Department, the Department of Alternative Energy Development and Conservation, and the Water Resources Information Institute) to develop a comprehensive simulation model on the agricultural system's complexity. The data used covers the period from 2013–2024 and contains 34 individual variables. To minimize differences in data ranges and facilitate the learning process and stability of the model, all data has been modified by applying Min–Max normalization. Moreover, the long-term nature of the data also improves the model's generalization ability spatially and temporally [24].

The results of this study are expected to contribute to improving the accuracy of rice yield forecasting in the context of a humid tropical climate. At the same time, it will create new knowledge on neural network optimization with multi-dimensional agricultural data, which can support production planning, water resource management, supply chain risk reduction, and the development of smart agricultural technology for sustainable food security in the future.

OBJECTIVES

The objectives of this study was to develop and evaluate a neural network model. (Artificial Neural Network (ANN) that has been optimized for forecasting Thailand's annual rice production. Based on agricultural data Climate, Water Resources, and Energy. This research aims to: (1) Study the influence of the important hyperparameters of ANN, including the number of hidden layers and the number of nodes, batch size, dropout rate, learning rate, etc. Stimulation function Optimizer and number of training cycles Impact on model performance (2) Identify the optimal ANN structure and parameters to achieve maximum forecasting accuracy and stability, and (3) Evaluate the predictive

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power of a tuned ANN model using several types of statistical indicators. The ultimate objective of this study is to enhance the reliability of rice yield forecasting. To support production planning, water resource management, and smart agriculture development in the context of Thailand's tropical climate.

METHODS

2.1 Artificial Neural Network Model Design

An artificial neural network model was constructed as a feedforward artificial neural network to be used to predict the rice yield of Thailand. The response variable is defined as AVERAGE_YIELD (average rice yield), and the input variables cover spatial data, cultivation data, production factors, water resource indicators, and climate variables. This is in accordance with the practice of previous reports that ANN models are appropriate for dealing with intricate agricultural data and nonlinear correlations between multidimensional variables [25], [26]. The architecture of an ANN is created with 1-2 hidden layers with a flexible range of nodes to learn nonlinear relationships and multi-factor relationships between the input variables and rice yield. This idea has been verified in previous works comparing ANN with conventional forecasting which demonstrated that ANNs exhibit better accuracy. Specifically, for climate data and crop data combined [27], [28], various hyperparameters such as batch size, learning rate, activation function, optimizer, and epochs, were defined as a framework for training the model and further fine-tuning. The data on input variables and range for all hyperparameter values are given in Table 1, which became the basis for developing and measuring the performance of a neural network model.

Table 1 Variable Details and Hyperparameter Determination of Neural Network Models

Variables / Hyper parameters	ANN Variants
Response variable	AVERAGE_YIELD
Experimental variable	YEAR, PROVINCE, DISTRICT, HOUSE, PLANTED, NEW PLANTED, DAMAGED, HARVEST, SELLING_PRICE, WATER_VOLUME, WATER_USE, FERTILIZER_AREA, FERTILIZER_USE, VAPOR_PRESSURE, WIND_SPEED, EVAPORATED_WATER, AIR_PRESSURE, VISIBILITY, AIR_PRESSURE_MIN, AIR_PRESSURE_MAX, CLOUD_VOLUME, DEWDROP_DAY, FOG, RAIN_DAY, DEWDROP, WET_WEIGHT, DRY_WEIGHT, SOLAR_RADIATION, HUMID, RAIN, SUN, MAXT, MINT
Nodes (Hidden Neurons) 1	1 - 128
Nodes (Hidden Neurons) 2	1 - 128
Batch Size	16, 32, 64
Dropout Layer	0.10, 0.20, 0.30, 0.40, 0.50
Learning Rate	0.01, 0.001, 0.0001
Optimizers	Adam, SGD, RMSprop
Activation	ReLU, Sigmoid, Tanh
Epochs	100, 200, 300, 400, 500

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2.2 Data preparation and variable selection

Data from several sources are collected and standardized before data preparation to avoid problems arising from different origin [29], [30]. Data pre-processing involves performing data integrity checks, dealing with missing values, and scaling to increase the stability and maintainability or learnability of the model [31]. To reduce redundancy and the effect of multicollinearity, commonly used to mitigate the stability and generalization issue of the model [32], [33], correlation analysis is used for variable selection. Using the calculation of Pearson's correlation coefficient and rendering it as a correlation matrix it is possible to look more systematically at the relationship patterns between the variables. The correlation analysis is represented in Figure 1, showing the correlation matrix based on Pearson's coefficients.

Figure 1. Correlation matrix of the variables.

Parameter	YR	HS	PLA	NPL	DAM	HAR	SEL	WV	WU	FA	FU	VP	WS	EW	AP	VS	APM	APX	CV	DDD	FGD	RD	DD	WW	DW	SR	HUM	RN	SUN	MAX	MIN
YR	1	0.061	-0.024	-0.025	0.017	-0.017	-0.086	0.066	0.098	-0.029	0.008	0.049	-0.168	-0.106	-0.090	0.123	-0.056	-0.100	-0.014	-0.027	-0.222	0.264	0.039	0.017	-0.057	-0.009	0.172	0.148	-0.001	-0.114	-0.045
HS	0.061	1	0.684	0.680	0.163	0.671	0.011	0.134	0.088	0.679	0.618	0.038	-0.046	0.035	0.015	0.044	0.053	0.005	0.090	-0.128	-0.144	-0.064	0.039	0.062	0.072	0.058	-0.063	0.065	0.152	0.077	0.106
PLA	-0.024	0.684	1	0.995	0.257	0.945	0.021	0.122	0.061	0.999	0.954	0.095	0.053	0.036	0.078	0.029	0.137	0.051	0.110	-0.092	-0.170	-0.083	0.127	0.166	0.161	0.020	-0.066	0.025	0.143	0.097	0.151
NPL	-0.025	0.680	0.995	1	0.248	0.944	0.019	0.121	0.061	0.994	0.949	0.093	0.048	0.037	0.077	0.030	0.137	0.051	0.107	-0.095	-0.170	-0.081	0.123	0.163	0.157	0.020	-0.064	0.026	0.145	0.093	0.148
DAM	0.017	0.163	0.257	0.248	1	0.073	0.014	-0.014	-0.005	0.251	0.271	-0.006	0.160	0.010	-0.032	-0.010	-0.020	-0.103	0.156	-0.010	-0.057	-0.141	0.002	0.074	0.170	-0.090	-0.143	-0.092	-0.055	0.074	0.128
HAR	-0.017	0.671	0.945	0.944	0.073	1	0.030	0.126	0.066	0.945	0.906	0.092	0.014	0.022	0.085	0.038	0.144	0.072	0.076	-0.095	-0.165	-0.055	0.123	0.153	0.129	0.042	-0.041	0.037	0.167	0.076	0.129
SEL	-0.086	0.011	0.021	0.019	0.014	0.030	1	0.027	0.001	0.020	0.014	-0.023	0.010	0.007	-0.035	-0.002	-0.038	-0.033	0.028	-0.014	0.035	-0.024	-0.030	-0.052	-0.035	-0.006	-0.003	0.012	-0.027	0.003	-0.024
WV	0.066	0.134	0.122	0.121	-0.014	0.126	0.027	1	0.904	0.127	0.179	0.427	-0.017	0.058	-0.221	-0.302	-0.159	-0.295	0.164	0.028	0.124	-0.067	0.461	0.285	-0.013	0.247	0.221	0.098	0.339	0.109	0.053
WU	0.098	0.088	0.061	0.061	-0.005	0.066	0.001	0.904	1	0.066	0.119	0.374	0.047	0.066	-0.305	-0.319	-0.272	-0.341	0.167	0.113	0.185	-0.038	0.401	0.213	-0.075	0.223	0.317	0.107	0.302	-0.056	-0.021
FA	-0.029	0.679	0.999	0.994	0.251	0.945	0.020	0.127	0.066	1	0.961	0.106	0.056	0.039	0.076	0.023	0.138	0.053	0.114	-0.099	-0.171	-0.091	0.142	0.182	0.170	0.023	-0.061	0.021	0.150	0.106	0.164
FU	0.008	0.618	0.954	0.949	0.271	0.906	0.014	0.179	0.119	0.961	1	0.210	0.101	0.051	0.074	-0.060	0.159	0.038	0.122	-0.078	-0.168	-0.136	0.273	0.317	0.255	0.016	-0.035	-0.041	0.178	0.142	0.211
VP	0.049	0.038	0.095	0.093	-0.006	0.092	-0.023	0.427	0.374	0.106	0.210	1	0.257	-0.043	0.078	-0.352	0.183	-0.024	0.075	0.169	-0.012	-0.111	0.868	0.755	0.263	0.075	0.336	-0.057	0.189	0.217	0.229
WS	-0.168	-0.046	0.053	0.048	0.160	0.014	0.010	-0.017	0.047	0.056	0.101	0.257	1	0.023	0.010	-0.130	-0.006	-0.064	0.508	0.396	0.126	-0.133	0.318	0.413	0.447	-0.112	-0.149	-0.232	-0.177	0.120	0.360
EW	-0.106	0.035	0.036	0.037	0.010	0.022	0.007	0.058	0.066	0.039	0.051	-0.043	0.023	1	-0.105	-0.013	-0.083	-0.098	0.032	-0.100	-0.043	-0.157	-0.026	0.011	0.056	-0.072	-0.078	-0.060	-0.002	0.039	0.022
AP	-0.090	0.015	0.078	0.077	-0.032	0.085	-0.035	-0.221	-0.305	0.076	0.074	0.078	0.010	-0.105	1	0.079	0.961	0.914	-0.120	0.091	-0.099	0.078	0.087	0.128	0.161	-0.104	0.011	0.067	0.060	0.116	0.026
VS	0.123	0.044	0.029	0.030	-0.010	0.038	-0.002	-0.302	-0.319	0.023	-0.060	-0.352	-0.130	-0.013	0.079	1	0.024	0.095	-0.021	-0.220	-0.391	0.264	-0.384	-0.353	-0.116	-0.155	-0.167	0.225	-0.073	-0.088	-0.120
APM	-0.056	0.053	0.137	0.137	-0.020	0.144	-0.038	-0.159	-0.272	0.138	0.159	0.183	-0.006	-0.083	0.961	0.024	1	0.840	-0.088	0.065	-0.195	0.040	0.197	0.253	0.209	-0.058	0.024	0.064	0.079	0.121	0.095
APX	-0.100	0.005	0.051	0.051	-0.103	0.072	-0.033	-0.295	-0.341	0.053	0.038	-0.024	-0.064	-0.098	0.914	0.095	0.840	1	-0.223	0.021	-0.035	0.108	-0.028	0.030	0.126	-0.138	-0.007	0.111	0.135	0.108	0.023
CV	-0.014	0.090	0.110	0.107	0.156	0.076	0.028	0.164	0.167	0.114	0.122	0.075	0.508	0.032	-0.120	-0.021	-0.088	-0.223	1	0.025	-0.150	-0.102	0.168	0.213	0.284	0.067	-0.165	0.017	-0.255	0.054	0.291
DDD	-0.027	-0.128	-0.092	-0.095	-0.010	-0.095	-0.014	0.028	0.113	-0.099	-0.078	0.169	0.396	-0.100	0.091	-0.220	0.065	0.021	0.025	1	0.373	0.171	0.167	0.051	-0.051	-0.093	0.228	-0.074	-0.306	-0.284	-0.286
FGD	-0.222	-0.144	-0.170	-0.170	-0.057	-0.165	0.035	0.124	0.185	-0.171	-0.168	-0.012	0.126	-0.043	-0.099	-0.391	-0.195	-0.035	-0.150	0.373	1	-0.026	-0.032	-0.178	-0.201	-0.020	0.205	-0.156	-0.088	-0.119	-0.303
RD	0.264	-0.064	-0.083	-0.081	-0.141	-0.055	-0.024	-0.067	-0.038	-0.091	-0.136	-0.111	-0.133	-0.157	0.078	0.264	0.040	0.108	-0.102	0.171	-0.026	1	-0.190	-0.346	-0.429	-0.028	0.241	0.514	-0.152	-0.377	-0.326
DD	0.039	0.039	0.127	0.123	0.002	0.123	-0.030	0.461	0.401	0.142	0.273	0.868	0.318	-0.026	0.087	-0.384	0.197	-0.028	0.168	0.167	-0.032	-0.190	1	0.859	0.314	0.185	0.355	-0.090	0.165	0.239	0.269
WW	0.017	0.062	0.166	0.163	0.074	0.153	-0.052	0.285	0.213	0.182	0.317	0.755	0.413	0.011	0.128	-0.353	0.253	0.030	0.213	0.051	-0.178	-0.346	0.859	1	0.701	0.075	-0.068	-0.294	0.204	0.506	0.571
DW	-0.057	0.072	0.161	0.157	0.170	0.129	-0.035	-0.013	-0.075	0.170	0.255	0.263	0.447	0.056	0.161	-0.116	0.209	0.126	0.284	-0.051	-0.201	-0.429	0.314	0.701	1	-0.130	-0.627	-0.431	0.194	0.706	0.675
SR	-0.009	0.058	0.020	0.020	-0.090	0.042	-0.006	0.247	0.223	0.023	0.016	0.075	-0.112	-0.072	-0.104	-0.155	-0.058	-0.138	0.067	-0.093	-0.020	-0.028	0.185	0.075	-0.130	1	0.140	0.114	0.138	-0.056	0.060
HUM	0.172	-0.063	-0.066	-0.064	-0.143	-0.041	-0.003	0.221	0.317	-0.061	-0.035	0.336	-0.149	-0.078	0.011	-0.167	0.024	-0.007	-0.165	0.228	0.205	0.241	0.355	-0.068	-0.627	0.140	1	0.351	-0.072	-0.511	-0.467
RN	0.148	0.065	0.025	0.026	-0.092	0.037	0.012	0.098	0.107	0.021	-0.041	-0.057	-0.232	-0.060	0.067	0.225	0.064	0.111	0.017	-0.074	-0.156	0.514	-0.090	-0.294	-0.431	0.114	0.351	1	0.000	-0.438	-0.170
SUN	-0.001	0.152	0.143	0.145	-0.055	0.167	-0.027	0.339	0.302	0.150	0.178	0.189	-0.177	-0.002	0.060	-0.073	0.079	0.135	-0.255	-0.306	-0.088	-0.152	0.165	0.204	0.194	0.138	-0.072	0.000	1	0.338	0.302
MAX	-0.114	0.077	0.097	0.093	0.074	0.076	0.003	0.109	-0.056	0.106	0.142	0.217	0.120	0.039	0.116	-0.088	0.121	0.108	0.054	-0.284	-0.119	-0.377	0.239	0.506	0.706	-0.056	-0.511	-0.438	0.338	1	0.569
MIN	-0.045	0.106	0.151	0.148	0.128	0.129	-0.024	0.053	-0.021	0.164	0.211	0.229	0.360	0.022	0.026	-0.120	0.095	0.023	0.291	-0.286	-0.303	-0.326	0.269	0.571	0.675	0.060	-0.467	-0.170	0.302	0.569	1

Figure 1. Correlation matrix of the variables.

YR: Year; HS: House; PLA: Planted Area; NPL: New Planted; DAM: Damaged Area; HAR: Harvest Area; SEL: Selling Price; WV: Water Volume; WU: Water Use; FA: Fertilizer Area; FU: Fertilizer Use; VP: Vapor Pressure; WS: Wind Speed; EW: Evaporated Water; AP: Air Pressure; VS: Visibility; APM: Air Pressure Min; APX: Air Pressure Max; CV: Cloud Volume; DDD: Dewdrop Days; FGD: Fog Days; RD: Rain Days; DD: Dewdrop; WW: Wet Weight; DW: Dry Weight; SR: Solar Radiation; HUM: Humidity; RN: Rainfall; SUN: Sunlight Hours; MAX: Max Temperature; MIN: Min Temperature;

Figure 1. Correlation Matrix of the Variables

Correlation analysis across variables showed the majority of variables present low to moderate relationship, indicating each categorical dimension could offer information and can be used to explain the rice production system in different ways. Nevertheless, the correlation of some cultivated area variables, namely Planted Area (PLA), New Planted Area (NPL), and Harvest Area (HAR), was comparatively high, in line with the interconnected spatial and temporal nature of the rice production process.

In addition, there was a high correlation between some pairs of weather variables including maximum temperature (MAX) and sunlight hours (SUN), vapor pressure (VP) and relative humidity (HUM). This reflects the physical mechanisms of the atmosphere. Reviewing these relationships will help the choices of the input variables and reduce data redundancy, and lead to the construction of a more robust and responsive NNs model for rice yield prediction.

2.3 Data Collection

The data for this study was gathered from various credible resources to represent the main determinants of Thailand's annual rice production in both spatial and temporal dimensions. Rice production data have been sourced from the Department of Agricultural Extension and the Office of Agricultural Economics on the basis of planted area, harvested area, input usage, selling price, and yield. This information is representative of the structural and management characteristics of rice production. Climate data was obtained from the Meteorological Department based on data of rainfall, temperature, relative humidity, air pressure, wind speed, and sunshine hours, which had direct impact on physiological processes, growth, and biomass accumulation of rice. Solar energy data was also taken from the Department of Alternative Energy Development and Conservation as a proxy for plant photosynthetic potential, while water resource data from the Water Resources Informatics Institute reflected water limitations and fluctuations affecting rice yield stability, both in irrigated and rain-fed systems.

2.4 Adjusting and processing data before learning

In order to ensure that the scope of all values of the input variables is the same level, all data were scaled to a range of 0 to 1 using the Min–Max scaling method with the goal of minimizing the level of data scale differences. Upon scaling, the data was divided into a training set, a validation set, and a test set with 80%, 10%, and 10% ratios, respectively. This data split was planned to train the model and tweak it to fit the training dataset, validate performances on the validation dataset, and measure the final performance of the model on an unseen test dataset.

2.5 Hyperparameter customization of the model

Hyperparameter tuning of the neural network is done by assigning ranges of values to parameters both for the structure of the model and for the process of learning, so as to optimize the prediction process to increase forecasting efficiency and stability. Model parameters taken into account include the number of hidden layers, number of nodes in each layer, batch size, dropout rate, learning rate, optimizer, activation function, and number of training epochs. By setting the dropout rate in the range of 0.10–0.50, the goal is to avoid overfitting and improve the quality of the overall model. Meanwhile, several optimizers, including Adam, Stochastic Gradient Descent (SGD), and RMSprop, were compared to evaluate the stability and learning performance under different parameter settings. Table 2 summarizes the ranges of all hyperparameter values used in the experiments for both training and evaluation of the model performance, this way providing a general framework.

Table 2 Parameters used to train and adjust neural network models

Nodes	Batch Size	Dropout Layer	Learning Rate	Optimizers	Activation	Epochs
1,2	16,32,64	0.10, 0.20, 0.30, 0.40, 0.50	0.01,0.001,0.0001	Adam,SGD, RMSprop	ReLU,Sigmoid,Tanh	100,200,300,400,500

- **Nodes**

Set the number of nodes in the hidden layer to 1 or 2 nodes to determine the model's representation capability.

- **Batch Size**

Set the sub-data cluster size to 16, 32, and 64 for updating weights in each training iteration.

- **Dropout Layer**

Set the dropout rate to 0.10, 0.20, 0.30, 0.40, and 0.50 to prevent model overfitting.

- **Learning Rate**

Set the learning rate to 0.01, 0.001, and 0.0001 to control the learning process dynamics.

- **Optimizers**

Use Adam, SGD, and RMSprop optimizers for updating model weights.

- **Activation**

Use ReLU, Sigmoid, and Tanh functions for simulating the nonlinear relationships of the data.

- **Epochs**

Set the number of training cycles to 100, 200, 300, 400, and 500 cycles to evaluate the effect of training duration on the model's performance.

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2.6 Computational and experimental environment

The training and evaluating of the neural network model was done using Python version 3.12 on Windows 11 Pro operating system, plus the TensorFlow and Keras libraries, widely accepted standard tools for developing and applying deep learning models. The processing was done on an Intel® Core™ i7-10750H CPU with 64 GB of RAM, which is adequate to train medium to large-scale neural network models and supports iterative experiments for the tuning of parameters.

2.7 Evaluating the performance of the model

The performance of the model with respect to the neural network was assessed using a range of quantitative statistics to capture the model's predictive accuracy along several aspects, in a comprehensive picture. The metrics were Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) which measure the absolute error between predicted and actual results. RMSE weights big errors while MAE is a measure of the average error and is less sensitive to outliers [34]. The MRAE was performed to quantify the relative error of the forecast results, which is appropriate for comparing forecast results and when the values are at different scales [35]. Also, Mean Absolute Scaled Error (MASE) was implemented as it had the advantage of considering each different scale data context, and coefficient of determination (R^2) was applied to measure the model performance in explaining the actual rice production data variance. Multiple metrics combined provide a more complete assessment of the model's performance, alleviating the disadvantages of focusing on just a single metric. And it properly reflects the accuracy of the forecast, both by statistics and through application.

RESULTS

Results from the development and refinement of 20neural network models showed that the model's hyperparameters played a significant role in the forecasting performance of paddy rice yield, which is consistent with recent research on crop yield forecasting using deep learning techniques, which has shown that optimal parameter settings can significantly improve the accuracy and stability of the model [23], [29].

Table 3 Results of hyperparameter tuning of neural network models (ANN) for forecasting rice yields.

Model	Nodes 1	Nodes 2	Batch Size	Dropout Layer	Learning Rate	Optimizers	Activation	Epochs	Accuracy
1	22	115	16	0.2	0.001	SGD	Tanh	500	73.60
2	55	65	64	0.5	0.001	SGD	Tanh	500	62.80
3	61	41	16	0.4	0.01	Adam	Sigmoid	400	98.00
4	78	25	16	0.5	0.0001	SGD	Sigmoid	200	53.20
5	77	91	64	0.4	0.0001	SGD	Sigmoid	100	53.20
6	21	78	32	0.4	0.01	RMSprop	Tanh	300	95.60
7	15	23	64	0.2	0.01	RMSprop	ReLU	200	94.80
8	117	44	32	0.2	0.001	Adam	ReLU	100	98.40

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Model	Nodes 1	Nodes 2	Batch Size	Dropout Layer	Learning Rate	Optimizers	Activation	Epochs	Accuracy
9	39	100	32	0.5	0.01	Adam	Sigmoid	300	98.00
10	74	42	16	0.5	0.001	SGD	Sigmoid	400	53.20
11	85	114	16	0.5	0.01	RMSprop	Sigmoid	300	98.00
12	5	11	32	0.1	0.01	SGD	Sigmoid	300	60.80
13	121	127	16	0.3	0.0001	Adam	Tanh	100	74.40
14	74	20	64	0.4	0.001	RMSprop	Tanh	100	76.00
15	61	36	32	0.3	0.0001	SGD	ReLU	400	58.40
16	108	61	32	0.3	0.001	SGD	ReLU	400	67.60
17	118	23	16	0.5	0.01	SGD	Tanh	400	74.40
18	29	97	16	0.2	0.0001	SGD	Sigmoid	500	53.20
19	72	66	64	0.4	0.01	RMSprop	Tanh	500	97.60
20	94	33	64	0.2	0.01	RMSprop	Sigmoid	100	96.80

Following the experiment results in Table 3, the 8th order model obtained the highest accuracy (Accuracy = 98.40%) with a two-layer hidden structure (117 and 44 nodes) using the ReLU activation function and the Adam enhancer with a learning rate of 0.001. Then the 3rd and 9th order models yielded an Accuracy of 98.00%

Although Accuracy reflects the overall accuracy of the forecast, quantitative model evaluation requires additional indicators to describe the errors and the ability to fully explain the variance of the real data. Therefore, this research further evaluated models with high Accuracy using RMSE, MAE, MRAE, MASE and coefficient of determination (R^2) [35], [34], as shown in Table 4.

Table 4 Error and Accuracy Indicator Values of Tuned ANN Models

Model	RMSE	MRAE	MASE	MAE	R^2
3	0.1334	0.0354	0.0360	0.0178	0.9288
8	0.0780	0.0121	0.0128	0.0061	0.9757
9	0.2175	0.0946	0.0922	0.0473	0.8106
11	0.1600	0.0516	0.0511	0.0256	0.8975
19	0.1062	0.0227	0.0224	0.0133	0.9548

Based on the results of the statistical analysis, it emerged that the 8th order model provided the best performance overall, with the lowest RMSE and MAE; it gave a high R^2 value of 0.9757. This shows the model effectively accounts for variable rice yield

DISCUSSION

These outputs indicate that the multilayer architecture with the adaptive learning rate enhancer is well capable to manage the nonlinear correlations and multidimensional data, which is in line with deep learning approach in tropical crops prediction [31], [26].

When we compare the impacts of the optimizers, Adam and RMSprop yield a much better forecasting performance compared to SGD. The accuracy of most models for SGD was less than 75%, and some of Adam and RMSprop accuracy was in the range 95%+. Such process aligns with previous published work that demonstrates adaptive learning rate optimizers can handle highly variable data sets and assist in more efficient convergence [36].

Regarding stimulation function, it was discovered that ReLU and Sigmoid achieved better predictive performance than Tanh with Adam or RMSprop, and this is similar to all studies that demonstrated that ReLU can learn complex patterns from the data in deep networks while the Sigmoid model is ideal for moderate to high learning cases [37]. Furthermore, dropout rate obviously plays a role in the general success of the model, i.e., dropout values in the 0.2–0.4 region are statistically more predictive, while too high (0.5) dropout values lead to lower model performance in a majority of scenarios, which are similar to Srivastava and colleagues [38] that the dropout rate needs to be in the neighborhood of preventing overfitting, but preserving the model's learning potential [38].

These results were in agreement with recent predictions about rice and tropical crop yield from recent studies, showing that well-tuned ANNs are able to yield strong prediction results with high stability [39]. The experimental results indicate that a hyperparametric tuned ANN model, with multidimensional statistical indicators, has the ability to predict rice yield accurately, which leads to reliability. In fact, the research findings revealed that using artificial neural networks with multidimensional agricultural data effectively aligns with Thailand's tropical climate and further contributes to the development of forecasting models for a country of tropical nature and meets the research trends worldwide in which forecasting models to contribute to production planning, water resource management, and the development of sustainable smart agricultural technologies are gaining momentum.

CONCLUSIONS

This study describes the implementation of an ANN-based model to predict the rice yield for Thailand by tuning the hyperparameter process on an agricultural data set including factors affecting production, climate, water resources, and solar energy, which is accurately capturing the rice production systems context in tropical weather. Such finding proves that the tuning of hyperparameters is beneficial for improving the accuracy and stability of prediction significantly when compared to poorly tuned models [23], [29]. The evaluation of the 20 ANN models revealed that the network architecture and adaptation of the hyperparameters, namely, the selection of the enhancer, the excitation function and the neural drop rate have a massive effect on the model performance. Models with adaptive learning rate enhancers also obtained the best prediction results, Adam and RMSprop models with excitation function ReLU had a high rate of rice yield variance and low error in many statistical indicators [36], [37].

It contributes to advancing scientific knowledge on rice yield forecasting with research on input data from different sources at the data structure level. In addition, it emphasizes the development and testing of models using multidimensional indicators. From an applied perspective, the proposed model may be useful for production planning, water resource management, or formulation of food security policy in Thailand, due to uncertainties caused by climate change. However, future work requires high-resolution spatial data and comparisons with other types of deep learning models, such as LSTMs or Transformer models, for improved long-term forecasting capabilities.

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