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Forecasting of Rice Crop Production Using a Recurrent Neural Network

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ABSTRACT

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Keywords— validation loss, training loss, mean squared error (MSE), and R-squared metrics

Rice holds immense significance in Filipinos' diets, is consumed nearly three times daily, and is a crucial dietary component. Using a recurrent neural network (RNN), this study seeks to develop and evaluate a web application for predicting rice crop production in Davao del Sur. The system enables the Davao del Sur agriculturist to anticipate rice crop production over the next four quarters. The model used in the system was designed to process and analyze sequential data, such as time series, by capturing and retaining long-term dependencies and patterns. The researcher used the rapid application development model for system development. It started with data preprocessing and prototyping, which involved close coordination with end users to collect their feedback for interface enhancements. The model's performance is evaluated using validation loss, training loss, mean squared error (MSE), and R-squared metrics. The model's parameters were fine-tuned by utilizing these metrics, resulting in an improved capability to learn from data and generate accurate forecasts. The web application offers administrators a login feature, providing them with data administration and reporting functionalities. In addition to accessing the forecasting information, users can generate reports to assist with decision-making. The model is trained and validated in testing, and the front-end's functionality is evaluated. The training results indicated the optimal model

configuration; the optimal epoch for the model with a batch size of 16 is 200. Acceptability testing based on ISO 9126 standards demonstrates that the system satisfies all criteria for forecasting rice production, with the Office of the Provincial Agriculturist expressing high approval. In conclusion, the web application provides relevant forecasts and generates graphical reports to satisfy the end users' requirements. Despite a limited dataset, the system's use of an LSTM model and evaluation metrics guarantees commendable performance. The system helps the Office of the Provincial Agriculturist forecast future rice production.

INTRODUCTION

The primary goal of technology in agriculture is to create accessible, innovative, and proper methods to increase productivity and raise profitability.

Rice is a staple food consumed by Filipinos almost three times a day, making it a crucial dietary component. It is also a significant source of income for millions of Filipino farmers. Additionally, rice provides the body with protein and calories (Ali et al., 2017). In a study conducted by the International Rice Research Institute (Smil, 2005), the issue of food scarcity for the growing global population was analyzed, and the research suggests that the demand for rice will reach 800 billion tons by 2025. Laborde (2021) reported that according to the Philippine Rice Research Institute (PhilRice), the typical Filipino consumes three cups of rice per meal, up to nine cups daily.

Furthermore, the Philippines is the largest rice importer worldwide, and climate change remains a significant hindrance to the country's rice production (Hollaus, 2019). In a natural calamity, food reserves become crucial to meet the food demand, a pressing issue in numerous developing nations worldwide. Several factors, such as weather-related environmental impact, soil type, farmers' use of fertilizers, pests and diseases, and water management, can significantly affect production (Ali et al., 2019).

Davao del Sur province is recognized as one of the primary rice-producing regions in Region XI. It is considered the leading rice-yielding province in Mindanao due to the exceptional yield performance of its municipalities. According to the 2020 census of population and housing in Davao del Sur, the province is experiencing rapid growth (Hondrade, 2007).

Over the past few years, machine learning techniques have garnered significant interest for their potential in predicting and forecasting financial markets. Many methods have been extensively studied, including multi-layer feedforward neural networks, support vector machines (SVMs), reinforcement learning, relevance vector machines, and recurrent neural networks, which are among the most popular approaches for forecasting (Dargan, 2020). Unlike traditional statistical models, neural networks have greater noise tolerance and reliability. Due to this noise tolerance, they are more flexible, allowing them to be trained using incomplete or overlapping data. Additionally, the flexibility of neural networks means they can learn dynamic systems by retraining using new data patterns (Lusci et al., 2013).

Short-term memory is a recurrent neural network introduced by Sepp Hochreiter and Jürgen Schmidhuber in 1997 (Singh & Kaur, 2023). LSTM is designed to forecast, predict, and classify time series data even when there are huge time gaps between essential events. LSTMs have been used to solve a variety of issues, including handwriting recognition and speech recognition, which made the LSTM famous (Karim et al., 2017).

A forecast is a projection of potential outcomes based on past experiences and current conditions. It is a foundation for determining the action to achieve a desired result. The concern of predicting rice crop production has been a constant priority since the inception of agriculture. The forecasting methods have progressed and now prioritize acquiring accurate, detailed, comparable, and timely data (LeCun et al., 1998).

With this, the researcher aimed to forecast rice production based on climatic parameter data and quarterly rice production. This was expected to support decision-making and help the agriculture department with any actions to increase rice production in Davao del Sur. To assist the Provincial Agriculture of Davao del Sur, the researcher developed the study entitled Forecasting of Rice Crop Production Using a Recurrent Neural Network.

Objectives of the Study

The project's primary goal is to create a web application to forecast rice crop production in Davao del Sur and provide information to the provincial rice program management using a recurrent neural network (RNN). Specifically, this project aims to:

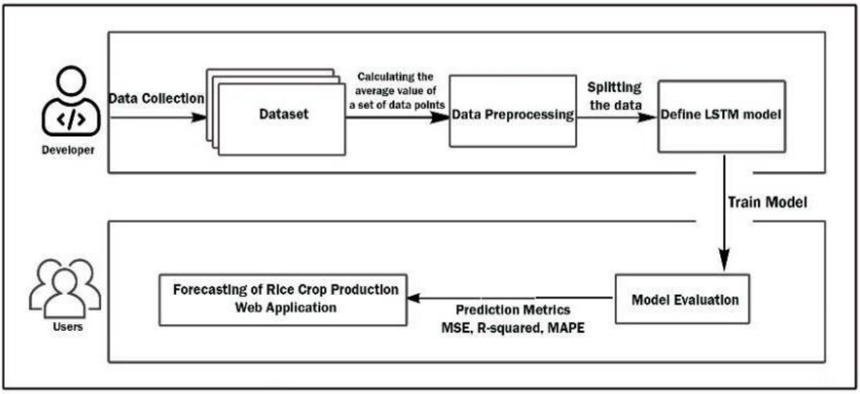
- Train a model that will predict the volume of rice production in Davao del Sur.
- Evaluate the performance of the model.
- Create a web application to visualize the forecast of rice crop production and;
- Implement the web application to ensure its acceptability.

Conceptual Framework

Figure 1 depicts that this study starts with data collection from authorized government agencies by the researcher and ends with the generation of prediction reports displayed for the end user. The weather data were collected from PAG-ASA, while the rice production data were collected from the Philippine Statistics Authority (PSA). Weather data comprises four factors: minimum temperature, maximum temperature, humidity, and rainfall. These datasets were transformed into multiple rows and columns to enable the researcher to calculate the average and summarize the weather data.

The next step includes training the model, which utilized 80% of the gathered data for training and 20% for validation, following the pedagogy presented by Gholami et al. (2021). An LSTM architecture is trained using preprocessed data to capture the temporal dependencies and relationships of weather factors that influence rice production. The dataset was subsequently fed into the LSTM model sequentially, where the number of samples in a sequence corresponds to the maximum number of steps to backpropagation through time. Once the model training is finished, the model is evaluated using prediction metrics such as mean squared error, mean absolute percentage error, and R-squared. These metrics aid in assessing the model's accuracy and performance, which is also used to refine or improve the forecasting accuracy. After evaluation, the data will now be displayed on the system webpage.

Figure 1
Conceptual Framework of the Study



MATERIALS AND METHODS

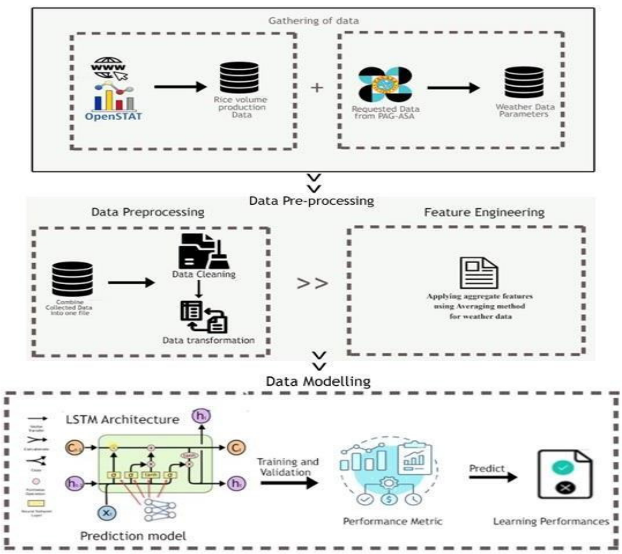
Process Flow of the Study

Figure 2 illustrates the flow of this study. The data collection process involved acquiring weather data from PAG-ASA and rice production data from the Philippine Statistics Authority, which served as the basis for creating the necessary dataset. Subsequently, specific data preprocessing techniques, including feature engineering techniques such as aggregated features, were applied to prepare the data for neural networks. To attain the average weather conditions, the weather data was collected and analyzed in three-month periods, grouped into quarters, and average values were calculated for each period. The data was consolidated into a single file after gathering complete weather data and rice volume. This file was then prepared for data modeling.

A long-short-term memory (LSTM) model was utilized and trained using data from 1990 to 2015 to capture temporal dependencies. The model has 1 LSTM layer with 50 units of cell, which determines the dimensionality of the layer's output. The activation function used in the LSTM layer is 'real,' which introduces non-linearity into the model. The output of the LSTM layer is then passed to the dense, fully connected layer. Furthermore, the dense layer has a single unit in the model, producing a single scalar output. The purpose of the dense layer is to transform the hidden representation learned by the LSTM layer into the desired output format. Since the dense layer has a single unit, it is likely used for regression tasks, where the model predicts a continuous numerical value. This model architecture with one LSTM layer followed by one dense layer is a simple yet effective setup for sequence prediction tasks, particularly in cases where it is needed to capture dependencies and predict continuous values.

After training, the model is compiled with the loss and optimizer functions. This step is the learning process for the model. The learning process is designed in the model fit step, and specific callbacks are utilized for guidance and extra functionalities during the training. Lastly, the performance of the trained model was evaluated by validating it against the data from 2016 to 2022.

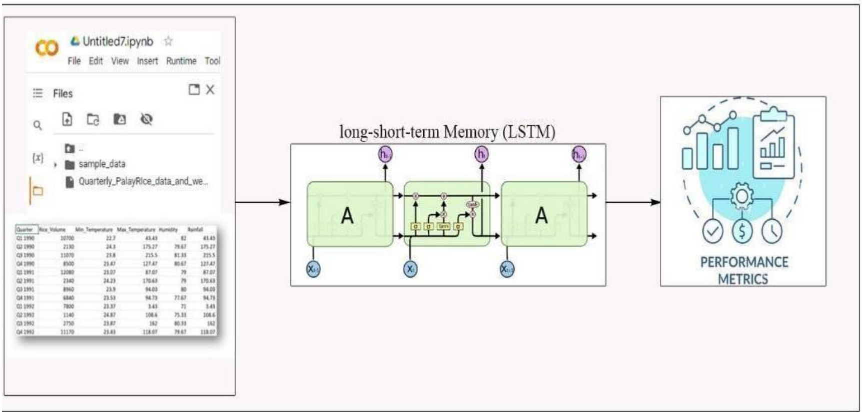
Figure 2
Process Flow of the Study



Preprocessing of Data

Figure 3 shows the dataset's preparation for the model. First, the dataset was organized correctly, and aggregated features were ready to be encoded into the system. Second, the researcher used Google Colaboratory, as shown in Figure 11, to provide free access to GPUs, where numerous datasets were imported for training. Also, all necessary libraries, like Pandas and Numpy, were included, which added support for large matrices, along with an extensive collection of high-level mathematical functions for array operations.

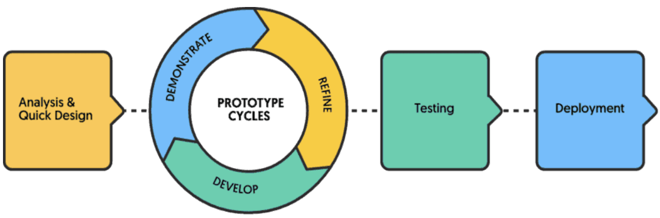
Figure 3
Learning Workflow



Development Model

The researcher used rapid application development in developing the system in this research, as shown in Figure 4. Each phase of the model guided the researcher through the necessary sequence for compiling the system.

Figure 4
RAD Development Model



Analysis and Quick Design

After the data preprocessing, the researcher uploaded the dataset in a CSV format from 1990 to 2020. After this method, the researcher created a design draft for the system's UI, which included all the components needed to generate the expected output.

Prototype Cycles

In this phase, the researcher closely coordinated with the Office of the Provincial Agriculturist personnel, as they were identified as the end users. During the demonstration regarding the manipulation of the system, the users directly gave their comments and suggestions for improving the interface. The researcher then modifies the code to address the end user's concerns.

Four different metrics quantified the performance of the crop production prediction model. The metrics used for the performance measure of the model were validation loss, training loss, mean squared error (MSE), and R-squared. During the model training, the researcher attempted to come up with an optimal epoch value for acceptable values of R-squared that is 0.50–0.99 (Ozili, 2022), mean squared error, which usually accepts lower values (Adabanija et al., 2016), validation loss, and training loss which preferably <0.02 to be lower if not 0 (Dantas et al., 2020). The model was trained using various numbers of epochs and batch sizes, where the results served as a basis for determining the optimal number of epochs. This is in connection with multiple studies that show that the number of epochs significantly impacts how often internal model parameters are improved (Saealal et al., 2022).

Table 1
Experimental Setup and Hyperparameters

Observation	Epoch	Validation Loss	Training Loss	Mean Squared Error	R-squared
1	12	0.0803	0.0767	0.0936	0.056
2	25	0.0554	0.0575	0.0987	0.391
3	50	0.0246	0.0354	0.1411	0.729
4	80	0.0148	0.028	0.1552	0.837
5	100	0.0138	0.0253	0.1654	0.848
6	112	0.0136	0.0213	0.1548	0.85
7	125	0.0128	0.0241	0.1663	0.859
8	150	0.0123	0.0178	0.1753	0.093
9	200	0.0127	0.0161	0.19	0.86

The reference for the base data on the number of epochs used in the training experiments was determined by the values shown in Table 1. The researcher started the training experiments with an epoch value of 50 since the R-squared and the MSE values were within the acceptable range. However, the acceptable validation and training loss are within epoch 80.

Testing

After completing the final module, the researcher trained and tested the model based on the predefined attributes and expected outputs. After the validation test, the researcher proceeded to acceptance testing by the end users.

The first testing was done in the data preprocessing phase, where the collected weather data from PAG-ASA and rice production data from PSA were cleaned and reorganized according to a sequence of relevant parameters that would be used in the data model for testing and validation. Out of 133 quarters from 1990 to 2023, 80% of them (approximately 106 quarters) were fed into the model for training, while 20% or 26 quarters were used for validation.

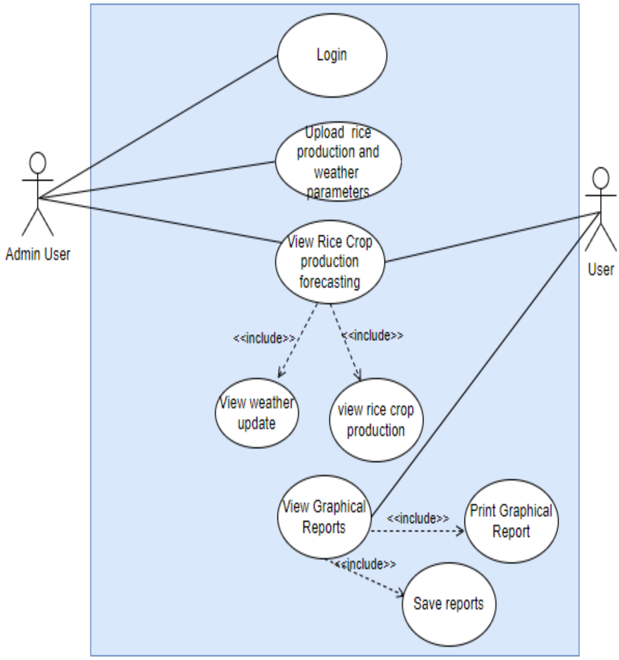
The crop production prediction model's performance is evaluated using four distinct metrics. These metrics include validation loss, training loss, mean squared error (MSE), and R-squared. Throughout the model training process, the researcher aimed to identify the most suitable epoch value based on acceptable ranges of R-squared (0.50–0.99; Ozili, 2022), mean squared error (which generally prefers lower values; Adabanija et al., 2016), validation loss, and training loss (preferably <0.02 or close to 0; Dantas et al., 2021). The model underwent training with different numbers of epochs and batch sizes, and the outcomes served as a basis for determining the optimal epoch value. This approach aligns with existing research studies that highlight the significant influence of epoch numbers on enhancing internal model parameters (Saealal et al., 2022).

On the other hand, the researcher conducted acceptability testing using a survey questionnaire patterned after ISO/IEC 25010 Software Product Quality. The project evaluators were personnel from the Office of the Provincial Agriculturist. They were the Davao del Sur agriculturists, municipal agriculturists, Students, and IT Experts.

Development

The development of the web-based system includes the front end, which is the UI, and the system's aesthetics, utilizing HTML, CSS, and JavaScript. On the other hand, the back end handles the logic and operation of the website, which also utilizes Django. MySQL was utilized as the database management system for data storage. The database stored data related to historical rice information, weather data, user information, and any additional data required for the application, ready for future use. Figure 5 depicts the use case analysis the researcher used to determine the system's behavior.

Figure 5
Use Case Diagram



The web application incorporates a login feature specifically for website administrators. Once authenticated, administrators gain access to additional functionalities, such as managing and uploading new data for weather parameters and rice crop production volume. They can effortlessly add, edit, and delete data as necessary.

The administrators are provided with the capability to view the rice crop production forecasting. They can also save and print reports in various file formats, offering flexibility in document storage and sharing options. This functionality lets administrators conveniently store important forecasting reports and generate hard copies when required.

On the other hand, application users can also view the forecast for rice crop production. Like administrators, they can save and print reports in different file formats based on their preferences and needs. This ensures that users can access and utilize the forecasting information effectively, allowing them to make informed decisions related to rice crop production.

Overall, the web application caters to administrators and users, offering distinct features and privileges to each group. The administrators possess additional data management capabilities and advanced reporting options, while users can access the forecasting information and generate reports tailored to their needs.

The system was measured based on functionality, reliability, portability, usability, efficiency, and acceptability. The overall percentage and total mean were calculated using a numerical basis, along with descriptive remarks, using a Likert scale. Below are the techniques for determining the system acceptance level and unit testing.

The Likert Scale was used to convert the quantitative data into qualitative data. This corresponds to the numerical value assigned to each potential choice, and all the responses were computed at the end of the survey.

Table 2. *Likert Scale for Acceptability*

Range	Verbal Interpretation	Description
4.21–5.00	Strongly Agree	Strongly Agree. The respondent agrees with the statement without reservation.
3.41–4.20	Agree	Agree. The respondent agrees with the statement.
2.61–3.40	Neutral	Neutral. The respondent cannot tell whether to agree or disagree with the statement.
1.81–2.60	Disagree	Disagree. The respondent disagrees with the statement with reservations.
1.00–1.80	Strongly Disagree	Strongly disagree. The respondent disagrees without reservation.

RESULTS AND DISCUSSION

In this study, the researcher specifically took note of the highlights of the training. Since two significant tests were done, there were also expected to be two categories of results—the training results and the results from the system's acceptability.

Training Results

The following table and graphs present the model training and validation outcomes. As previously discussed, the researcher used fifty epochs as the base number for the experiment.

In batch size 16, as presented in Figure 6, the optimal epoch is 200, where all the evaluated parameters are within the acceptable value ranges.

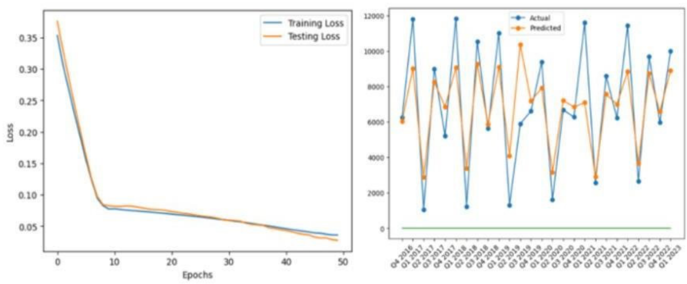
Table 3. *Observation of Batch Size 16*

Batch Size	Experiment	Epoch	Validation Loss	Training Loss	Mean Squared Error	R-squared
16	1	50	0.0242	0.0343	0.141	0.734
16	2	100	0.0125	0.0225	0.166	0.863
16	3	150	0.0122	0.0186	0.175	0.866
16	4	200	0.0125	0.0155	0.157	0.862

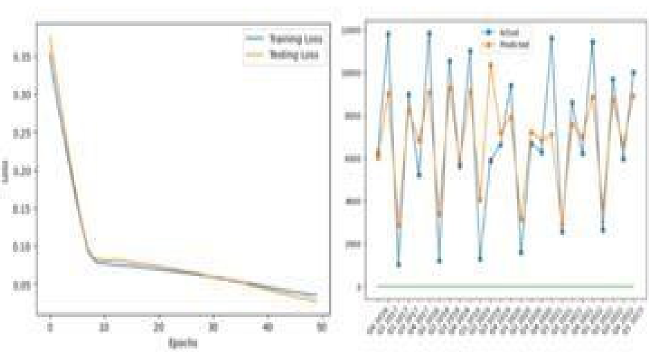
Figure 6

Testing Results at Batch 16

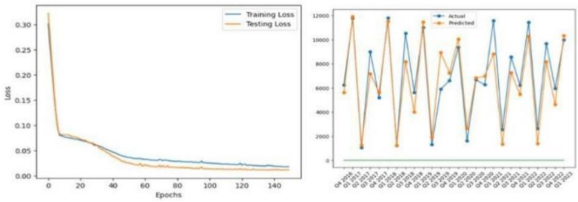
Epoch = 50



Epoch = 100



Epoch = 150



Epoch = 200

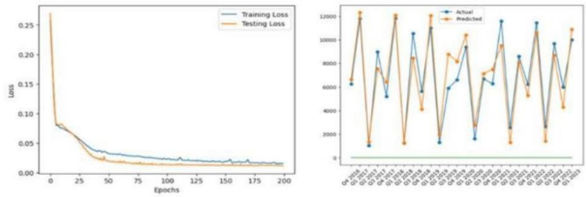


Figure 7 shows that epoch 200, at batch size 32, also resulted in the lowest training and validation loss values. However, the mean squared error (MSE) and R-squared were slightly higher than other numbers of epochs, which means this was not the optimal value.

Table 4. *Observation of Batch Size 32*

Batch Size	Experiment	Epoch	Validation Loss	Training Loss	Mean Squared Error	R-squared
32	1	50	0.0541	0.0571	0.0993	0.405
32	2	100	0.0167	0.0283	0.149	0.816
32	3	150	0.0157	0.0281	0.1504	0.827
32	4	200	0.0128	0.0214	0.1709	0.859

Figure 7
Testing Results at Batch 32

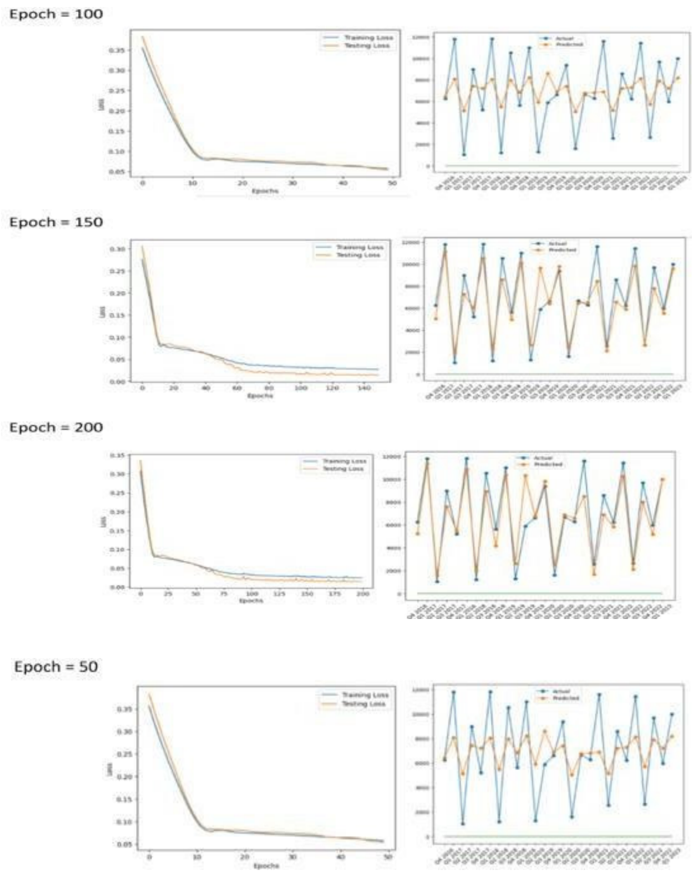
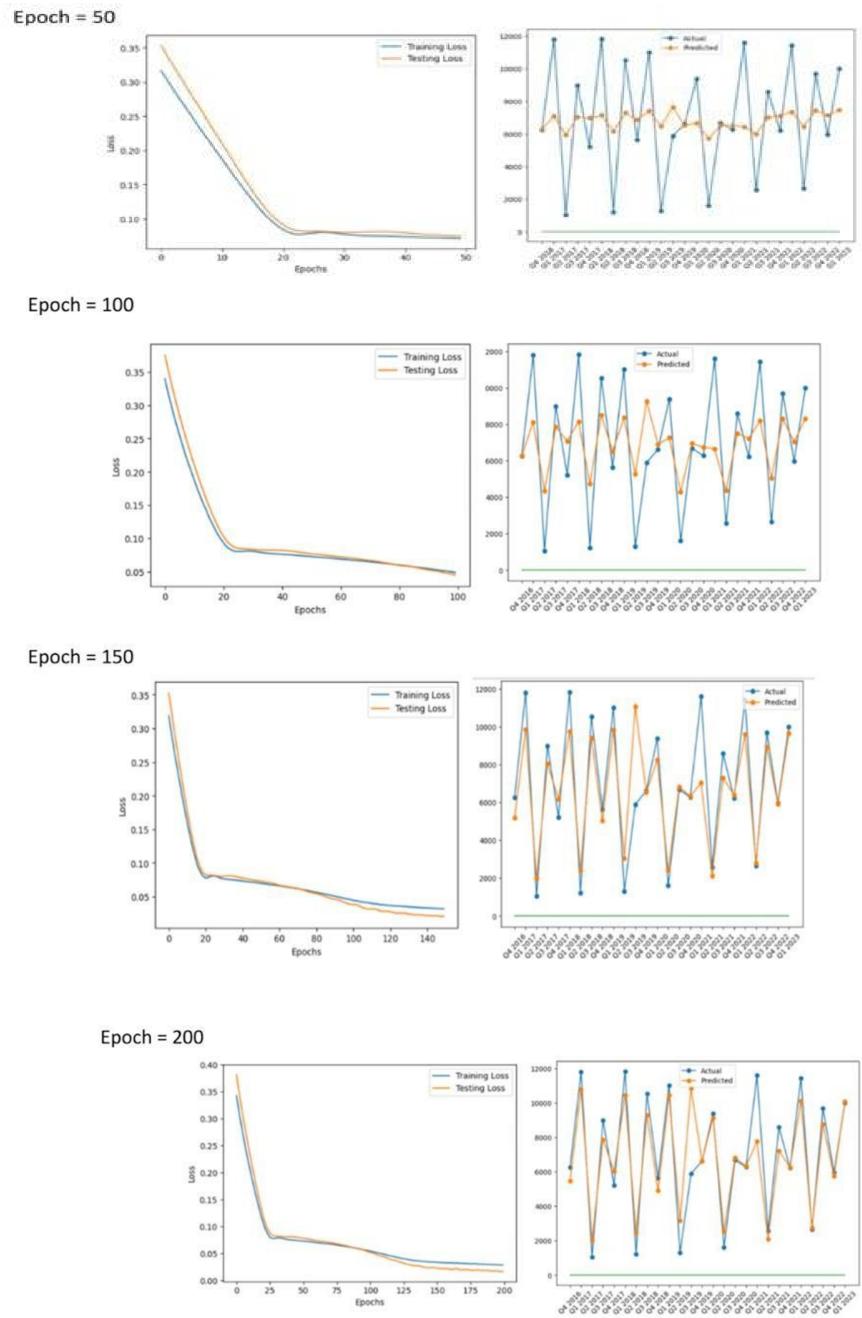


Table 5. *Observation for Batch 64*

Batch Size	Experiment	Epoch	Validation Loss	Training Loss	Mean Squared Error	R-squared
64	1	50	0.0787	0.0737	0.0926	0.135
64	2	100	0.0263	0.0383	0.1132	0.711
64	3	150	0.0204	0.0324	0.1496	0.775
64	4	200	0.014	0.0249	0.1513	0.846

Figure 8
Testing Results at Batch 6



Observation

Examining the tabulated results, the researcher found that the optimal setup for the model was the one with 200 epochs using a batch size of 16. Comparing all tables, this setting has the lowest validation and training values. According to Cubuk et al. (2019), the lowest number of training and validation errors was more significant in testing the model than in the number of epochs.

Acceptability Results

The instrument utilized in this study is based on the ISO 9126 standard, which outlines software quality characteristics.

Table 6. *Survey Mean Result*

Criteria	Mean	Description
Functionality	4.41	Strongly Agree
Reliability	4.38	Strongly Agree
Portability	4.76	Strongly Agree
Usability	4.4	Strongly Agree
Efficiency	4.52	Strongly Agree
Acceptability	4.5	Strongly Agree
Grand Mean	4.47	Strongly Agree

Based on Table 6, the system passed all the criteria for which the respondents strongly agreed without reservations that the system possessed all the requirements for forecasting the rice production in Davao del Sur. This claim was supported with a grand mean of 4.47.

Table 7. *Descriptive Ratings from the Respondents' Acceptability of the System*

Respondents	Total Number of Respondents	Mean	Description
IT Expert	6	4.29	Strongly Agree
Licensed Agriculturist	6	4.41	Strongly Agree
Licensed Agricultural Engineering	3	4	Agree
Agriculture Faculty	4	3.94	Agree
Office of the Provincial Agriculturist	2	4.53	Strongly Agree
Office of the Municipal Agriculturist	1	4.35	Strongly Agree
School Agricultural Technician	1	4.07	Agree
Agriculture Students	2	3.92	Agree
Overall	25	4.19	Agree

Table 7 shows that the developed system was highly acceptable to the respondents from the Office of Provincial Agriculturists. Though all of the respondents' responses were considered, the researcher thought it best to highlight that the system's primary users could find it highly acceptable. Therefore, the researcher claimed that the system was able to serve its very purpose—to provide information to the provincial rice program management, which they may use as minor decision support.

Observation

Among the responses from different user groups, the faculty and student testers from IATES gave the lowest scores. The researcher noted that these testers could not fully appreciate the system's output and could not relate it to their field, as the reports generated were not directly relevant to their current roles.

SUMMARY

The researcher gathered data from multiple sources, which were then combined into one file suitable for training and validating the proposed model. The complete dataset was structured into rows and columns. The rice crop production forecasting system was specifically developed to anticipate production for four years, allowing the application to predict output up to four quarters in advance. Experimentation demonstrated that forecasts extending beyond four quarters resulted in significant deviations from expected values; thus, the model focuses on forecasting four quarters to ensure accuracy and reliability.

This study acknowledges that forecasting rice production cannot rely solely on weather conditions, as many factors can impact production. Therefore, building a comprehensive model that incorporates all relevant factors influencing rice production is essential for accurate forecasting. By considering various contributing elements, a robust rice crop forecasting model can be developed. Despite a limited dataset, employing an LSTM model and performance optimization evaluation metrics enabled the generation of reliable reports. The system offered to the Office of the Provincial Agriculturist (OPAG) and the Office of the Municipality Agriculturist (OCAG) of Davao del Sur aids them in gaining valuable insights into anticipated rice production over the next four quarters.

CONCLUSION

The LSTM (Long Short-Term Memory) model proved to be a valuable tool in time series analysis and prediction tasks. Its unique architecture, including memory cells and gates, enables the capture and retention of long-term dependencies in sequential data. In this study, the researcher optimized the model's performance using specific evaluation metrics, fine-tuning parameters for more accurate and reliable predictions. The generated visual reports and forecasts for rice crop production were found to be relevant and understandable for end-users, and the system received high acceptability ratings.

The research achieved its primary goal of developing a web application for forecasting rice crop production in Davao del Sur using a recurrent neural network (RNN), providing valuable information to the provincial rice program management. Even with limited data, the application of the LSTM model and robust evaluation metrics enabled the generation of commendable forecasts. Both OPAG and OCAG benefited from insights into projected rice production for the coming four quarters.

RECOMMENDATION

- Based on the evaluation of the forecasting system, several recommendations are offered to enhance its application:
- Incorporate additional significant factors such as municipality-specific data, weather patterns, market prices, crop diseases, type of soil, and more, as these can influence rice production.
- Utilize dynamic data retrieval from authoritative sources like PAG-ASA and PSA to integrate timely and relevant information into the forecasting system.
- Apply aesthetic and design principles to create an engaging and visually appealing interface, enhancing usability and user experience.
- Improve the website's mobile compatibility to ensure users can

conveniently access forecasting information, which will support increased accessibility and usability.

- Implement a feedback mechanism so users can provide suggestions, report issues, and contribute to ongoing system refinements based on their needs and preferences.

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