Journal of Theoretical and Applied Information Technology
30th November 2024. Vol.102. No. 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

LSTM NEURAL NETWORKS WITH BAYESIAN OPTIMIZATION FOR REORDER SIMULATION IN RETAIL INVENTORY MANAGEMENT

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ABSTRACT

This research tries to improve the accuracy of demand forecasting in grocery store with optimization of LSTM neural networks by using Bayesian Optimization. Research Design Data and Methodology: This study aim to forecast the demand by using Brand AB instant noodles daily sales data from a grocery store in one year period. Well-tuned by Bayesian optimization, LSTM model can encode intricate temporal structure and long-term dependency in sales sequences. Result: The results show that the optimized LSTM model has a low value of mean squared error (MSE) 0.0056, which means good predictability, a simple reorder simulation incorporates the enhanced forecast model to refine optimal inventory management decisions. Through this simulation, critical reorder points will be established to ensure that the product is always available and there is no risk of stock outs or overstocked items. Conclusion: The results in this study demonstrate a great potential of sophisticated neural networks and the Bayesian optimization approach to achieve better inventory management within retail industry.

Keywords: *LSTM Neural Networks, Bayesian Optimization, Inventory Management, Reorder Simulation*

1. INTRODUCTION

In post-pandemic period Indonesia economy continue to face challenge from inflation and sharply increased interest rate by Bank Indonesia that make it hard for investors to increase the price of their consumption [1]. While these measures are introduced to stabilize the economy, it affect multiple sectors [2].

The retail sector, especially grocery stores, is one of the most affected sector. Due to the high operational costs and an overall shift in consumer behavior towards shopping, these stores have had to approach their businesses strategically [3]. Many grocery stores have changed their pricing strategies and product offerings in order to stay competitive [4]. For instance, while some firms paid more attention to improve quality and consider new ways to leverage online expansion in order to get as many customers as possible [5], others have reduced their inventory or renegotiated the conditions of contracts with suppliers Sustrova [6]. Some grocery stores have, however, also been able to adapt to shifting consumer behavior and economic conditions [7]. The retail industry and neighborhood food shops in Indonesia will play a major role in determining how the economy develops once the pandemic-related crisis is passed [8].

With their provision of necessities, grocery shops are an integral element of Indonesian everyday life [9]. But the state of the economy now has a big effect on these businesses; increased running expenses and changes in customer behavior present serious problems [10]. Grocery shops are a mainstay of the retail sector that sustain regional supply chains, provide jobs, and guarantee food security, therefore adding to the larger economic ecology. Grocery shops have to change with the market and with customer wants in order to be competitive and sustainable [11].

Government regulations and encouragement of the retail industry might also lessen some of the difficulties Indonesian grocery retailers encounter.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Grocery shops are essential to Indonesian economy, hence inventory management has become increasingly important [12]. Supply chain disruptions and changes in consumer demand during times full of uncertainty, such as the pandemic, can be mitigated through effective inventory management [13]. The key to overcoming this problem is to predict demand accurately, and finding the right balance between stockouts and overstocks. This allows retailers to serve consumer needs without the risk of having to spend more [14]. Although the statistical techniques currently used by retailers can predict demand, [15], complex and dynamic market changes require a more sophisticated prediction approach [16].

Advances in computer processing power have given rise to new opportunities to improve the accuracy of consumer demand predictions [17]. With increasingly sophisticated computers, large volumes of data can be analyzed quickly and more accurately. Thus providing deeper insight into market demand predictions and consumer behavior [18]. Grocery stores can improve their predictive capabilities by integrating real-time data such as social media trend data, weather, and so on using artificial intelligence to be better able to adapt to market changes [19]. Also more flexible in the decision-making process [20].

One neural network model that can be used well to predict time series data is the Long Short Term Memory model or LSTM model. This neural network model is superior in detecting patterns in time series data so it is suitable for predictions [21]. By using LSTM Neural Network groceries store can improve their inventory management, increase prediction accuracy and reduce the risk of stockout or over stocking [22]. LSTM neural networks are capable of handling long sequential data, this is very important to pay attention to if you want to predict consumer demand [23]. Furthermore, by using better predictions a company can ultimately increase customer satisfaction, increase profits, and so on. [24].

Although several studies have used machine learning models for demand forecasting, only a few have explored the combination of using LSTM neural network using Bayesian optimization for inventory management in retail. This research bridge the gap by demonstrating how such integration can produce predictions with low error that are able to respond to demand fluctuations and overcome operational constraints faced by grocery retailers.

The aim of this research is to show how LSTM neural networks are optimized using Bayesian optimization to predict consumer demand. Next, the prediction results are used to calculate important measurements in inventory management. Furthermore, in this research, a simple simulation is carried out to find out when a reorder will be made, using the results of previous LSTM predictions.

2. LITERATURE REVIEW

In inventory management, demand prediction is very important. The ability to predict good demand can help companies determine the right quantity when reordering from suppliers [14]. However, traditional forecasting techniques are often too slow to meet today's fast-moving market demand. Incorporating real-time data into demand forecasts can provide significant benefits [25]. Successful companies leverage their data resources such as social media data, climate data to identify common roles in consumer behavior and market conditions, thereby enabling more accurate inventory management and informed decision making [19].

Meanwhile, models for making predictions using light period data have developed rapidly. Optimization techniques for optimizing machine learning models are also developing rapidly. So it can be applied in such a way as to understand today's increasingly dynamic market [17]. This adaptation is especially important for grocery stores, given changing consumer preferences and intense competition [11]. More sophisticated demand forecasting and better inventory management strategies are increasingly needed to deal with complex problems due to increasing costs and changing consumer behavior. This is necessary to ensure a sustainable company [3]. Apart from that, better experience is needed in pricing strategies and product offerings. Several companies are adopting cost efficiency or increasing sales online [4]; [5]. This illustrates a gap in research namely the development of demand forecasting and inventory management strategies that will be effective in current conditions.

Grocery stores are still relevant and they continue to focus on effective inventory management. The reorder simulation techniques are methodologies that asses the right amount and right moment for replenishments, seeking to balance overstock and stockout risks . While traditional methods are based primarily on historical sales data supplemented with statistical models [15], the deepening complexity of market structure demands new, more advanced methodologies.

With reorder simulation, companies can ensure that they always have enough stock on hand while also reducing the expense of carrying sufficient inventory. Using these models to predict the optimal inventory replenishment, companies can also determine which type of order in what conditions will be most beneficial. Considering that markets are dynamic and unpredictable, it is an important aspect. The development in computational strength has ushered in extra accurate demand forecasting [17].

Machine learning algorithms are robust tools, even the neural network for analysing large data sets and extracting meaningful patterns [18]. Moreover, the degree of prediction is increased by utilizing real-time social media trends and weather pattern data.

A grocer will always have to restock their inventory due to various situations, and must consider supply chain reliability as well as seasonality [26]. Conditions like that are very suitable for the LSTM model. LSTM models are effective for forecasting demand based on past behavior. This model can identify complex patterns over long periods of time [27]. Companies can use LSTMs to better manage their inventories and reduce uncertainty regarding stockouts or overstocking [22]. LSTM neural network is a subset of recurrent neural network (RNN) where this model can learn from temporal sequences and is able to remember for longer periods more effectively than other models. This network can include cells with an internal state that allows them to retain data for extended periods of time, which is crucial for accurately forecasting demand fluctuations in retailers [28].

In general, neural networks function similarly to the human brain and consist of layers with nodes called neurons. These neurons are interconnected so that the network is able to recognize patterns, then make predictions based on these patterns. Furthermore, it can help solve complex problems by studying data. [29].These can vary from simple feedforward networks to more complicated structures such as CNNs or RNNs. Neural networks are flexible with respect and applicable to many areas including demand prediction or forecasting, inventory management etc [30]. It could be observed that better performance of neural networks, especially LSTM's can be achieved using the bayesian optimization method [31]. This probabilistic model-based search optimizes the hyperparameters by creating a surrogate model of the objective function and choosing the most promising points to evaluate by their posterior mean. By doing so, the point to be evaluated is most likely to optimize the hyperparameters, and the model's performance is improved [32]. Since inventory management is critical to retail operations, particularly in grocery stores, it should provide a balance between supply and demand for the store. Thus, this requires a systematic approach to procurement, storage, and sale of stock to avoid either excesses or stock-outs. In turn, this could improve financial performance by optimizing financial gains and customer satisfaction. By carefully managing the inventory, grocery stores can improve their operations on multiple levels, which ultimately lead to the long-term success of the business.

3. METHOD

This research method is initialized by analyzing transaction data that occurs in a grocery store in Bandung originating from January to December. Brand AB instant noodles was considered high, therefore proving among many it had the highest sales volume. The sales data that can be extracted from it are also perfect for demand forecasting exercises as well as inventory analysis. Research methodology is illustrated in Figure 1. The next step after collecting the data is pre-processing of the data. Clean and select data to ensure its' accuracy and validity, as well as selecting sales data which only contains records of Brand AB instant noodles. It would be developed by narrowing focus thus, demand patterns and inventory needs of this specific item can be examined in greater details.

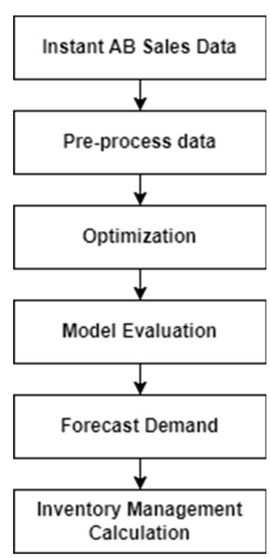

Figure 1. Research Methodology

The next phase involves optimizing the neural network model using. This technique fine-tunes the hyperparameters of the Long Short-Term Memory (LSTM) neural network, such as the number of layers and neurons, learning rate, and dropout rate. Bayesian optimization works because it forms a probabilistic model of the relationship between hyperparameters and their effectiveness. In this way, options will arise more quickly to choose an optimal set for networkv training which has good properties.

When optimization is complete, our next step is to evaluate the model using these hyperparameters Using TimeSeriesSplit, model performance evaluate based on mean absolute error (MAE), and root mean squared error (RMSE) to confirm its predictive reliability. With the verified model, demand forecast for Brand AB instant noodles is extended by 31 days through the next of January. These predictions are key inputs for subsequent inventory management calculations. From the model's output, safety stock (SS), reorder point, and Economic Order Quantity (EOQ) can be determined for Brand AB instant noodles

that products remain available right up until their last-on-hand stock is used up--at the same time avoiding accumulation of excess inventory. This elaborate procedure could raise the accuracy of inventory control and lead to more efficient overall store operations.

Table 1. Dataset Sample

DATE	Quantity
2022-01-17	84
2022-01-18	162
2022-01-19	203
2022-01-20	158
2022-01-21	185
2022-01-22	95
2022-01-23	100

Table 1 provides a snapshot of daily sales data from a dataset spanning one week. The dataset includes the dates from January 17, 2022, to January 23, 2022, and the corresponding amount recorded for each day.

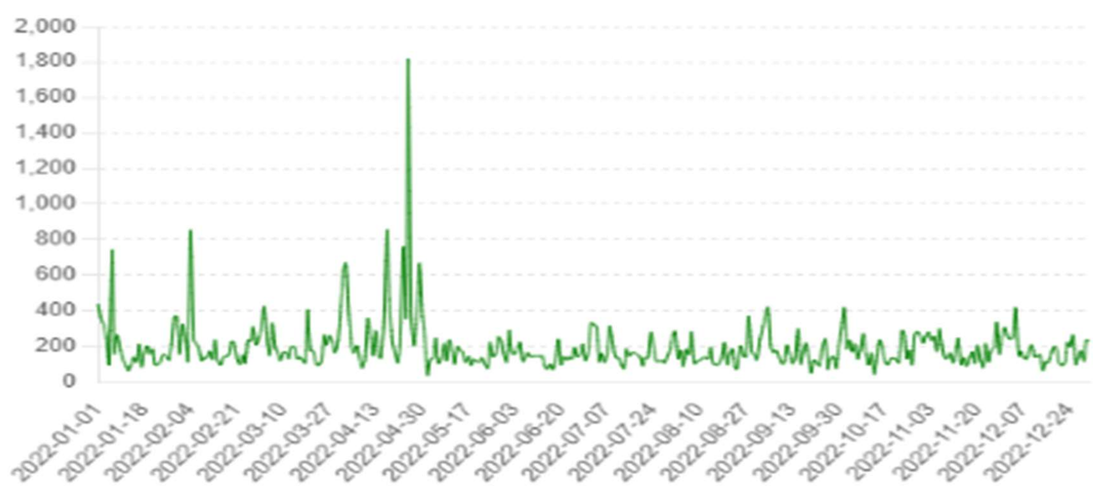

Figure 2. Product Sales Over Time

This research also simulates the reordering schedule based on forecast demand and computed inventory metrics. By simulating the day when orders should be placed in any specific month, we can make sure

The chart displayed in figure 2 illustrates the trend in the dataset from January 2022 to December 2022. The sales figures during this period exhibit significant fluctuations. One notable peak is observed, where sales nearly reached 2,000 units, which can be

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

attributed to Eid al-Fitr. Subsequently, sales gradually decline but still occasionally experience spikes, indicating intermittent increases in demand. Considering the fluctuating sales pattern, it is essential to make accurate predictions for effective inventory management. The variability in demand underscores the significance of precise forecasting to optimize stock levels and avoid both overstocking and stockouts.

4. RESULT AND DISCUSSION

This study examines daily sales data from retail stores for 1 year with a special focus on sales of AB brand instant noodles. The collected data is initially available in Excel format after undergoing several processing steps to ensure it is suitable for analysis using advanced machine learning techniques.

The first step in preparing the data involves loading and parsing the Dataset using the Pandas library in python. The sales data is imported directly from an Excel file. To facilitate time series analysis, the 'DATE' column was transformed into a datetime format, which allows more efficient manipulation and sorting of data. This column is also defined as the index of the data frame, an important step in organizing data for time series analysis.

After the data is formatted correctly, normalization is carried out on the sales figures for AB brand instant noodles. This step is achieved using the MinMaxScaler from the Scikit-learn library. Normalization is an important step in machine learning especially when using neural networks to ensure that all input values have the same scale in the range usually between 0 and 1. This transformation can improve the performance and speed of training neural networks thereby ensuring that each feature contributes equally to the learning process of the model.

To transform time series data into a format suitable for machine learning, a custom function, create_dataset, was used. This function is effectively capable of transforming time series data into supervised learning problems, thus enabling the application of long short-term memory neural networks (LSTM). Specifically, the data set is then structured in such a way that the sales figures from the previous day will serve as input and the sales figures from the current day will serve as output. This transformation is important in time series forecasting because it allows the model to learn patterns and trends from past data to predict future sales.

The core of the modeling process involves the construction and optimization of the LSTM neural network. Where this LSTM is very suitable for time series forecasting because it can study long-term dependencies in sequential data. In this study, the Keras library is used to build an LSTM model. The architecture of the model used includes two layers. The first LSTM layer is configured with return_sequences=True, which allows the model to handle sequential data more effectively by passing the output sequence to the next layer to reduce the risk of overfitting. Drop Out layer is added. This layer randomly ignores certain descending neurons during the model training process, thus making the model have to generalize better.

One of the main aspects of this research is to optimize the hyper parameters of LSTM so that the LSTM model can have better performance. The optimized hyper parameters include the learning rate, the number of LSTM units (neurons), and the batch size. Hyper parameter optimization is performed using Bayesian optimization, a method that systematically explores various combinations of parameters to minimize the mean squared error of the model (MSE). After more than 50 optimization iteration, Bayesian was able to identify the optimal hyper parameters that yield the lowest MSE.

The optimization process using Bayesian showed that the model with the best performance had a learning rate of 0.0093, 44 LSTM units, and a batch size of 123. This configuration yielded an MSE of 0.0056, which value is a fairly strong indicator of the model's ability to capture and predict sales patterns accurately. A low MSE value can be an indication that the model can predict future sales reliably enough to be an important model for inventory management.

The results of the optimized model using Bayesian are then used to estimate sales for the next 31 days, namely sales in January of the following year. The predicted sales figures were as follows:

Table 2. Sales Prediction

Day	Sales Prediction	Day	Sales Prediction
Day 1	218.17	Day 16	162.93
Day 2	217.28	Day 17	175.53
Day 3	216.80	Day 18	177.78

Journal of Theoretical and Applied Information Technology
30th November 2024. Vol.102. No. 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Day 4	207.66	Day 19	170.64
Day 5	212.02	Day 20	181.41
Day 6	185.46	Day 21	204.33
Day 7	177.80	Day 22	203.13
Day 8	176.63	Day 23	209.68
Day 9	182.46	Day 24	234.21
Day 10	151.12	Day 25	233.30
Day 11	152.22	Day 26	231.77
Day 12	148.18	Day 27	218.91
Day 13	142.96	Day 28	225.14
Day 14	135.52	Day 29	225.11
Day 15	151.23	Day 30	231.30
		Day 31	222.69

This sales forecast is important because it can determine the main inventory management matrix such as Economic Order Quantity (EOQ), reorder points, and safety stock levels. This measure can help to maintain optimal inventory levels thereby ensuring that retail stores avoid running out of stock or overstocking.

Assuming a lead time of seven days, an ordering cost of $30, and a holding cost of $1 per unit, the following inventory management measures were calculated:

- Safety Stock: 123.58 units
- Average Daily Demand: 193.01 units
- Reorder Point: 702.62 units
- Economic Order Quantity (EOQ): 2,055.96 units

Simulations were then performed to model daily inventory levels for one simulation month starting with the initial inventory of 80% of the EOQ (approximately 1,644.77 units). Each day, the forecasted sales were subtracted from the inventory. When the inventory level fell below the reorder point of 702.62 units, a reorder was triggered, replenishing the stock up to the EOQ. The simulation identified three days where reorders were necessary:

- Day 5: Reorder of 2,055.96 units
- Day 17: Reorder of 2,055.96 units
- Day 27: Reorder of 2,055.96 units

The daily inventory levels for the month are as follows:

Table 3. Inventory Level Prediction

Day	**Inventory Level**	**Day**	**Inventory Level**
Day 1	1426.60	Day 16	862.28
Day 2	1209.32	Day 17	686.75
Day 3	992.52	Day 18	2564.93
Day 4	784.86	Day 19	2394.29
Day 5	572.85	Day 20	2212.88
Day 6	2443.34	Day 21	2008.54
Day 7	2265.54	Day 22	1805.41
Day 8	2088.91	Day 23	1595.73
Day 9	1906.45	Day 24	1361.52
Day 10	1755.32	Day 25	1128.22
Day 11	1603.10	Day 26	896.45
Day 12	1454.92	Day 27	677.54
Day 13	1311.96	Day 28	2508.36
Day 14	1176.45	Day 29	2283.25
Day 15	1025.21	Day 30	2051.95
		Day 31	1829.26

This study attempts to improve the accuracy of sales forecasting for retail inventory management purposes by using a Long-Shorterm Memory LSTM neural network which is then optimized using Bayesian optimization. This study focuses on instant noodles with the AB brand, thus providing a concrete case to explore the model's ability to predict sales and then simulate it for decision making in inventory management.. The results demonstrated that LSTM, when carefully optimized, can significantly reduce forecasting errors, achieving a Mean Squared Error (MSE) of 0.0056. These results show that the model built has the ability to capture the nuances of daily sales data.

The use of baby stuffing optimization plays an important role in improving the performance of the LSTM model by systematically exploring various combinations of hyperparameters. Specifically, the model performed best with a learning rate of 0.0093, 44 LSTM units, and a batch size of 123. The setting of the hyper parameters found allows the model to accurately predict the trend of future sales capturing both shorterm fluctuations and longterm dependencies in time series data..

by using sales forecasts generated by models that have optimized important measures of inventory management such as economic order quantity, reorder points, and safety stock levels can be predicted more accurate. These measurements are important to maintain the balance of inventory levels in the store so that the store does not experience stock outs or excess stop simulation of daily inventory levels based on sales forecasts clearly illustrates when reorders need to be made as in Day 5, Day 17, and Day 27. This practical application of the model demonstrates its potential for real-world retail operations, enabling businesses to optimize their inventory management processes with greater precision.

5. CONCLUSSION

The results of this study indicate that the optimized LSTM model using Bayesian can significantly reduce forecasting errors and provide low MSI values. This level of accuracy shows the model's ability to capture complex sales patterns and provide fairly reliable predictions, which are very important for inventory management.

By applying the model LSTM on daily sales data of AB brand instant noodles, this study can then calculate important inventory management matrices such as Economic Order Quantity, Reorder Point and Safety Stock. This metrics is very important to maintain optimal stock levels so that it can minimize the risk of frequent stockouts while avoiding unnecessary inventory accumulation due to excess stock. The practical value of this approach is further demonstrated through simulations that show the days when reorders are needed. The use of this optimization to refine the hyperparameters of the LSTM model where this optimization is an important part of achieving optimal results. This shows the efficiency of this method in improving the performance of machine learning models for time series forecasting.

While the findings of this study are promising, there are a few limitations worth noting. First, the inventory simulation was based on fixed assumptions regarding lead time, ordering costs, and holding costs, which may not fully reflect the variability present in real-world retail environments. Additionally, the model was only applied to a single product category, limiting the generalizability of the results across other types of retail goods. Although these findings are interesting, they use assumptions regarding light time and fixed costs, which may not reflect the natural dynamics of real-world scenarios. Additionally, applying this model to a broader product category and including supplier variables will better validate the results for application of this model to multiple retail environments. Future studies could address these limitations by incorporating real-time, dynamic data for inventory-related variables, such as fluctuating supplier lead times and variable ordering costs. Future research could focus on applying the LSTM-Bayesian optimization framework to other product categories to assess its scalability and effectiveness across different retail sectors. By incorporating dynamic inventory variables, such as real-time changes in lead time and fluctuating costs, and integrating external factors like promotional campaigns and competitor pricing would further enhance the model's robustness.

Data Availability Statement:
The dataset used in this research is publicly available. The data can be accessed at the following link: https://osf.io/b7nzc/

Author Contribution
Intan Rahmatillah: Conceptualization, Methodology, Data Curation, Writing – Review & Editing.
Iman Sudirman: Formal Analysis, Visualization, Supervision, Validation.
Anton Mulyono Azis: Software Development, Investigation, Resources, Project Administration.
Ivan Diryana Sudirman: Writing – Original Draft, Data Processing, Corresponding Author.

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