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Predictive Analysis for Inventory Management of Coconut Warehouse (Case Study: Banio Lahewa)

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ABSTRACT: Inventory management plays a pivotal role in the coconut farming business, directly influencing sales and income. An essential component of this management is warehousing, which not only affect revenue but also involves suppliers in the coconut storage process. Warehousing management and technology are two elements that can help companies operate more effectively and efficiently. This research focuses on efforts to improve warehouse management efficiency in the agricultural sector, particularly at Banio Lahewa, a company that operates as a coconut supplier in a small village with limited resources. Currently, the company still records data manually and lacks a real-time system to monitor demand patterns, stock rotation, and restocking frequency in the warehouse. This situation is caused by uncertainty about the products entering the warehouse, leading to the company's focus being more limited to daily operational issues rather than future planning. To address this challenge, this research uses future event prediction methods, specifically forecasting by applying two neural network models: the Feed Forward Neural Network and the Long Short Term Memory. The implementation of this system is expected to provide new insights to the company, enabling them to be more adaptive in efficiently managing warehouse systems. With an understanding of patterns and predictions of future events, it is expected that the company can be more prepared and responsive to changes in customer demand and able to expand products more quickly. The results of this research are expected to make a positive contribution to the company, helping them optimize warehouse management and become more adaptive to market dynamics.

KEYWORDS: Data Analytics, Forecasting, Neural Network, Warehousing.

INTRODUCTION

Indonesia, a leading global coconut producer, cultivates coconuts extensively in coastal areas, especially in regions like North Sulawesi, North Sumatra, West Nusa Tenggara, and South Sulawesi. The country's coconut industry, estimated to produce 2.87 million tons by 2022 (Statista, 2023) , significantly impacts its GDP. This production creates jobs, benefiting farmers and laborers involved in processing, production, and export. The income generated enhances rural economies, particularly in coconut-growing areas. The integration of technology in the agricultural industry, exemplified by Industry 4.0 (Bartodziej, 2017), has significantly impacted supply chain management. Warehousing, traditionally considered a non-value-adding activity, has evolved with the rise of Warehouse Management Systems (WMS) under Industry 4.0 (Lu et al., 2015). This development influences profitability and is crucial in anticipating market dynamics, resource conservation, and globalization effects on warehousing processes. In the coconut industry, profit depreciation is influenced by factors such as coconut rot and sprouting. Banio Lahewa, a supplier to a flour mill, faces challenges due to the perishable nature of young coconuts and the germination process of old coconuts. The study proposes leveraging historical data and technology to manage inventory efficiently, specifically anticipating daily coconut arrivals to minimize the risk of spoilage. Predictive analytics, particularly forecasting methods, enhance inventory management efficiency (Jomaa et al., 2013), contributing to increased productivity and reduced storage costs in various industries, including manufacturing and services.

BUSINESS ISSUE EXPLORATION

Banio Lahewa, situated in the small town of Lahewa, North Nias, encounters operational challenges due to limited resources, hindering an efficient process. The current warehouse strategy makes the company inflexible to changes, making it unable to meet customer needs promptly. Challenges arise from a lack of understanding of demand patterns, stock rotation, and restocking frequency, compounded by manual data recording and the absence of real-time monitoring tools. Decision-makers lack awareness of the supply chain's comprehensive understanding and the strategic role of storage in operational efficiency. Focused on daily

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issues, the company, specializing in coconut farming, struggles with adapting to the daily variations in coconut supply. To address this, Banio Lahewa seeks a solution for predicting and minimizing coconut inventory risks, aiming to enhance warehouse productivity, deliver goods faster, and facilitate informed decision-making based on historical data. Integrating technology into inventory management, especially predictive analytics, becomes crucial for optimizing freight operations and reducing losses. The study aims to improve Banio Lahewa's logistics processes, enabling responsiveness to customer demands and ensuring a stable supply for farmers.

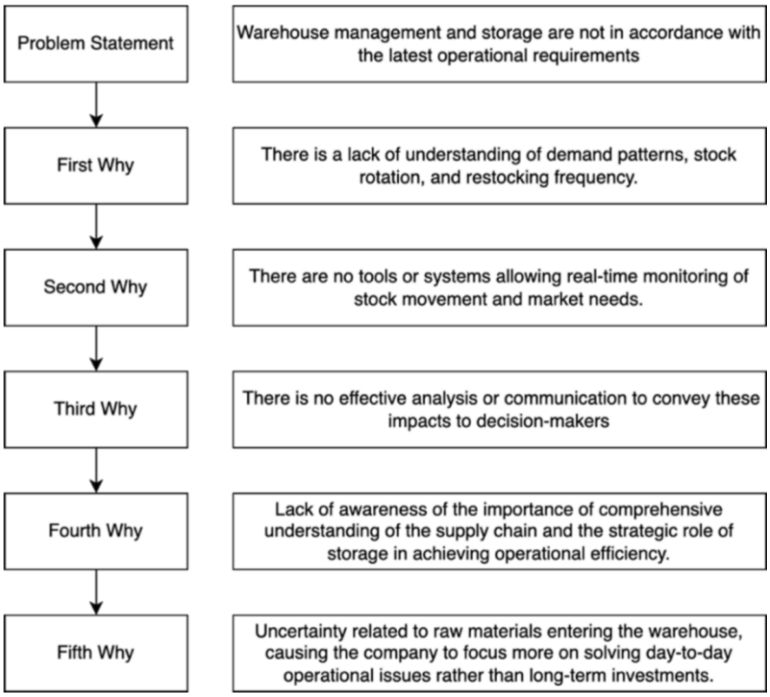

Figure 1. Five Whys Analysis

FORECASTING

Forecasting is the method of anticipating forthcoming events or trends by analyzing past and current data. It serves as a crucial tool for businesses and organizations to facilitate decision-making and strategic planning. Trade forecasting integrates both quantitative and qualitative techniques to enhance precision. Internally, managers employ forecasting to make decisions on capital allocation and to assess the feasibility of ventures like acquisitions, expansions, or divestments (Tuovila et al., 2023). The significance of crafting an appropriate forecasting process is underscored by (Danese & Kalchschmidt, 2011), emphasizing alignment with users' intentions and organizational strategy. Precise forecasting aids in resource allocation, inventory management, and various critical areas, fostering informed decision-making. Operating more efficiently, businesses can anticipate future demand and adjust production or staffing levels, minimizing waste and promoting long-term savings. Additionally, forecasting enables organizations to proactively plan for potential risks and opportunities, establishing realistic and measurable goals based on current and historical data. Armed with accurate data and statistics, businesses can formulate effective strategies, preemptively addressing potential failures or losses.

ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks (ANN) emulate the structure and function of the human brain, comprising interconnected nodes or neurons organized in layers. With various architectures like Feedforward Neural Networks, Recurrent Neural Networks, Convolutional Neural Networks, and Long Short-Term Memory Networks, ANNs excel in tasks ranging from pattern recognition, image classification, and natural language processing to prediction, time series analysis, and recommendation systems. Their ability

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to handle complex, nonlinear problems, adapt from data, and operate efficiently on parallel hardware makes them versatile. Particularly, Long Short-Term Memory Networks, a form of recurrent neural network, excel in capturing long-term dependencies and find applications in natural language processing and speech recognition. With advantages such as learning from data, adaptability, anti-interference, and adeptness with incomplete or unclear data, ANN stands as a powerful tool in machine learning, impacting decision-making across diverse fields.

FEED FORWARD NEURAL NETWORK (FNN)

This study employs the feedforward neural network method, particularly suitable for analyzing time series data related to daily coconut entries into the warehouse. In this model, the artificial neural network structure ensures that node connections do not create cycles. Comprising layers of neurons in a hierarchical arrangement, the feedforward neural network facilitates unidirectional information flow, with input nodes guiding the data through the network without feedback connections. This simplicity, marking it as the earliest designed type of artificial neural network, involves several steps: inputs entering through the input layer undergo weight multiplication, resulting values are added to form a weighted sum, this sum passes through an activation function, and the process repeats until the final output layer is reached. Successful applications of feedforward neural network models include pattern classification, clustering, regression, association, optimization, control, and forecasting. Capable of estimating functions of any complexity, these models often utilize the backpropagation algorithm for training by adjusting connection weights between neurons.

LONG SHORT TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) neural networks are a type of recurrent neural network (RNN) that have significant application value in many fields, including business forecasting. LSTM networks are suitable for random nonstationary sequences such as stockprice time series. LSTM networks have been used to forecast stock prices, workload in cloud data centre, and power demand. For example, (Fahim et al., 2021) developed a forecasting algorithm called SAM-LSTM, which is a fusion method of self-attention mechanism (SAM) and LSTM, to forecast the reform of scientific research in Morocco. (Qiu et al., 2020) added investor sentiment tendency in model analysis and introduced empirical modal decomposition (EMD) combined with LSTM to obtain more accurate stock forecasts. (Choi et al., 2020) proposed a power demand forecasting model called Power LSTM, which uses LSTM neural networks to forecast power demand. In summary, LSTM neural networks have been used in business forecasting to predict stock prices, workload in cloud data centres, and power demand. These models have shown promising results and have the potential to be useful tools for businesses in making informed decisions.

CONCEPTUAL FRAMEWORK

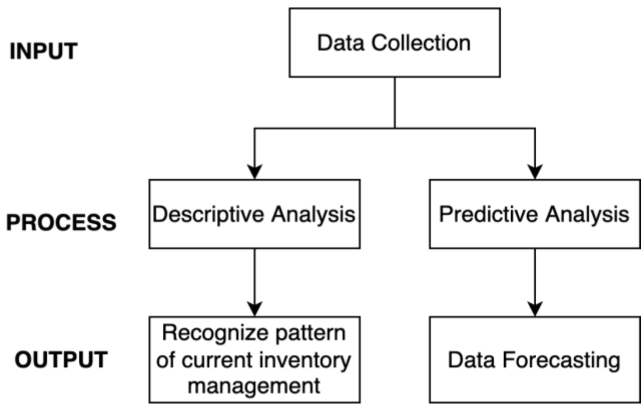

Figure 2. Five Whys Analysis

Descriptive analysis, a method aimed at detailing specific phenomena, proves invaluable for forecasting business strategy by delving into past performance and trends. It involves identifying patterns in historical data to understand how various factors influenced previous outcomes. This method facilitates predictive analytics, enabling companies to adjust strategies based on trends. Descriptive analysis also aids in benchmarking against industry averages or other company data, revealing strengths and weaknesses for targeted improvement. The comprehensive view provided by this analysis allows companies to assess current performance, identify areas for enhancement, and make informed strategic decisions. By relying on accurate and reliable data, businesses can understand customer behavior, market trends, and other influential factors, fostering a data-driven decision-making approach. Additionally, descriptive analysis helps companies identify past performance drivers, guiding resource allocation, investment decisions, and goal-setting for future strategies. Predictive analytics utilizes data, statistical algorithms, and machine learning techniques to forecast future outcomes based on historical data. This method aids companies in predicting likely outcomes of strategy changes through data-driven predictions, enabling adjustments based on historical information. By leveraging predictive analytics models, companies can uncover new growth opportunities, optimize operations, and reduce operating costs. This approach assists in identifying future opportunities, enhancing customer service, and making informed business decisions. Through data analysis, businesses can recognize patterns and trends that reveal growth opportunities and increase customer engagement. Predictive analytics also supports revenue growth by identifying contributing factors and formulating strategies to replicate them. Additionally, it helps companies mitigate risks by identifying potential threats and developing strategies to address them, fostering a proactive risk management approach.

RESEARCH DESIGN

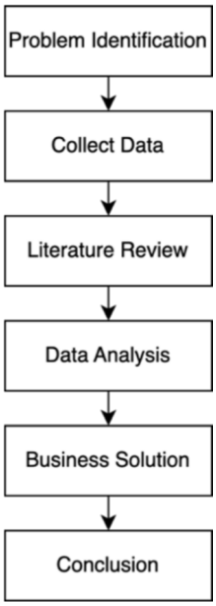

Figure 3. Research Design

The research template guides the development of the research plan for predictive analytics in finding business solutions. The process involves problem identification, where business problems requiring predictive analytics are clarified through interviews with owners, providing insights into sales and revenue. Once the problem is defined, relevant data is collected, and a literature review is conducted to guide the development of research hypotheses. The study adopts a quantitative approach, specifically using predictive analytics with a focus on predicting the daily participation of product vendors. The chosen method is Artificial Neural Network (ANN), applying statistical techniques to generate forecasts and predictions. After analysis, interpreting the findings enables the identification of a business solution to the current problem.

DATA COLLECTION METHOD

The type of data used is primary data that is processed and researched directly from the research subject. The data comes from the company's internal historical data. The data used is a quantitative data. The collection technique was carried out by means of participant observation where the researcher was directly involved in the observed situation as a source of data. The data used to

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perform predictive analysis is the number of coconuts that come in every day. The document is about the recapitulation of amount coconut that enter warehouse everyday. The document contains features such as date, initial stock, number of coconuts that come in every day, number of coconuts that come out of each shipping, total stocks, description of what ships are used for shipping the goods, and total number of suppliers in a day. Data collected from June 2020 to August 2023.

Table 1. Features in Data Collection

Feature	**Description**
Date	Warehouse operating date
Initial Stock	The number of coconuts from the previous day's accumulation
Coconut In	The number of coconuts that came in that day
Coconut Out	The number of coconuts that come out at the time of shipping by ship
Total Stock	Total current stock
Supplier	The number of supplier that came in that day

DATA ANALYSIS METHOD

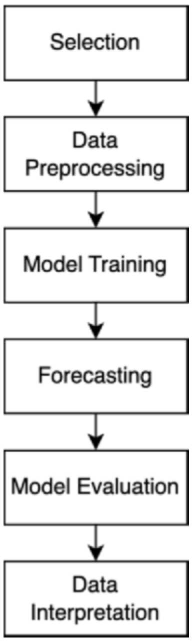

Figure 3. Data Analysis Method

Data analysis methods encompass a systematic approach to interpreting and extracting meaningful insights from data. The choice of a specific method for predictive analysis hinges on the data type and the selected forecast model. The analytical approach in this study follows a well-defined sequence of steps. Firstly, in the Selection phase, decisions are made regarding the data collection method, data storage, programming language for analysis, and the type of artificial neural network (ANN) architecture. Subsequently, in the Data Pre-processing step, the emphasis is on preparing the data through cleaning, modification, and normalization—eliminating irrelevant or missing data, ensuring the data is in an appropriate format, and normalizing it for consistency. Model Training comes next, where historical data is utilized to train the model, with potential optimization by adjusting

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parameters such as the number of hidden layers, learning rate, or activation function. Following the training phase, the Forecasting step involves using the trained model to predict future values by importing relevant data. Model Evaluation assesses the performance by comparing predicted values with actual ones, utilizing metrics like mean absolute error or mean squared error to gauge accuracy. Finally, Data Interpretation presents the analyzed results in a visually clear form, offering insights that can inform an implementation plan to address current business challenges.

ANALYSIS SELECTION

1) Data

The company provides documents with daily coconut warehouse data. In this data, there is a feature that will be used for predictive analysis, which is Coconut In. Data is saved in files in CSV format.

2) Method

Based on the literature review and problem exploration, a more suitable method to the problem is the Artificial Neural Network (ANN) method. There are many neural network architecture method that can be use as forecasting method, but the most suitable architecture to forecast with time series data is Feed Forward Neural Network (FNN) and Long-short Term Memory (LSTM). With a network architecture using a Feed Forward neural network, information only flows in the forward direction within the network through the nodes and no return connection. This method is used to analyze historical data and make forecasts for future periods. Long-Short Term Memory capturing long-term dependencies and making it ideal for sequence prediction tasks. This can help identify complex patterns and relationships in data that may not be visible with other methods. These two architecture method will be compared with error evaluation and prediction test.

3) Programming Language

This analysis uses quantitative methods that are also combined with computer programming. Indeed, the company's data is quite voluminous and to increase research analysis time, a program was used to analyze this research. The programming language used is Python.

DATA PRE-PROCESSING

Figure 4. Data Pre-Processing

Data pre-processing includes three procedural steps. From data cleaning, specifically the process of removing missing value or irrelevant data. In the data used, the data containing the number of coconuts entering the warehouse on a daily basis, there were some missing values and empty rows. The company provides daily data from 2020 to 2023. At that time, the company usually does not work on Sundays and holidays, so data on Sundays and holidays has a value of 0 in the "Coconut In" features. This rows will be removed from the data used.

Table 2. Sample of Data before Data Cleaning

Date	Initial Stock	Coconut In	Coconut Out	Total Stock
23 December 2022	116.155	25.474	0	141.629
24 December 2022	141.629	58.153	0	199.782
25 December 2022	199.782	0	0	199.782
26 December 2022	199.782	0	0	199.782

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27 December 2022	199.782	23.271	0	223.053
28 December 2022	223.053	42.446	145.573	119.926
29 December 2022	119.926	31.115	0	151.041
30 December 2022	151.041	44.248	0	195.289
31 December 2022	195.289	0	144.940	50.349

Table 3. Sample of Data after Data Cleaning

Date	Initial Stock	Coconut In	Coconut Out	Total Stock
23 December 2022	116.155	25.474	0	141.629
24 December 2022	141.629	58.153	0	199.782
27 December 2022	199.782	23.271	0	223.053
28 December 2022	223.053	42.446	145.573	119.926
29 December 2022	119.926	31.115	0	151.041
30 December 2022	151.041	44.248	0	195.289

Then, Data Transformation is performed to change all data formats to Integers (int). This is intended to balance all types of data to make it easier for the program to recognize which features are used. The final step is Data Reduction. Data reduction aims to reduce the size of the data used. Since this study only requires prediction of the feature "coconut in", other features will be removed from the data to be used.

Table 4. Feature Reduction

Features	Feature after Data Reduction
Date	Coconut In
Initial Stock	
Coconut In	
Coconut Out	
Total Stock	
Description	
Supplier	

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MODEL TRAINING

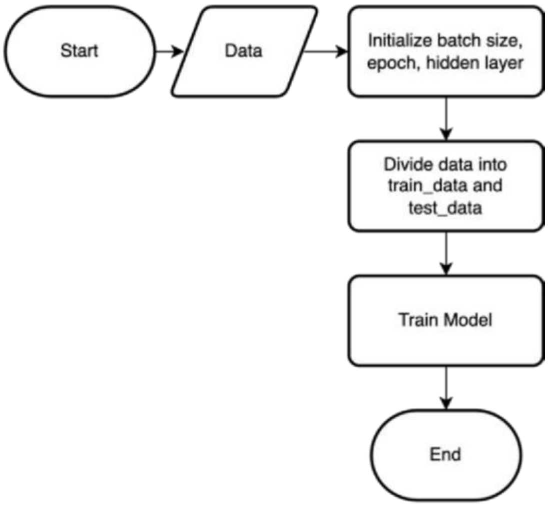

Figure 5. Training Model

The training model begins by inputting data, specifically documents containing a recapitulation of the amount of coconut entering the warehouse every day. The data is trained using available company data. The training data spans from June 2020 to December 2022, serving as the training set, while January 2023 to August 2023 is designated as the testing set. The goal of training this model is to enable the method to learn from the data and achieve an optimal fit that aligns the data with the method. Using the feature "Coconut In," the model will be separately constructed using two methods: Feed Forward Neural Network and Long Short Term Memory. Both models share the concept of training models as they are derivatives of the Artificial Neural Network. However, the difference lies in the mathematical formulas during the Train Model process for each model. This study utilizes Python-supported libraries, and the detailed process of training each method is not provided. The objective of the training model is to identify parameters that best suit the respective model's formulas. Both methods employ parameters such as look back 365, hidden layer 12, epoch 1000, and batch size 365. The hidden layer is positioned between the input layer and the output layer. Epoch represents the number of iterations for the entire dataset and functions to optimize the learning process. Batch size indicates the number of data groups used in one epoch.

FORECASTING

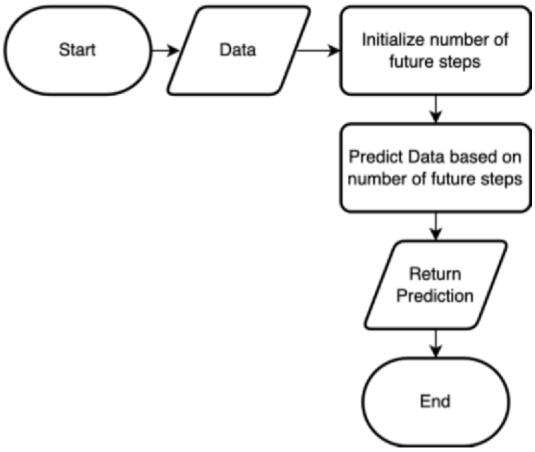

Figure 6. Forecasting

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After the model is trained, the next step is forecasting to obtain information about future events. It begins by initiating future steps, which contain the quantity of daily information desired. Subsequently, each program is created in accordance with the model to execute the predict() function, predicting according to the specified number of initiated future steps. At this stage, the result of the prediction is generated, which also serves as the outcome of the forecasting for this research.

MODEL EVALUATION

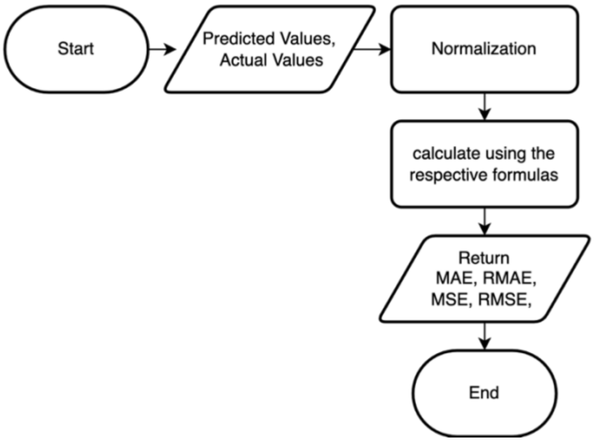

Figure 7. Model Evaluation

In the model evaluation stage, data is divided into two types: training data and test data. The training data used spans from June 2020 to December 2022, while the test data covers January 2023 to August 2023. Based on the actual results and the predicted results, or what can be termed as forecasting results, both values are compared, and their errors are tested using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Root Mean Absolute Error (RMSE) for each method—namely, the Feed Forward Neural Network method and the Long Short Term Memory method. The model evaluation process begins by comparing two sets of inputs: actual values, representing the company's data from January 2023 to August 2023, and predicted values derived from forecasting using both the Feed Forward Neural Network (FNN) and Long Short Term Memory (LSTM) methods.

Table 5. Model Evaluation

Evaluation	Feed Forward Neural Network	Long Short Term Memory
Mean Squared Error (MSE)	0,0948	0,0894
Root Mean Squared Error (RMSE)	0,3079	0,2991
Mean Absolute Error (MAE)	0,2548	0,2453
Root Mean Absolute Error (RMAE)	0,5048	0,4953

Two different evaluation methods are used to test both models: Mean Squared Error (MSE) and Mean Absolute Error (MAE). MSE is a more sensitive error measurement to extreme values since it uses the squared difference values between actual data and predicted data. Meanwhile, MAE is a measurement in the original unit, making it more resistant to outliers as it only utilizes the absolute difference between actual data and predicted data. From the results of the executed model evaluations, both models yield evaluation values that are closely aligned. With slight differences between the two models and evaluation results approaching 0, both models can be considered to tend towards low errors in predicting actual values. From the two tested models, Long Short Term Memory has a lower error value than the Feed Forward Neural Network.

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DATA INTERPRETATION PEAK SEASON AND LOW SEASON

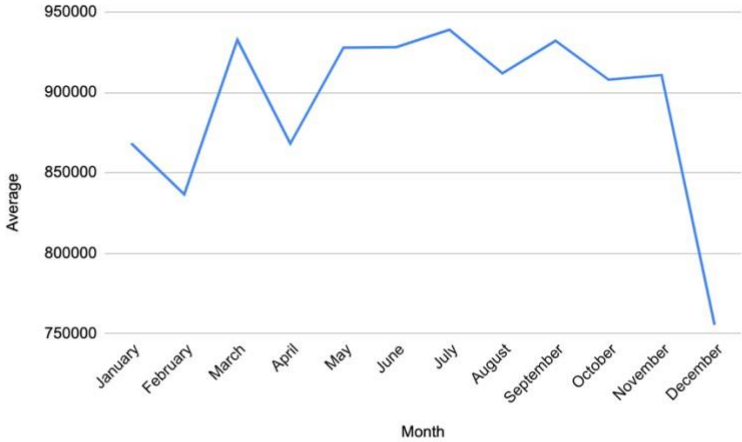

Figure 8. Peak Season and Low Season

To obtain information about Peak Season and Low Season, all data is processed by comparing it based on monthly periods and compared for each year. The data used to analyze this is Coconut In, counted from June 2020 to August 2023. Each month is accumulated by summing from the 1st to the last day of the month for each year. From all the received data, the average is calculated for each month's accumulation. Thus, in January, the average is calculated using the accumulation of January for the years 2021, 2022, and 2023, divided by the number of years. The average results for each month are also displayed in graph form to clearly observe Peak Season and Low Season. Based on the average calculation and visualization from the graph, Peak Season occurs in the middle of the year, from May to November. Meanwhile, Low Season occurs at the end of the year to the beginning, from December to April. This is because there are many national holidays at the end and beginning of the year. December is the month with the lowest coconut intake because the company is closed from early Christmas to the New Year holiday.

DELIVERY FREQUENCY

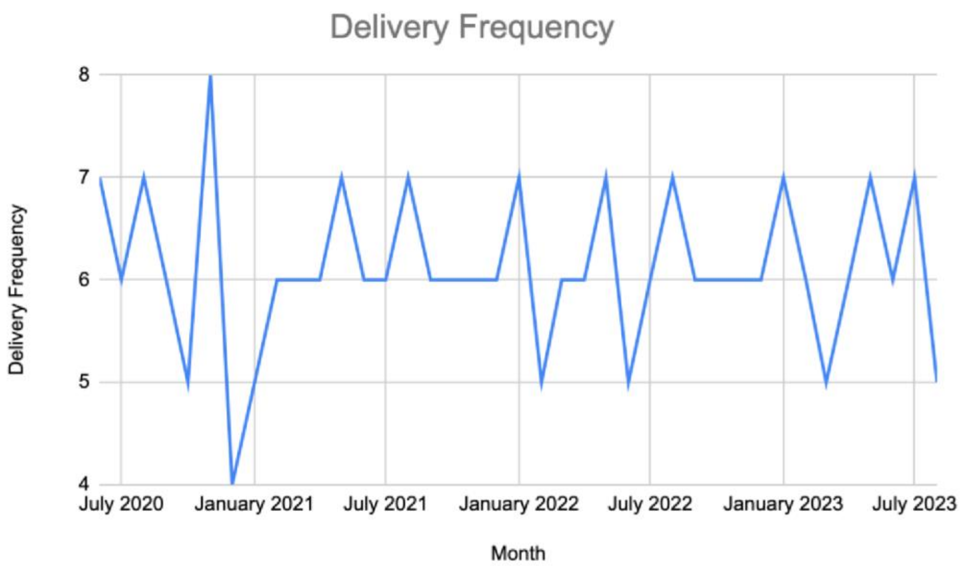

Figure 9. Delivery Frequency

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Delivery frequency is the number of coconut delivery frequencies to the factory via sea routes by vessels owned by the company. This service is also one of the forms of services offered by the company to build cooperation with the factory. Delivery can only occur if the coconut weight has reached the ship's capacity, which is 130,000 – 150,000 kgs. Since the company currently has only two vessels, the frequency of delivering goods using vessels is only 1-2 times per week. The sea route journey and the process of loading and unloading goods can take 4-5 days in one delivery. The graph above is obtained from the accumulation results for each month from June 2020 to August 2023. From the graph, it can be concluded that in one month, the minimum number of deliveries is 4 times, which occurred in December 2020, and the maximum is 8 times, which occurred in November 2020. According to information from the owner, in December 2020, there was an accident where one of the vessels hit a coral reef, causing the ship to be damaged and broken during the journey. Therefore, the company's operations were slightly disrupted. The average deliveries made during regular operations are 6 times a month.

OUTPUT FORECASTING

Comparing the forecast results by comparing the Feed Forward Neural Network (FNN) and Long Short Term Memory (LSTM) models for the next 90 days and 120 days, the forecast with 120 days has graph lines that are almost identical between the two models. Meanwhile, in the next 90 days, the graph line of the FNN method experiences a slight decline. However, the difference in forecast results between these two methods is not significantly different. It can also be concluded that both models are reliable for the processed data. The forecast results for the next 120 days using the Feed Forward Neural Network (FNN) and Long Short Term Memory (LSTM) models are as follows. FNN has data ranging from 24,038 kgs to 43,581 kgs, with an average of 35,138 kgs. Meanwhile, LSTM has forecast data ranging from 26,263 kgs to 42,517 kgs, with an average weight of 34,669 kgs.

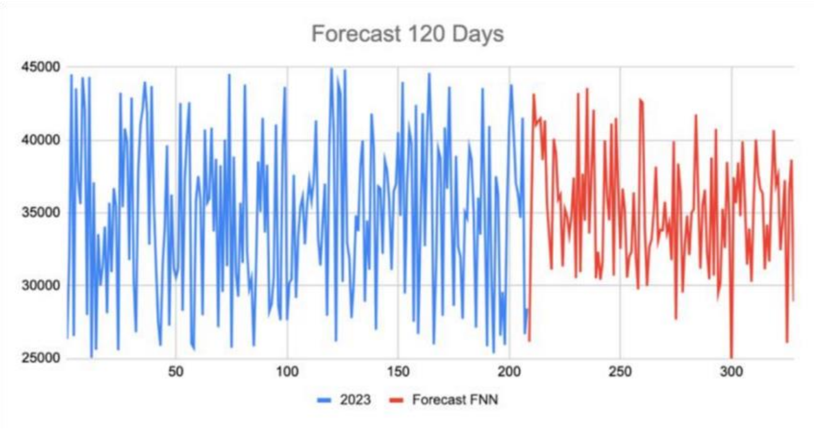

Figure 10. Forecasting results using Feed Forward Neural Network (FNN) in 2023

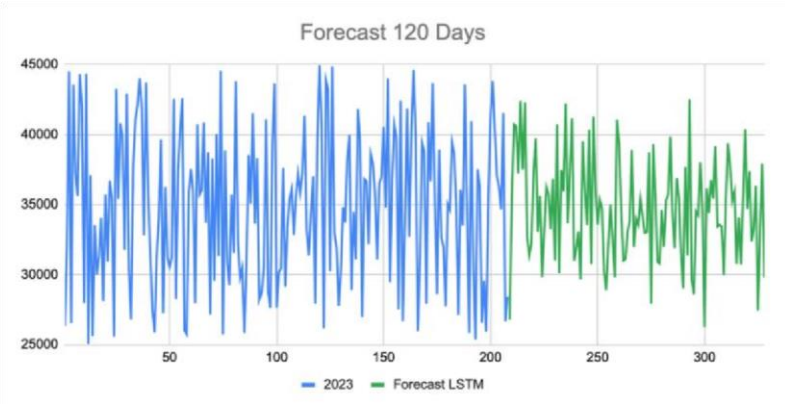

Figure 11. Forecasting results using Long Short Term Memory (LSTM) in 2023

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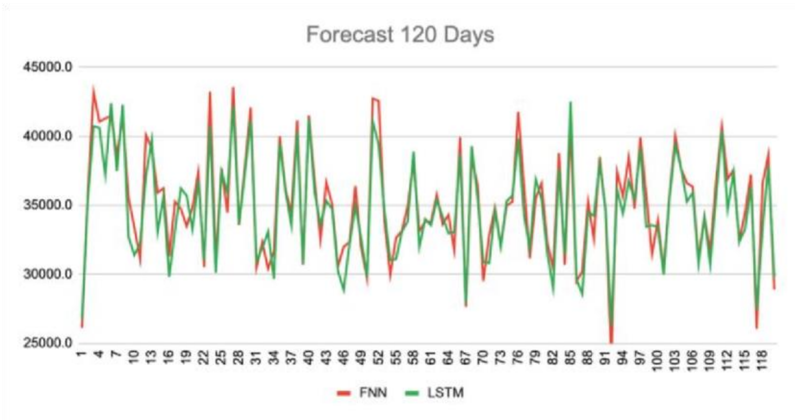

Figure 12. Comparison Forecasting results of FNN and LSTM in 2023

BUSINESS SOLUTION

COCONUT WEIGHT TARGET

The first thing to do is to set a new target for the weight of coconuts entering the warehouse each day. The company aims to change the delivery frequency from 1-2 times per week to 2-3 times per week. This change is also supported by the company's purchase of a new vessel and the relocation of the coconut warehouse to a larger space. Each vessel can carry 130,000 kgs to 150,000 kgs of coconuts in one delivery. In determining the coconut weight target, the company uses the average weight capacity of the vessel, which is 140,000 kgs. From this weight, the minimum and maximum weight that must be achieved in one week of delivery will be calculated. This calculation is based on the delivery frequency multiplied by the average vessel load. Thus, the results are as follows.

Table 6. Target Weight

Delivery Frequency	Target Weight (Weekly)
2	280,000 kgs
3	420,000 kgs

Next, the two weight targets will be compared with the forecast results. This serves for the company to know how much more needs to be fulfilled so that the increase in delivery frequency can be achieved. The forecast data used is data for the next 120 days using the Long Short Term Memory (LSTM) method.

Figure 13. Targeted Weight and Predicted Weight

From the graph of this data, it can be seen that the gap the company has to bridge is quite significant to reach the target. To achieve the minimum target weight, the company must increase the amount of coconuts entering from the range of 52,269 kgs to 83,645 kgs. Meanwhile, to achieve the maximum target weight, the company must increase the amount of coconuts from the range of 192,269 kgs to 223,645 kgs. Furthermore, since this data is still in the form of weekly targets, the daily data on coconut weight that must be achieved must be calculated. This is calculated by dividing the difference between the forecasted data and the target weight data by 6 working days. The following are the results of the calculation of the daily data that must be achieved. Based on those calculations, the company needs to find additional coconut weight ranging from 8,000 kgs to 37,000 kgs.

TARGET NUMBER OF SUPPLIERS

In an effort to increase the quantity of coconuts entering the warehouse, the company needs to add coconut suppliers or farmers. The number of suppliers is directly proportional to the quantity of coconuts entering. The more coconut farmers coming to the warehouse, the greater the quantity of coconuts in the warehouse. Therefore, the next step is to determine the number of suppliers that need to be added by the company. However, because explicit data regarding the quantity of coconuts brought in by farmers is not provided by the owner, the first step in the process of determining the additional number of suppliers is to find out the average quantity of coconuts brought in by suppliers. Here are the results of the average weight brought in by farmers

Table 6. Average Supplier's Coconut Weight

Year	Coconut In (kgs)	Supplier	Annual Average (kgs)
2020	6.325.367	4.640	1.363
2021	10.732.880	8.144	1.318
2022	10.908.275	8.246	1.323
2023	7.256.906	5.534	1.311
Average			1.329

For each Coconut In and Supplier data, an accumulation is calculated for each year. From the total accumulation, the average is calculated by dividing the total coconut in and the number of suppliers. Next, the average is calculated based on the annual average from 2020 to 2023. The result shows that, on average, a farmer delivers 1,329 kgs. Next, the number of suppliers that need to be added by the company is calculated based on the previously outlined additional weight target.

STORAGE PERIOD AND STACKING LEVEL

During the storage process in the warehouse while waiting for the delivery day, coconuts should be stored in the warehouse for a maximum of 5 days with the First In First Out (FIFO) stock rotation system, ensuring that the coconuts stored first are also the first to be shipped. This can prevent coconuts from being stored for too long. In an effort to anticipate losses due to coconut breakage and spoilage, coconuts should only be stacked up to 3 levels. This is also supported by the owner's experience, where stacking more than 3 levels led to broken coconuts and leaking coconut water, causing the surrounding coconuts to rot. Stacking levels more than 3 can also disrupt and complicate the workers in moving coconuts to/from the vessel. To anticipate spoilage and quality decline, the company can also provide specialized training to workers for routine quality checks on stored coconuts. Regular checks serve to move or rearrange stacked coconuts in case of breakage.

IMPLEMENTATION PLAN

The Implementation Plan consists of four stages: Preparation, Planning, Action, and Evaluation.

1) Preparation

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IJCSRR @ 2023

Preparation is the stage to determine the resources needed to achieve its goal, which is the creation of a new strategy for the Banio Lahewa warehouse inventory that is more effective. The activities that occur during the preparation phase are as follows. a. Collecting inventory data

In the inventory data, various types of data such as the daily quantity of coconuts entering, the quantity of coconuts shipped, the number of suppliers, and other inventory costs are included. The amount of demand and supply for coconuts is crucial to know for effective warehouse management planning.

b. Lead time evaluation

The operational and management teams need information on lead time evaluation of the company's activities so far. This is to identify which activities need improvement or modification. Lead time also helps in planning the company's delivery frequency.

2) Planning

Planning is the stage to create tactical plans, schedules, and determine the budget needed for each step and resource that will be used to achieve business goals.

a. Demand Forecasting

The operational team needs to build a forecasting system to estimate future events so that the system can run more effectively in the future.

b. Financial Planning

The finance team needs to plan adaptive financial changes in response to the changes in warehouse management that will be implemented.

c. Develop plans to get new suppliers

Management, together with finance, can plan contracts that can attract the interest of new coconut suppliers in the warehouse.

3) Action

Action is the stage to take the planned steps. Coordination and control are crucial to ensure that each stage proceeds according to the plan.

a. Employees Training

Employees need training to understand how to use the demand forecasting system and adapt to the latest warehouse system for coconut stacking and periodic storage quality checks.

b. Get additional suppliers

The company can seek new suppliers by collaborating with brokers in the area and offering attractive deals to new suppliers.

c. Collecting inventory data

In every process in the warehouse, all data must be recorded and stored everyday.

4) Evaluation

Evaluation is the stage to track progress and measure performance against the goals of the business plan. Reporting on evaluations and adjusting business plans may be necessary depending on the evaluation results. Identify whether there are changes in the business environment or other factors that require strategy adjustments.

a. Demand rate evaluation

The predicted results of the forecasting will be compared with actual data to determine if the system used is suitable for the existing issues.

b. Inventory cost evaluation

The finance team must evaluate the finances to see if the required costs for the new system can be covered by the company or not.

c. Lead time evaluation

To monitor all activities, the operational team needs to get information about lead time and evaluate the company's activities. This aims to determine the effectiveness of the implemented system.

CONCLUSION

The data used in this study is primary data sourced directly from the company. Utilizing data from June 2020 to August 2023, it has been processed and analyzed using forecasting methods. The forecasting methods aim to predict future events in the warehouse

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based on the uncertainty of coconut intake daily. Two Neural Network models, specifically the Feed Forward Neural Network (FNN) and Long Short Term Memory (LSTM), were employed for the analysis. This analysis serves to develop a new strategy for warehouse management at Banio Lahewa. From the forecasting results, targets will be set for future warehouse planning. These targets are established based on the changes required by the company. Subsequently, new plans are formulated to address the disparities between the target quantities and the forecasting outcomes. These new plans impact the daily quantity targets for coconut intake, the number of suppliers, storage periods, and stacking levels within the warehouse. Predictive models were constructed using two types of Neural Network models. The evaluation of the error values between the two methods revealed only slight differences. Despite these minor variations, the Long Short Term Memory (LSTM) method proved superior, exhibiting lower errors compared to the Feed Forward Neural Network (FNN), with MSE at 0.0894 and MAE at 0.2453. Consequently, the company conducted forecasts using the Long Short Term Memory (LSTM) method to predict future events in the Banio Lahewa warehouse.

RECOMMENDATION

This study presents recommendations for both Banio Lahewa and future research endeavors. For Banio Lahewa, it is advisable to implement forecasting techniques to optimize coconut inventory levels, preventing overstocking or stockouts. Additionally, a thorough evaluation of the impact of forecasting on supply chain efficiency and inventory costs is suggested, along with the identification of risk factors affecting raw material availability and the development of effective mitigation strategies. Furthermore, maintaining detailed records of all warehouse-related information, including incoming and outgoing goods, prices, and processing times, is crucial. In terms of future research, it is recommended to apply the method with larger datasets and explore alternative forecasting approaches for a more comprehensive analysis. Additionally, advocating for analyses based on various time periods, such as weekly, monthly, and yearly intervals, is proposed to enhance the accuracy and effectiveness of results over time.

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