2024 11th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE) | 979-8-3503-8930-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICITACEE62763.2024.10762812

Advanced Deep Learning and Hybrid Models for Forecasting Rice Production in Indonesia

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***Abstract*— Forecasting rice production supplies in Indonesia can help state planning by predicting rice production so that the state is able to determine decisions in various aspects such as inventory levels, procurement planning, distribution scheduling, resource allocation, and price strategies that will be taken based on forecasting results using artificial intelligence. This research focuses on developing proposed machine learning, deep learning, and hybrid models so that researchers can determine their respective abilities in executing data they collect from official Indonesian sites. The methods used in the research include the ARIMA model, LSTM, and the ARIMA-LSTM hybrid model. Several evaluation methods used in research are R2, MAE, RMSE, MAPE, and SMAPE. Based on research that has been conducted, the LSTM-ARIMA hybrid residual model outperforms every evaluation result with R2: 0.97, MAE: 0.15, RMSE: 0.18, MAPE: 7.26%, SMAPE: 7.06%.**

Keywords—Forecasting, Rice Production, Deep Learning, Machine Learning, Hybrid Model.

I. Introduction

Supply Chain Management (SCM) is a system that facilitates a wide variety of important processes related to the production of goods and services. in this technology, the importance of supply and demand needs in accordance with the target market is highlighted in real terms that companies are able to handle the available supply and real field needs, with the rapid development of technology thus technology is able to help humans in estimating or forecasting, especially in the case of supply needs in real terms, artificial intelligence technology is able to increase efficiency [1], [2] in the operations of a company in handling the supply and demand for the products needed, until now researchers see the potential role of this technological development in being able to face the challenges of the future with data more intelligently and adaptively.

Currently, various production sectors are faced with many complex scenarios that are uncertain there are many variables that can affect the results of human forecasts such as unpredictable tragedies such as pandemics, natural phenomena, global climate, and many others [3], however, with the presence of the rapid development of artificial intelligence, it is hoped that it will be able to help humans predict all the possibilities that will occur in the future [4], including in terms of forecasting consumer needs and production needs in the industrial thus world that the amount of production in the future can be overcome by forecasting consumer needs or vice versa in the world of SCM and being able to increase consumer confidence with the industry that produces these products. In the context of this research, production forecasting and supply management play a crucial role. By utilizing artificial intelligence, researchers can anticipate and overcome the challenges of rice production in Indonesia by monitoring rice production forecasts every month so that the country is able to manage and prepare for all possibilities that will occur in the future. in the future, as well as ensuring sustainable food security for the community. Rice production in Indonesia increases every year along with the development of the Indonesian population because the staple food of citizens is rice. The demand for rice has increased by 4.66 million tons between 2008 and 2020 which represents an average population growth of 1.16%, but rice production has only experienced a development of 0.81% [5]. This raises national problems between suppliers in rice production and the needs of people who consume rice as a daily staple food. Not to forget that production is not only directly proportional to the needs due to the need for reserve supplies carried out to deal with future threats, imports to increase state revenue [6] and the influence of national and international government policies on the value of the scarcity of rice products themselves.

There are several studies related to forecasting in SCM systems, including [2], [7], [8] applied the Long Short-term Memory (LSTM) model in his research, but with several developments tailored to the needs of each research such as Naveen Parthasarathy M K et al proposed a hybrid LSTM and 1D CNN model that focused on the pharmaceutical sector, then compared it with the LSTM model using Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) evaluation metrics. In contrast, Aicha El Filali et al, used LSTM for forecasting and the LSTM method was compared with ARIMA as measured by Root Mean Square Error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE) evaluation. At the same time, Rong Liu et al combined Bayesian Optimization (BO), CNN, and LSTM models that focused on the consumer goods sector and inventory.

This paper is organized as follows. The second section describes the work related to the analysis using deep learning time series to forecast the supply and demand of rice products with several related variables in Indonesia. Section three describes the data collection and methods used in this study. Section four reveals the experimental results of deep learning in a comprehensive manner. Finally, section five shows the conclusion of this research.

II. Related Work

There are many studies that focus on demand forecasting in SCM with various approaches carried out by various researchers, Naveen Parthasarathy M K et al [7] focus on the use of hybrid deep learning models, especially 1D Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) to handle SCM specifically in the pharmaceutical sector. The research also explains the importance of accurate demand forecasting, especially in SCM. This research applies a hybrid deep learning model consisting of LSTM and 1D CNN and the results of the hybrid model will be compared with the LSTM model which has the best value from several tests carried out previously. The comparison method used is to use the MSE and MAPE metrics, thus researchers can conclude that the hybrid CNN-LSTM model is in accordance with the applied science of forecasting supply needs for pharmaceutical ingredients, where CNN-LSTM gets a better score than ordinary LSTM. Researchers also review the importance of deepening other deep methods in testing such as ANN, RNN to see the increase in accuracy that will be experienced in the hybrid model.

Aicha El Filali et al [8] conducted a study discussing demand forecasting in SCM using deep learning with the LSTM model for demand forecasting. Forecasting in this research emphasizes accuracy in meeting customer demand, anticipating stock-outs, and preventing wastage of resources. In LSTM research, it is compared with the statistical methods Autoregressive Integrated Moving Average (ARIMA), Exponential smoothing, and RNN, the evaluation is measured using RMSE and SMAPE, therefore research is able to conclude that the proposed LSTM model shows effectiveness in forecasting demand in SCM, especially in capturing non-linear features in the time series. However, researchers also emphasize the importance of optimizing the model using hyperparameters to increase the accuracy of the forecasting model.

Rong Liu et al [2] conducted demand and inventory forecasting research by combining deep learning techniques to overcome the limitations of traditional methods in handling complex and large data patterns, the proposed method is a combination of Bayesian optimization (BO), convolutional neural network (CNN), and long-term short memory (LSTM). This approach is validated with experimental results that show superiority compared to traditional methods as well as its success in implementing SCM systems. The research also highlights the importance of model forecasts in optimizing demand forecasting by managing complex and large data, overall, the researcher deepens the discussion on the combination of the BO-CNN-LSTM method to overcome the limitations of previous methods to overcome the complexity and size of data that the method is able to manage it better effective.

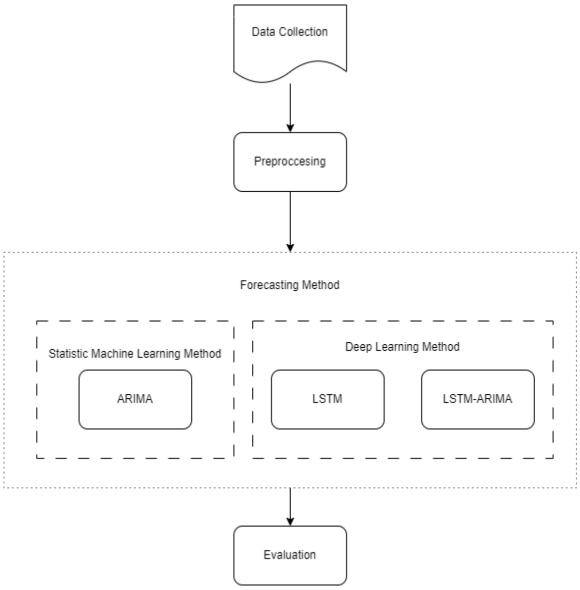

Fig 1. Proposed Method

Daniel Kiefer et al [9] discuss the application of artificial intelligence (AI) in SCM which focuses on special demand forecasting using time series with deep learning which highlights the challenges of inconsistent patterns. Research that explores understanding using transfer learning experiments based on computer vision can enhance the accuracy of time series predictions using deep learning. The results of the research show that the transfer learning method can significantly reduce forecast errors, with benefits seen especially in the short term (65% reduction) and intermediate (91% reduction). This study validates that deep learning techniques can derive advantages from a transfer learning strategy, particularly when predicting volatile demand.

Based on the research discussed previously, researchers tend to estimate demand in SCM. Many LSTM deep learning methods are used either alone or in combination with other deep learning methods, but there are several gaps between the lack of use of optimization such as hyperparameters, and optimization of the complexity of structured data consisting of supply and demand data. Rice in a country has many variables that will influence forecasting results, the hybrid model proposed by researchers is expected to improve forecasting results that are faced with handling complex data.

III. Methodology

The research steps for supply forecasting using statistical algorithms and deep learning can be seen in Fig 1.

A. Data Collection

The first stage of the research was collecting datasets of rice production and consumption from previous periods to determine data movement patterns. The researchers obtained these data from official Indonesian government websites including *Badan Pusat Statistic* (BPS), *Badan Pangan Nasional* (BPN), and *Satu Data Indonesia* (SDI). The targeted dataset consists of the years 2010 to 2023, however, the data was obtained in 2011, 2016, 2017, 2018, 2021, 2022,

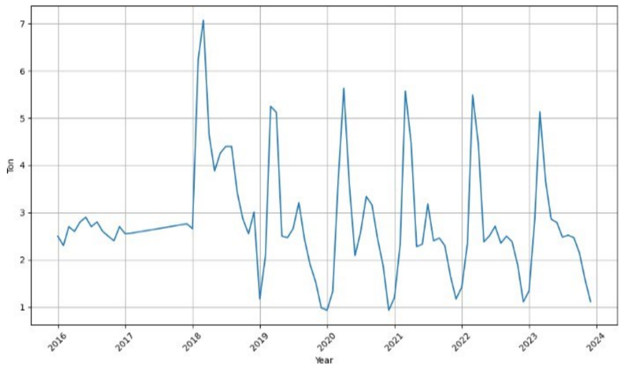

Fig 2. Historical Data Rice Production for the last few years

and 2023 and the researcher got 93 data in total consisting of year, type, month, production, consumption, and price.

B. Data Pre-processing

After collecting the dataset, the next step is to carry out preprocessing. The scaling that researchers use in the preprocessing stage is *minmaxscaler* which is useful in that the data is in the desired range [10] during the training process for steps of research, the researcher carried out 2 stages, where the first test was to evaluate the method by comparing forecasting data with original data in 2023 and the next was forecasting for 2024, it was necessary to partition the data consisting of previous data before 2023 data which became training data and 2023 to become test data, in testing the two previously partitioned data are put back together to be used as training data that the training data becomes more varied.

C. Forecasting Method

On research after going through the previous stages, several forecasting methods were implemented to predict rice production each month using several methods including ARIMA, LSTM, and LSTM-ARIMA. These methods were chosen because in previous research LTSM [8], [11] showed good performance and ARIMA was applied to serve as a comparison, then the researchers also applied the LSTM-ARIMA hybrid method [12] to deepen the hybrid methods [2], [7] that had been carried out in previous research and compared them with the methods tested previously.

1) ARIMA

ARIMA is a combination of ARMA and process integration. The SARIMA model is used for seasonal data and the ARIMA model is used for non-seasonal data [13]. SARIMA is formed by inserting seasonal terms into the ARIMA model use Equation (1).

$$\text{ARIMA}\,(p, d, q)\,(P, D, Q)\,s \qquad (1)$$

as seen in Equation (1) variable *s* is the seasonal cycle or seasonal pattern in data introduction, *q* is a form of seasonal variation, *d* is the average number of differences in seasonal data and p is the *autoregressive* component recognizing seasonal patterns from previous data [4]. The notation for the difference between lowercase and uppercase letters is divided into uppercase letters used for seasonal model parts and lowercase notation for non-seasonal models.

In this research, researchers optimized the performance of the ARIMA method using the Akaike information criterion (AIC) to determine P and Q in order to achieve stability between error and model complexity [14].

2) LSTM

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that is highly popular in sequential data modeling fields such as time series data [15], [16]. LSTM was developed to overcome the challenge of difficult training and to learn long-term dependencies in sequential data [17].

At the core of LSTM is its ability to "remember" long-term information and "forget" irrelevant information over long periods of time. This is achieved through the use of complex internal memory units and smart mechanisms called "gates" that regulate the flow of information into and out of the unit [18].

3) LSTM-ARIMA

ARIMA and LSTM each have advantages and disadvantages, ARIMA is faced with difficulties with non-linear time series, while the neural network method which is the parent of LSTM is able to work with linear and non-linear time series, but the application of neural networks requires training time which can be considered to take quite a long time [12], [19]. Based on these factors, researchers applied a hybrid method in that the models were able to work on their respective skills and were able to provide more accurate prediction results compared to models previously carried out individually [20], [21], use Equation (2).

$$p[t] = \text{trend\_pred}\,[t] + \text{s\_pred}\,[t] + \text{rest\_pred}\,[t] \qquad (2)$$

Equation (2) is used to improve the prediction accuracy of this model, Where the final prediction p[t] is a combination of the trend prediction component (trend_pred), seasonal component (s_pred), and residual component (rest_pred)

D. Evaluation

As previously explained, this research was discussed in 2 stages, the first test was to evaluate the method by comparing forecasting data with original data for 2023 and the second test was forecasting for 2024, with this testing stage the researcher was able to compare the accuracy of the forecasting results for each method by looking at real data or by using data comparison methods that have been carried out in previous studies such as *RMSE, R2* (R^2/R-Square)*, MAE, MAPE* [22], [23], and *SMAPE*.

The sequence of steps in the suggested method is illustrated in Fig 1. Datasets are obtained from the BPS, BPN, and SDI are first processed and aggregated. Then, using a machine learning model, a forecasting procedure is carried out to determine the forecast results based on movement patterns in previous data and factors that influence the outcome.

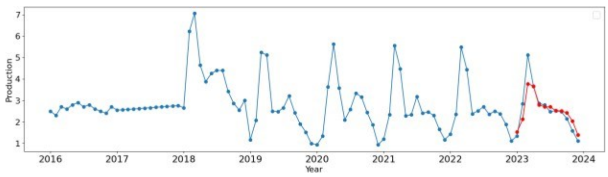

Fig 3. LSTM Evaluation

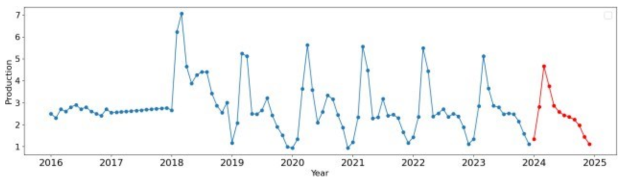

Fig 4. LSTM Prediction

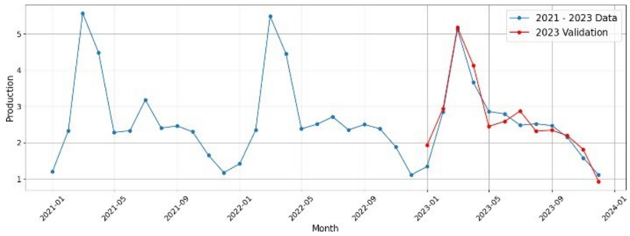

Fig 5. ARIMA Evaluation

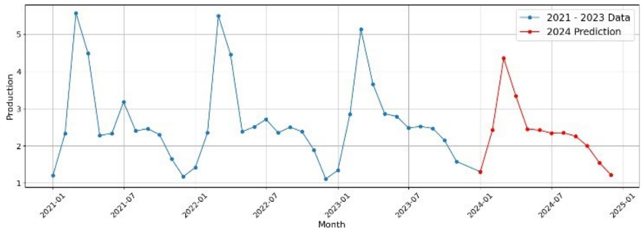

Fig 6. ARIMA Prediction

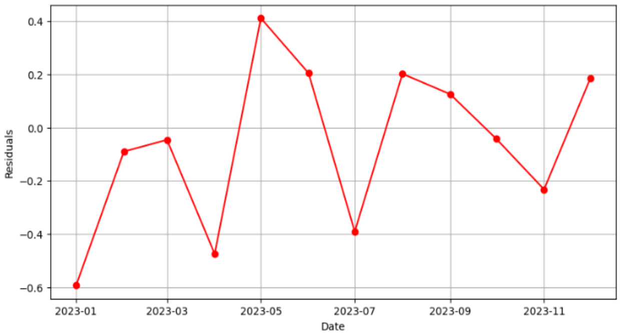

Fig 7. Residuals of SARIMA Prediction

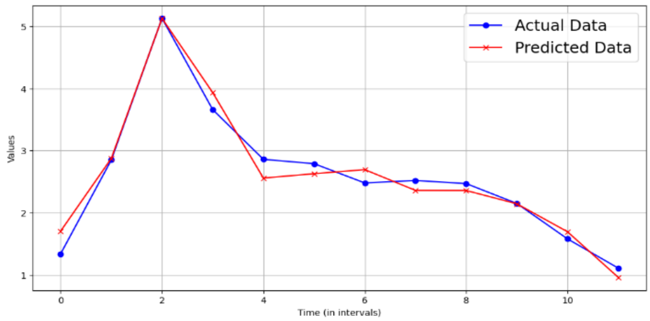

Fig 8. Comparison of Residuals Data

IV. Result and Discussion

A. Dataset

Researchers manually collected data by visiting official state websites such as BPS, BPN, and SDI. This was done in order to obtain the information that they needed to collect. During the process of collecting data beginning in 2010 and continuing through 2024, several columns have been taken into consideration. These columns include the following: Year, Type of food product, Month, Total food production (million tons), Food consumption (million tons), Food imports (tons), Food exports (tons), Food supplies, and Food prices.

The data collected in this process did not reach the entire year or month that was expected, the data obtained that we took included the years 2011, 2016, 2017, 2018, 2019, 2020, 2021, 2022, and 2023 where the researchers obtained a total of 120 data with details of 108 detailed data for each month and 12 data for detailed calculations per year. Because there is no dataset for 2012-2015, the data used in this experiment starts from 2016 to 2023.

The researchers decided to concentrate on rice production data because the available information was limited. Although food consumption data is also relevant, rice consumption patterns tend to be more stable over time. By concentrating on rice production, researchers will be able to identify broader patterns and understand the factors that influence production.

As can be seen in Fig 2, it shows that fluctuations in rice production results each year have the same pattern, the peak harvest is in March – April each year. This regularity suggests that specific climatic or agricultural conditions favor rice production during these months. Understanding these patterns can help optimize farming practices and resource allocation to enhance rice yield stability in Indonesia.

B. LSTM

Rice production prediction using LSTM models involves leveraging historical data to forecast future rice yields. During the training phase, the LSTM model learns from the historical data to make predictions about future rice production. The model is trained using the Adam optimization algorithm. This optimization algorithm helps the LSTM model converge faster and more reliably, resulting in improved prediction accuracy. The predicted result was tested in 2023 and can be seen in Fig 3.

Based on the LSTM model's performance in 2023 and utilizing the established optimizations, researchers extended predictions to 2024. The resulting projections for 2024 are visually represented in Fig 4.

C. ARIMA

Using the ARIMA method, researchers carried out 2 research stages, namely evaluation and prediction, the evaluation stage consisted of data fragments from 2021 to 2023. In the ARIMA experiment, researchers carried out optimization experiments to find ARIMA parameters using AIC, in this research they got the Best ARIMA Order (2, 1, 0), and with these parameters, the ARIMA model gets evaluation values *R2: 0.92, MAE: 0.25, RMSE: 0.30, MAPE: 12.09, SMAPE: 9.57,* a visual of the ARIMA model prediction results can be seen in Fig 5.

TABLE I. EVALUATION METRICS

Model	R2	MA E	RMSE	MAPE (%)	SMAPE (%)
ARIMA	0.91	0.25	0.30	9.97	9.57
LSTM	0.48	0.56	0.72	31.34	21.36
LSTM-ARIMA	**0.97**	**0.15**	**0.18**	**7.26**	**7.06**

Based on the prediction results of the ARIMA model in 2023, researchers also made predictions for 2024 using previously tested parameters, and the results of optimizing the ARIMA model parameters using AIC, then the prediction results for 2024 can be seen in Fig 6.

D. LSTM-ARIMA

The residuals of the SARIMA predictions, as shown in Fig 8, represent the difference between the actual data points and the predictions made by the SARIMA model at various dates throughout 2023.

The prediction results using the hybrid model on rice production in 2023 are shown in Fig 7, showing that the predicted values follow the trend of the actual data quite well. Although there are some differences between the predicted values and the actual data, the hybrid model generally succeeds in following the trend of the actual data.

E. Evaluation

In the first stage, namely testing by comparing forecast data with original data, evaluation at this stage uses several methods including R2, MAE, RMSE, MAPE, and SMAPE which can be seen in TABLE I.

Based on TABLE I evaluation of R2 which measures variability, the higher the data, the better the hybrid LSTM-ARIMA model is obtained with a value of 0.97, the lower the MAE value, the better the value obtained by the LSTM-ARIMA model with a value of 0.15, the lower the RMSE value, the better the value obtained by the LSTM model - ARIMA with a value of 0.18, MAPE is the average percentage of absolute difference with the actual value, the lower the value, the better the LSTM-ARIMA hybrid model is obtained with a value of 7.26%, and SMAPE is an adjusted version of MAPE evaluation, the lower the value, the hybrid model is obtained LSTM-ARIMA with a value of 7.06%, which in every evaluation method the LSTM-ARIMA hybrid model outperforms in every test.

V. CONCLUSION

This study focuses on forecasting rice production in Indonesia using deep learning techniques, specifically LSTM and ARIMA, to overcome SCM challenges. This research collects data from official Indonesian government websites and applies various forecasting techniques to predict rice production. The results show that the hybrid model LSTM-ARIMA model outperforms the separate LSTM and ARIMA models in terms of accuracy, as evidenced by evaluation metrics such as R2, MAE, RMSE, MAPE, and SMAPE.

Based on TABLE I see that the LSTM-ARIMA hybrid model is superior in several evaluation methods R2, MAE, RMSE, MAPE, and SMAPE because the LSTM-ARIMA hybrid model is able to provide better results in terms of variability measures, percentage of absolute differences and is able to provide better results. better at measuring errors and mean squared error. Thus, this research shows that the combination of LSTM and ARIMA models shows advantages by combining models with residual methods so that each model complements each other's shortcomings in dealing with model deficiencies.

Overall, the findings of this study contribute to the design and evaluation of the proposed hybrid LSTM-ARIMA model where the effectiveness of the model surpasses stand-alone ARIMA and LSTM models in terms of accuracy, thereby highlighting the potency of combining multiple forecasting approaches. Therefore, it will be useful in procurement planning, distribution schedules, resource management, and pricing, thereby increase efficiency in the supply of food products on food security in Indonesia. In further research, it is recommended to work on a different, more thoroughly designed deep learning model and include other parameters such as climate factors and economic activity to create a more comprehensive forecasting model in the future.

ACKNOWLEDGMENT

This research was funded by Institut Teknologi Sepuluh Nopember (ITS) under Penelitian Dana Departemen Program, Penelitian Keilmuan, Penelitian Flagship, Penelitian Kolaborasi Pusat and under the Project Scheme of the Publication Writing and Intellectual Property Rights (IPR) Incentive (Penulisan Publikasi dan Hak Kekayaan Intelektual/PPHKI) Program 2024.

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