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ANALYSIS OF RAW MATERIAL INVENTORY PREDICTION FOR PLASTIC ORE USING A COMBINATION OF CAUSALITY AND TIME SERIES METHODS: A CASE STUDY IN A TEXTILE INDUSTRY COMPANY

Frangky Rawung[*1], Agus Budi Raharjo[2], Diana Purwitasari[3]

[1,2,3]Informatics, Electrical Technology Faculty, Institut Teknologi Sepuluh Nopember, Indonesia
Email: [1]skywonder987@gmail.com, [2]agus.budi@its.ac.id, [3]diana@if.its.ac.id

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Abstract

Raw material inventory is a valuable company asset in production activities. Inadequate or excessive availability can lead to production failures or cost wastage. This research aims to predict raw material inventory based on factors such as initial stock, receipts, usage, final stock, and differences in usage. A causality-based approach with Multiple Linear Regression (MLR) is used as the basis, complemented by a time series data approach that processes data trends using the Bidirectional Long Short-Term Memory (BiLSTM) algorithm. The prediction results from both models are then combined using the harmonic mean. This research utilizes a dataset of raw material inventory and applies the Root Mean Squared Error (RMSE) and R-squared (R^2) performance parameters for model evaluation. The research is expected to provide useful information for companies in managing their raw material inventory and improving the efficiency of their production processes. Results show that, in the BiLSTM deep learning model, Polyethylene Terephthalate (PET) raw materials yielded an RMSE of 6.53 and an R^2 of 0.93. These results indicate that PET raw materials have a higher predictive value than other materials.

Keywords: *bilstm, causality, inventory, mlr, prediction, time series.*

1. INTRODUCTION

Increasing competition in the industrial sector requires companies to meticulously plan production parameters, including capacity adjustments and inventory management [1], [2]. As an essential company asset, inventory requires optimal management to minimize costs and prevent losses [3], [4]. An effective technique in inventory management is the use of the Inventory Turnover Ratio (ITO) [5], [6]. However, excess inventory can lead to wastage and burden the company [2]. This becomes critical in managing raw material inventories, where the right strategy is crucial for company performance [7].

As one of the leading textile producers in Indonesia, the Textile Industry Company plans its production based on the prediction of raw material inventory, which is vital for increasing production and creating new products. However, predictions of raw material stock are often inaccurate, especially with increasing market demand that is difficult to manage manually. Additionally, the lack of analysis of the raw materials frequently used in production impacts customer demand.

Efficient raw material inventory management requires accurate analysis and prediction related to demand to ensure a smooth production process and minimize the risk of raw material shortages [4], [2]. Factors such as demand fluctuations, usage, resource limitations, and logistics issues can obstruct inventory management, thus necessitating an integrated system [7]. Effective methods for analyzing and predicting raw material stocks are essential to ensure material availability and avoid the risk of excess or insufficient stock [7]. Therefore, this research analyzes raw material inventory prediction for plastic ore at the Textile Industry Company using a combination of causality and time series analysis.

Causality analysis serves to understand the cause-and-effect relationships among various relevant variables in a system, including in the context of raw material inventory management [8]. This research will use the Multiple Linear Regression (MLR) method for causality analysis [9].

Previous studies have successfully used the Multiple Linear Regression (MLR) method for predicting production and market forecasting [10], [11]. In addition to causality approaches, time series analysis is also effective in modeling and forecasting data that shows repeated patterns over a specific period [12].

Forecasting is a blend of art and science, predicting future events based on historical data [13]. Time series forecasting methods are divided into two main categories: traditional statistical methods, such as simple average and moving average, and machine learning methods, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) [14], [15]. The chosen forecasting method will depend on the data's characteristics and the research objectives. Previous research has applied this forecasting in various contexts, such as predicting stock sales demand [16] and stock price movements [17], [20].

This research will analyze and integrate quantitative forecasting methods using a causality approach with Multiple Linear Regression (MLR) [21] and a time series approach with Bidirectional Long Short-Term Memory (BiLSTM) [18], [20]. The primary goal of this research is to find the best forecasting method with the lowest error rate in predicting raw material inventory for products [25]. This method will be applied to the three main raw materials of the Textile Industry Company with the highest inventory turnover ratio [21], [20].

This research is designed to assist the Textile Industry Company in selecting the best forecasting method for optimal inventory management. The goal is to achieve better stock control and reach an ideal inventory level. Thus, this research aims to provide concrete solutions to the company's inventory management challenges.

2. RESEARCH METHODOLOGY

2.1. Materials and Methods

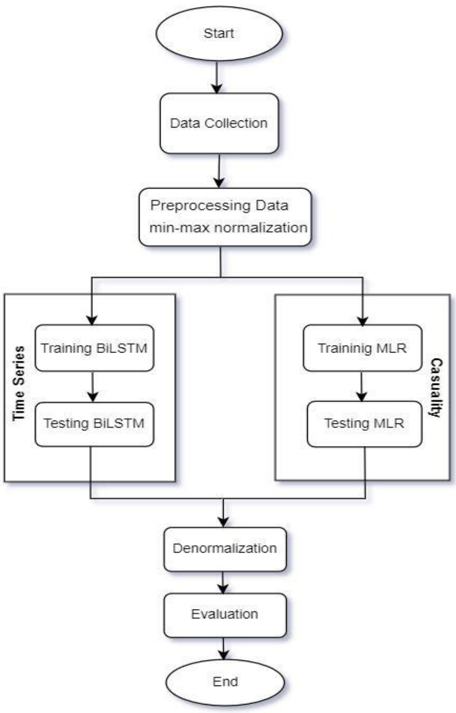

Figure 1. Workflow of the experiment we propose

The flow diagram in Figure 1 depicts the process starting with the data collection phase. This data is then subject to preprocessing, which includes min-max normalization to standardize the scale of the values. Subsequently, the normalized data proceeds through two parallel pathways: the first path involves training and testing using the BiLSTM model, an appropriate choice for sequential data. In contrast, the second path employs the MLR model for linear regression predictions with multiple variables. The outcomes from both models are subsequently integrated using the harmonic mean method, followed by the denormalization process to revert the data to its original scale. The subsequent step is the evaluation, aimed at assessing the overall efficacy of the model. This process concludes with the completion stage, signifying the end of the machine learning and evaluation cycle.

2.2. Data Collection

The data collection phase of this research involves gathering information about the inventory of raw materials used in the production process. The dataset comes from the daily records of raw material inventory spanning twelve months in 2022. The total data collected includes 1,095 rows and nine attributes. These nine attributes are post date, material group, code supp, supp, opening stock, tot receipt, tot issue, diff, and closing stock. Details of each attribute are provided in Table 1.

Table 1. List of Attributes

Attribute Name	Description
Post Date	Date of raw material inventory for that day
Material Group	Type of raw material group
Code Supp	Initials of the raw material group
Supp	Location of raw material supplier
Opening Stock	Amount of initial raw material inventory for that day
Tot Receipt	Total amount of raw materials received on that day
Tot Issue	Total usage of raw materials used for the production proccess on that day
Diff	The difference between the amount received and the amount used
Closing Stock	Total ending inventory of raw materials after use on that day

The material group in Table 1 of the dataset comprises a raw material group. The determination of this raw material group in the content group column of the conducted research is based on the varied characteristics and functions among these material types, which include Polypropylene (PP), Polyethylene Terephthalate (PET), and Meltblown (MB), each adjusted to distinct features and uses in the production process. PP is known for its strength and flexibility and is commonly used to make containers and pipes. PET, famous for its moisture resistance, is often used for packaging and textile fibers. On the other hand, Meltblown plays a crucial role in manufacturing masks and filters.

2.3. Data Preprocessing

This research involves data preprocessing, which includes selecting relevant attributes and handling missing values in the company dataset. The initial dataset had nine attributes and 1,095 rows. No missing values were found in the dataset, so the number of rows remained at 1,095. Next, data containing outliers were handled using the interquartile range (IQR) method. This process prepares the data for further analysis and modeling.

2.4. Data Normalization

This In this research, the input layer processes data normalization using the min-max normalization method. This method transforms the range of continuous numerical data into a predetermined interval of [0,1], aiming to improve both accuracy and system performance in making predictions. The MinMax Scaler from the sklearn library is used for this normalization process, as described in formula (1).

$$\boldsymbol{x'} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

2.5. Harmonic Mean

In this research, the harmonic mean method is used to combine predictions from the causality and time series models. This method emphasizes the lowest value in the data [26], representing the essential minimum stock for production. The harmonic mean enhances the accuracy of stock calculations and is responsive to changes in stock levels over a certain period, as illustrated in equation (2).

$$\boldsymbol{y'} = \frac{2}{\frac{1}{Y_c} + \frac{1}{Y_t}} \quad (2)$$

2.6. Denormalization

After the prediction stage, the denormalization process is carried out to return the data to its original values from the normalized interval range. This makes the output data easier to understand and more comprehensive. This process is conducted according to the formula shown in Equation (3).

$$\boldsymbol{d} = d'(max - min) + min \quad (3)$$

2.7. Splitting Data

We divided the dataset into training and testing subsets to train and evaluate the model's performance. We used the Python scikit-learn library to split the dataset into 80% for training and 20% for testing.

2.8. Implementation of Model and Data Analysis Algorithms

- Implementation of Model for Time Series Analysis

In the context of time series analysis, we adopt the Bidirectional Long Short-term Memory (BiLSTM) model. This model is specialized in understanding and processing time series-related data. We implement BiLSTM, focusing on two critical columns in the dataset: 'post date' and 'tot issue', with the 'tot issue' column acting as the target in this analysis. BiLSTM allows us to process information more efficiently by considering the data sequence from past to future and vice versa. This approach enables us to generate accurate predictions about data behavior over time, providing valuable insights into trends and patterns that may not be visible with conventional analysis [23].

- Implementation of Causality Model Analysis

We use the Granger causality approach to analyze causality or cause-and-effect relationships between variables. This method allows us to determine whether a variable is a valid cause (or predictor) of another variable. After identifying independent variables through Granger causality, the next step is to apply Multiple Linear Regression (MLR). MLR measures the magnitude of influence and the relationship between independent and dependent variables. With MLR, we can understand how independent variables collectively affect the dependent variable, providing deep insights into the relationships among variables in our dataset [24].

2.9. Evaluation

This research proceeds to the evaluation stage, where the prediction results are verified for accuracy. The metrics used in this evaluation are the Root Mean Squared Error (RMSE) and R-squared (R^2), commonly used in deep learning prediction problems [27]. The results of this evaluation will provide an understanding of the effectiveness of the developed models.

3. RESULTS

We extracted a dataset of raw material inventory into a CSV format by parsing the data for modeling. The dataset comprises nine attributes and 1,095 rows of data. These attributes are post date (the inventory date for raw materials on that day), material group (the category of materials), supp code (the abbreviation for the material group), supp (the location of the raw material supplier), opening stock (the total inventory of raw materials on that day), tot receipt (the total receipt of incoming raw materials on that day), tot issue (the full usage of raw materials for the production process on that day), diff (the discrepancy between the amount received and the amount used), and closing stock (the total remaining stock of raw materials after usage on that day).

3.1. Data Preprocessing

The initial data preprocessing step in this research phase involved cleaning the data. Remarkably, no missing or null values were found in the dataset, indicating that the initial data quality was already high. Nonetheless, using statistical methods such as the quartile principle, handling outliers was conducted to identify and eliminate values that significantly deviated. After preprocessing, the material group visualized the data using Matplotlib in Python, as illustrated in Figure 2.

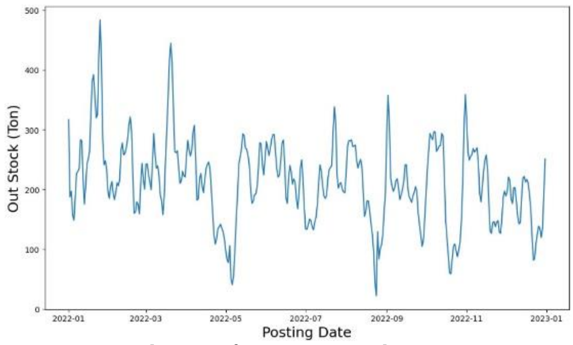

Figure 2. Visualization of PP Raw Material Usage Over 1 Year

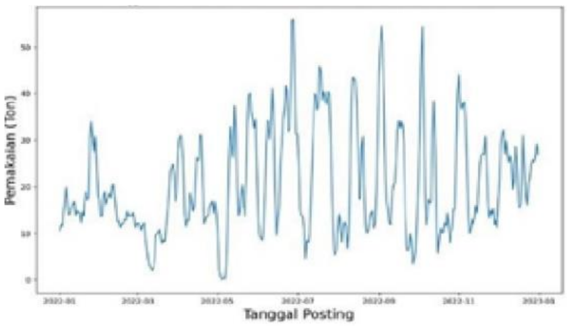

Figure 3. Visualization of MB Raw Material Usage Over 1 Year

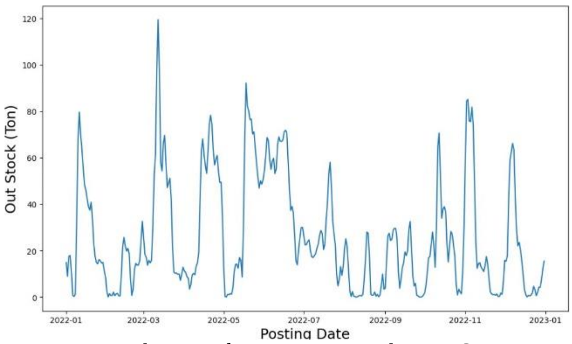

Figure 4. Visualization of PET Raw Material Usage Over 1 Year

The charts in Figures 2, 3, and 4 facilitated visualizations and comparisons concerning aspects like the amount of raw material expenditure or receipt in each material group over a specific period. These visualizations are instrumental in identifying trends, consumption patterns, and efficiency in inventory management.

3.2. Time Series Analysis Application

The research segmented the dataset into two primary parts: the training and testing sets. We began with a random separation to determine the appropriate ratio. Initially, we adopted a ratio of 80% of the dataset to the training set and 20% to the testing set to generate loss values for each material model. The modeling employed an optimizer, 50 epochs, a 10 batch size, and a 0.001 learning rate. Subsequently, we explored different ratios, including 70% for the training set, 30% for the testing set, 90% for the training set, and 10% for the testing set, to assess their effectiveness. Our findings indicated that the 80:20 ratio yielded the most optimal performance, with the lowest loss values, as depicted in Table 2.

Table 2. List of Loss Values

Rasio	PP	MB	PET
90:10	0.0028	0.0055	0.0052
80:20	0.0019	0.0045	0.0031
70:30	0.0021	0.0048	0.0049

The Correlation Heatmap illustrates the level of correlation among inventory variables, revealing patterns and relationships between opening stock, receipts, issues, and closing stock, as shown in Figure 5.

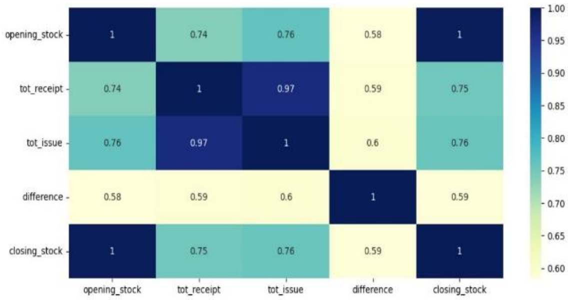

Figure 5. Correlation Heatmap

Figure 5 illustrates the correlation among variables in the dataset. Notably, the total_receipt and total_issue columns exhibit a very high correlation, suggesting that these two variables move in tandem, indicative of a close relationship between the receipt and expenditure of goods. Conversely, opening_stock and closing_stock also display a significant correlation, aligning with expectations that the closing stock is derived from the opening stock after accounting for the receipt and expenditure of goods. The results in Figure 2 have considered the outlier treatment for each feature utilized in this research. The interactive map demonstrates the distribution of supplier partners across various countries, highlighting their critical role in ensuring a reliable and high-quality supply of raw materials. This guarantees the continuity and availability of raw material products to satisfy international market demand, as illustrated in the figure.

This interactive map displays the distribution of supplier partners across various countries. They play a critical role in ensuring the supply of reliable and high-quality raw materials. This guarantees the continuity and availability of raw material products to meet the demands of the international market, as shown in Figure 6.

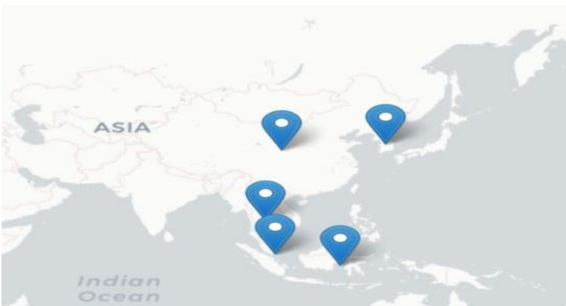

Figure 6. Location of Raw Material Supplier Countries

Figure 6 highlights several countries that supply raw materials. It shows that the raw materials used for production are sourced from various countries, including Singapore, Thailand, South Korea, China, and Indonesia.

3.3. Creating Time Series Model Timesteps

Timesteps refer to the number of time units required for the network to learn. They serve to segment the data into individual sections. A value of 30 timesteps is commonly accepted as standard in several time series analysis programs the researchers have encountered. However, the researchers have experimented with 30, 60, and 90 timesteps for PP, PET, and MB materials, as shown in Table 3.

Table 3. List of Timestep Values

Timestep	PP	MB	PET
30	0.0021	0.0030	0.0042
60	0.0068	0.0066	0.0045
90	0.0071	0.0069	0.0043

From the experiments conducted on PP, MB, and PET raw material types with 30, 60, and 90 timesteps for model training over 50 epochs with a batch size of 10, it was observed that 30 timesteps resulted in the lowest loss values of 0.0021 for PP, 0.0030 for MB, and 0.0042 for PET, indicating more efficient learning compared to the other two timesteps. Numerous studies also support this by using 30 timesteps for time series data.

3.4. Application of Causality Analysis

Granger causality tests were conducted to test the causal relationship between variables in the Multiple Linear Regression (MLR) model. In Granger testing, the p-value is determined. The threshold for the p-value is set below 0.05, as depicted in Figures 7, 8, and 9.

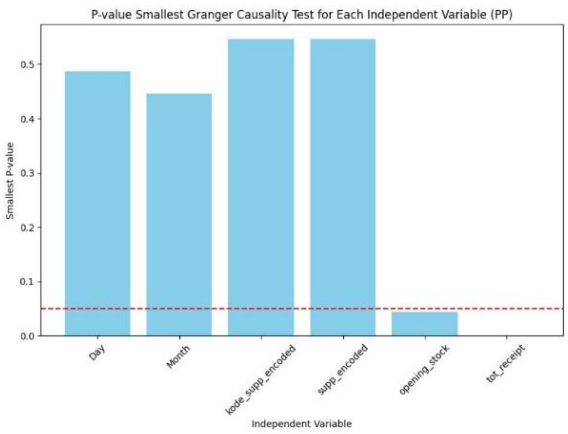

Figure 7. Visualization of Granger Causality Test Results for PP

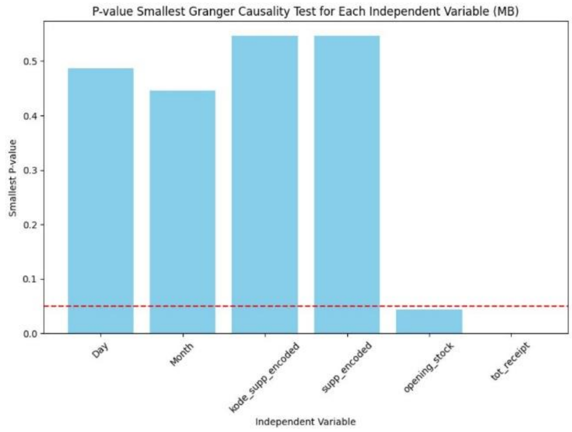

Figure 8. Visualization of Granger Causality Test Results for MB

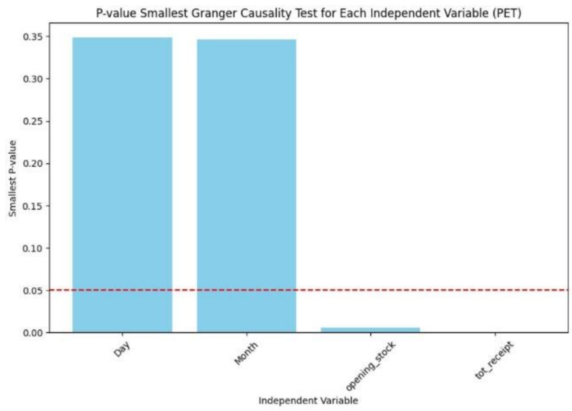

Figure 9. Visualization of Granger Causality Test Results for PET

The charts in Figures 7, 8, and 9 illustrate that each bar represents independent variables such as Day, Month, code_supp_encoded, supp_encoded, initial_stock, and total_receipts. The height of the bars indicates the lowest p-values obtained from the Granger causality tests for each variable. The presence of a horizontal dashed red line signifies the statistical significance threshold at the 0.05 level. Bars positioned above the red line suggest no significant causal relationship with the dependent variable at the 5% significance level. In contrast, bars located below the red line indicate an important causal relationship.

3.5. Combining Causality and Time Series Analysis

The combination of causality and time series analysis using the harmonic mean provides deep insights into the research on raw material usage. The use of the harmonic mean is particularly relevant in the context of stock management, especially in setting minimum inventory policies. Visualizations are provided to facilitate the analysis of comparative results between the predictive outputs from the BiLSTM and MLR models and the harmonic mean.

Figures 10, 11, and 12 visually compare the prediction values for the PP, PET, and MB material groups using BiLSTM, MLR, and Harmonic Mean. In these visualizations, the BiLSTM prediction data is represented by a blue line, the MLR predictions by a green line, and the harmonic mean predictions by a red line.

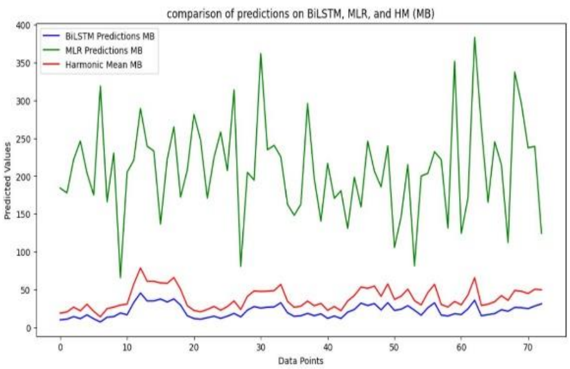

Figure 10. Comparison of BiLSTM, MLR, and HM (PP) Prediction Values

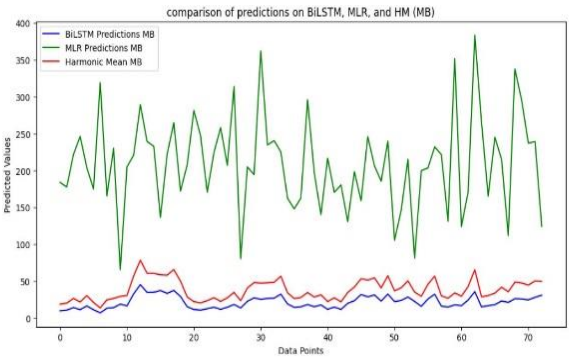

Figure 11. Comparison of BiLSTM, MLR, and HM (MB) Prediction Values

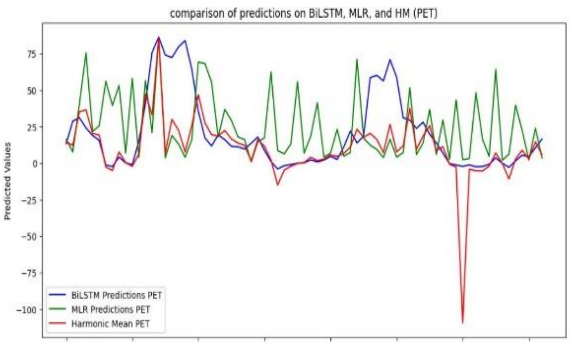

Figure 12. Comparison of BiLSTM, MLR, and HM (PET) Prediction Values

Table 4 presents the performance evaluation of the algorithms used in our dataset to construct the most suitable model, measured with RMSE and R².

Table 4. List Performance Evaluation of Algorithms

Material	**BiLSTM**		**MLR**		**BiLSTM + MLR**	
	RMSE	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**
PP	18.95	0.91	39.69	0.76	25.65	0.83
MB	3.82	0.80	39.69	0.76	6.97	0.78
PET	6.53	0.93	6.91	0.91	6.71	0.92

To evaluate the performance of algorithms, we utilized three types of materials, PP, PET, and MB, and tested with three distinct algorithmic methods: BiLSTM, MLR, and HM. For the BiLSTM model parameters, we recommend setting epochs to 50, batch_size to 10, and verbose to 1. Table 4 presents the performance evaluation of three different algorithms, BiLSTM, MLR, and a combination of BiLSTM with MLR, for three types of materials: PP, MB, and PET. The BiLSTM algorithm consistently demonstrated high performance with relatively low RMSE values and high R^2, indicating a good model fit with the data. For the PP material, BiLSTM achieved an RMSE of 18.95 and an R^2 of 0.91, while for MB and PET, the RMSE values were 3.82 and 6.53, with R^2 values of 0.80 and 0.93, respectively, signifying excellent predictive accuracy. Conversely, the MLR algorithm exhibited lower performance on the same materials, with higher RMSE values and lower R^2 values. Specifically, MLR noted an RMSE of 39.69 for PP and MB and 6.91 for PET, with R^2 values of 0.76 and 0.91, respectively. When combined (BiLSTM and MLR), the results indicated a significant improvement over MLR but were generally still below the performance of BiLSTM alone. This amalgamation of algorithms yielded an RMSE of 25.65 for PP, 6.97 for MB, and 6.71 for PET, with R^2 values of 0.83, 0.78, and 0.92, respectively.

4. DISCUSSION

The research findings underscore the significance of selecting a suitable prediction method for managing raw material inventories in the textile industry sector. It has been demonstrated that the BiLSTM Algorithm outperforms MLR and HM in forecasting the necessary raw material quantities, primarily due to its advanced capability to process time series data and interpret sequential patterns in inventory data.

Another research examines the comparison between ARIMA, LSTM, and BiLSTM methods to determine whether a reverse training strategy (from right to left) can enhance accuracy in time series prediction. The results indicate an enhanced training capability of the BiLSTM model, which notably increased the prediction accuracy by an average of 37.78% [19] . Furthermore, there is research that discusses the forecasting of PP-type plastic ore raw material production using the ARIMA method, which still exhibits an accuracy level below 80% [25].

Employing a combination of causality and time series methods in this study enables a deeper understanding of the cause-and-effect relationships among variables impacting raw material inventory and leverages data trends over time to yield more precise predictions. These outcomes offer valuable insights for companies in managing their raw material inventories, enhancing the efficiency of production processes, and minimizing the risks of stock shortages or excesses that could affect production operations and costs. Moreover, this study highlights the importance of diversification and security in the supply chain, as evidenced by the variety of countries of origin for the raw materials examined, reflecting global trade patterns and emphasizing the necessity of a robust supply strategy.

5. CONCLUSION

The research on analyzing raw material usage using the BiLSTM algorithm and its comparison with MLR and HM models has yielded several important conclusions. First, a detailed analysis of raw material usage shows that dividing the data into training and testing sets with an 80:20 ratio is highly effective. This approach resulted in optimal accuracy for the tested models. Second, there is a significant relationship between attributes in the dataset, particularly between tot_issue and tot_receipt, indicating a reciprocal influence between these variables in raw material usage.

Furthermore, in the performance evaluation of the algorithms, the BiLSTM model demonstrated higher efficiency in experiments with three types of materials: PP, MB, and PET. This model achieved a Root Mean Square Error (RMSE) of 18.95 and a coefficient of determination (R^2) of 0.91 for PP, an RMSE of 3.82 and R^2 of 0.80 for MB, and an RMSE of 6.53 and R^2 of 0.93 for PET. On the other hand, the MLR model showed lower performance on these three types of materials, with an RMSE of 39.69 and R^2 of 0.76 for PP and MB and an RMSE of 6.91 and R^2 of 0.91 for PET. However, the combination of BiLSTM and MLR showed an improvement over MLR alone, with an RMSE of 25.65 and R^2 of 0.83 for PP, an RMSE of 6.97 and R^2 of 0.78 for MB, and an RMSE of 6.71 and R^2 of 0.92 for PET, although its performance generally remained below that of pure BiLSTM.

From a geographical perspective, this research found that the analyzed raw materials originate from various Central Asian countries. This geographical spread reflects global trade patterns and emphasizes the importance of diversification and security in the supply chain. Moreover, by adopting the tested analytical techniques, this research can assist companies in gaining a deeper understanding of raw material inventory performance. This will significantly enhance inventory efficiency and processes, contributing to more timely and data-based decision-making. Thus, it will strengthen the company's position in a competitive market.

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