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The Impact of Indonesian Textile Imports on Employment: Predictive Analysis with Google Trends and News Sentiment

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ABSTRACT

The textile and textile products (TTP) industry in Indonesia is one of the import-dependent sectors. The increase in imports of the textile industry has the potential to reduce the number of workers. This study aims to identify Harmonized System (HS) codes of TTP import that correlate with the number of workers and to predict imports for those HS codes. This research employs conventional statistical methods, including Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA, ARIMA with Exogenous (ARIMAX), SARIMAX, and Holt-Winters, as well as machine learning methods such as Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost), and ARIMA-LSTM hybrid models. The best model is the ARIMAX model, which has the lowest Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). This model utilizes the most influential variables: the rupiah exchange rate, textile production index, percentage of news articles with positive sentiment, and Google Trends Index. This study also reveals that the volume of textile imports, as classified under HS codes 56, 60, and 63, is negatively correlated with the number of workers in the textile sector. Therefore, the government should consider import control policies for this product group. This step needs to be accompanied by an increase in the production capacity and competitiveness of the domestic textile industry. Additionally, the use of Google Trends data and news sentiment can serve as an early warning system to predict import surges more quickly and accurately.

Introduction

The textile and textile products (TTP) industry is one of the priority industries supporting the national economy. In the first quarter of 2024, the textile industry contributed 5.84% to the Gross Domestic Product (GDP) of the manufacturing sector (Kemenperin, 2024). The textile industry in Indonesia is one of the sectors that heavily relies on imports, particularly for raw materials. According to BPS-Statistics publications, Indonesia's textile import volume fluctuated between 2014 and 2023, but remained on a generally upward trend (BPS, 2024). The volume of textile imports in the period January to May 2024 reached 839.72 thousand tons, an increase of 10.2% compared to the same period last year. According to the World Integrated Trade Solution (WITS), a trade data platform developed by the World Bank together with the United Nations Conference on Trade and Development (UNCTAD), the International Trade Centre (ITC), and the World Trade Organization (WTO), Indonesia is among the top 10 largest textile importing countries in the world in 2022 (WITS, 2022).

Factory utilization in the TTP industry has been steadily declining since 2023. Currently, the average utilization of textile manufacturers stands at only 45%, indicating that most textile companies have reduced production levels and workforce numbers (DPR RI, 2024). The primary cause of this condition is the influx of imported textile products at low prices, despite consumers' purchasing power being relatively strong (DPR RI, 2024).

The increase in imports from the textile and apparel industry hurt employment (Ribeiro, 2024). The number of workers in the textile sector has decreased significantly, and the percentage of workers in the manufacturing sector among total industrial workers has dropped dramatically, from approximately 32% in 2000 to around 22% in 2021 (BPKP, 2024). One issue that has become a major concern recently is the potential for a wave of mass layoffs in national textile companies (BPKP, 2024). According to data released by the Ministry of Manpower of the Republic of Indonesia,

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there has been a significant increase in the number of layoff cases in the textile industry. Data show that in 2023, 64,855 layoff cases were recorded, representing a significant increase compared to the 25,114 cases that occurred in the previous year (Kemnaker, 2024b). During the January-August 2024 period, the number of layoffs reached 46,240 cases, with 23,365 cases occurring in the manufacturing industry sector, including textiles (Kemnaker, 2024a). It highlights the serious challenges faced by the textile sector in retaining its workforce amid continued economic pressures. Therefore, accurate import forecasting is needed so that the government can formulate anticipatory measures to protect the domestic industry and its workforce. It is expected to promote sustainable economic growth while minimizing the negative impact on the textile sector workforce.

In this study, textile import volume data are used as the main variable because they can reflect the quantity of textile products entering a country, making them more relevant for analyzing the impact on the domestic industry. Some previous studies also used textile import volume as the main variable. Tawaqal and Pujiyono utilized import volume as the main variable to analyze the factors affecting textile imports in Indonesia. Meanwhile, Mauliza and Andriyani demonstrated how the volume of textile imports is influenced by external factors, such as the exchange rate, as well as domestic production. Additionally, the increasing volume of textile imports presented significant challenges to the national textile sector, including the closure of several factories and layoffs.

In international trade, such as imports, product classification uses the standardized Harmonized System (HS) code. Textiles and textile products fall under HS codes 50-63, each of which has different product characteristics (Kemenkeu, 2022). Certain HS codes of textile imports could potentially hurt the number of workers in the domestic textile sector. It indicates the need for further identification of HS codes that have a negative correlation with the number of textile sector workers so that they can be considered in the formulation of more strategic trade policies.

In a dynamic economic environment, import forecasting serves as a crucial instrument to enhance both accuracy and timeliness in policy formulation. Accurate forecasting of import volumes is crucial for effective economic planning and designing policies that protect local industries (Gusleo & Passarella, 2025). The Organisation for Economic Co-operation and Development (OECD) emphasises that policymakers must transition from reactive approaches to anticipatory strategies by leveraging predictive analytics to avoid delays in responding to economic shocks (Van Ooijen et al., 2019). Therefore, forecasting not only accelerates the government's response to potential import surges but also enhances the effectiveness and efficiency of policies designed to protect domestic industries.

Prediction can be performed using various methods, including conventional statistics, machine learning, and hybrid approaches. Several conventional statistical methods, such as ARIMA, ARIMAX, and Holt-Winters, have been employed in previous studies for forecasting (Alam, 2019; Amri et al., 2023; Dave et al., 2021; Ghauri et al., 2020; Lindyawati et al., 2024). The Holt-Winter method yields satisfactory performance in forecasting warp yarn production, with an MAPE of 5.5437% (Lindyawati et al., 2024). The ARIMAX method can produce accurate forecasts for world crude oil prices, with an MAPE of 8.88% (Amri et al., 2023). Additionally, the ARIMA method yields promising results in predicting export values, with an RMSE of 0.106 and an MAE of 0.083 (Ghauri et al. 2020).

Machine learning methods are also widely used in forecasting (Dave et al., 2021; Ranjani et al., 2023; Wanto et al., 2019). The XGBoost method is the best method used in forecasting shrimp export volume in Indonesia, with an MAPE of 10.08% (Abyasa & Nurmawati, 2024). Additionally, the hybrid ARIMA-LSTM method is employed to predict Indonesian exports, yielding an MAPE value of 7.38% and an RMSE of 1.66 × 10^13 (Dave et al. 2021).

Machine learning and ARIMAX methods require the presence of exogenous variables in order to obtain more accurate results (Yucesan et al., 2021). Exogenous variables are those that are assumed to affect other variables but are not influenced by them in the model (Putri et al., 2018). Mauliza and Andriyani stated that the exchange rate of the rupiah against the USD and textile production partially significantly affect the volume of textile imports. If the exchange rate strengthens, the price of imported goods becomes cheaper, leading to an increase in imports. Conversely, if the exchange rate declines, the price of imported goods becomes more expensive, resulting in a decline in imports (Adhalia et al., 2020; Mauliza & Andriyani, 2021).

Meanwhile, the textile production index reflects the domestic production capacity in meeting market demand. Suppose domestic production is unable to meet demand. In that case, the country will increase imports to meet needs in accordance with the Heckscher-Ohlin theory of international trade, which states that countries import goods that are less efficiently produced domestically.

Meanwhile, the use of Google Trends Index and news sentiment has been widely used to improve forecasting accuracy (Abyasa & Nurmawati, 2024; Apriliani & Nurmawati, 2024; Ayuningtyas & Wirawati, 2021; Giri et al., 2019; Lukauskas et al., 2022). Google Trends can be used as an indicator of public sentiment or interest levels in the economic field, allowing for the prediction of macroeconomic conditions (Yusuf Kamal et al., 2024). Demonstrated that incorporating negative mass media sentiment in Lithuania for forecasting economic activity can reduce model error and yield more accurate forecasts, with a 1.3% lower MAPE (Lukauskas et al., 2022). Sentiment extracted from news articles contributes to macroeconomic indicator forecasts (Gerrish & Blei, 2011; Sukmana et al., 2022).

(Ranjani et al., 2023) have previously researched the prediction of import development in the textile industry group using Indonesian textile production data. This study takes a different approach by focusing the prediction on textile import volume and introducing innovation in the form of integration of Google Trends Index and online news sentiment as prediction variables, which has never been explored for textile commodities.

This study aims to develop an optimal prediction model for textile import volumes by utilizing exogenous variables, including the rupiah exchange rate against the USD, the volume of textile production, the Google Trends Index, and online news sentiment related to textile imports. Furthermore, this study also presents a correlation analysis to identify the HS codes of textile imports that potentially reduce the number of workers. This topic has not been investigated by previous studies to date. The findings of this study can serve as a reference for the government in designing trade strategies and policies to promote sustainable economic growth while protecting local industries from the negative impact of increased textile imports.

Research Methodology

The stages of this research start from data collection, data preprocessing, correlation analysis, sentiment labeling, feature selection, data modeling, evaluation, and finally determining the best model. the flow of this research can be seen in Figure 1.

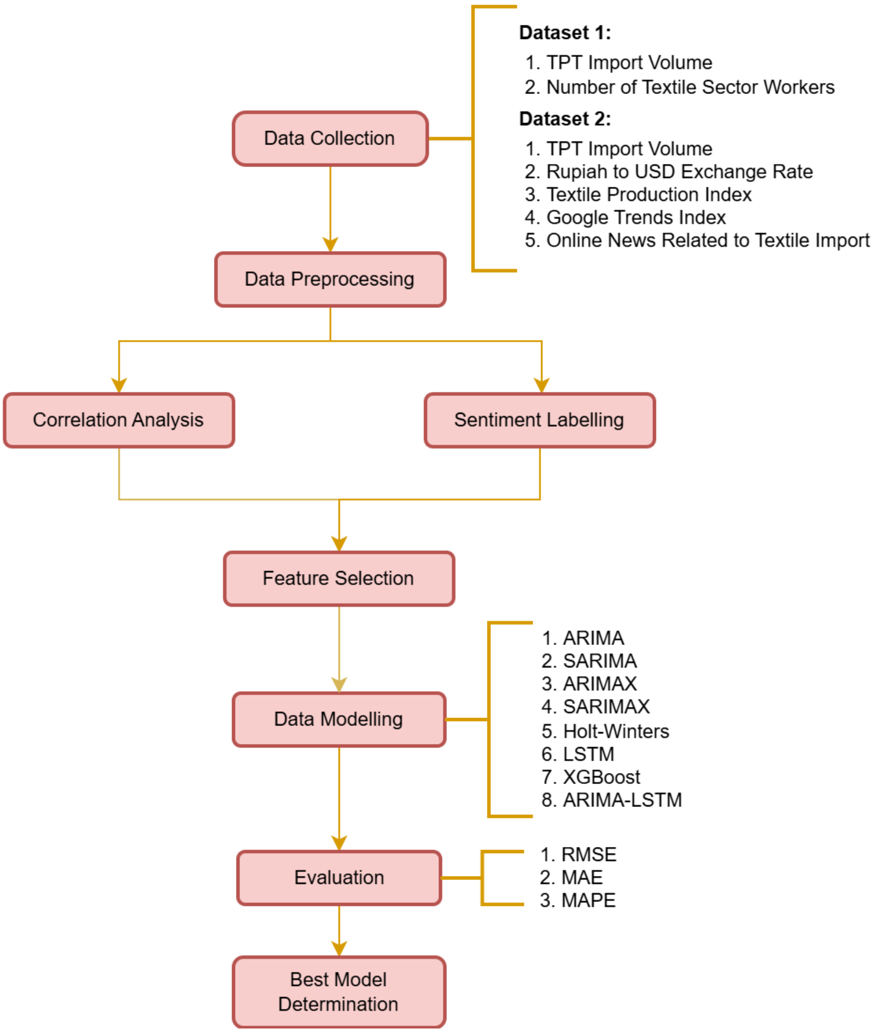


Figure 1. Research Flow

Data Collection

There are two datasets used in this study. The first dataset consists of textile import volume data for each HS code and textile sector workers data. Data on textile import volume and textile sector workers are taken from the official website of the Central Bureau of Statistics (BPS). TTP import volume data is obtained from the dynamic export and import table section. This research focuses on HS code category XI, which includes textiles and textile products, with HS codes ranging from 50 to 63. Labor data is available in annual form from 2014-2021. Therefore, the data on textile import volume was adjusted from monthly to annual form from 2014 to 2021 for each HS code 50-63. The first dataset is used to analyze the correlation between textile import volume and textile sector workers. HS codes that have a negative correlation are then used in the second dataset as target variables to be used in prediction modeling.

The second dataset consists of HS codes import volume that have a negative correlation with textile sector workers and exogenous variables, such as rupiah exchange rate against USD, textile production, Google Trends Index, and online news. Data on the exchange rate of the rupiah against the USD obtained from the Ministry of Trade. The Google Trends Index was obtained through the R application with package gtrendsR. Online news data is obtained from the Detik.com website. Online news data is retrieved by scraping method using python language. A total of 23 keywords were identified and collected based on their relevance to textiles and textile products. All exogenous variable data are presented in monthly periods from January 2014 to June 2024.

Data Preprocessing

In this case, the data that needs to be processed is textile import volume data and online news. The textile import volume data is aggregated by month and HS code because the initial data is still split by port. Data cleaning of online news data is done by removing irrelevant news and duplicate news.

Correlation Analysis

Correlation analysis is conducted to see the relationship between textile import volume and textile business field employment. The correlation analysis was conducted using the first dataset, which contains data on the volume of imports and the number of workers in the textile sector. HS codes import volume that have a negative correlation are then used in the second dataset as target variables to be used in prediction modeling.

Sentiment Labeling

The next stage after the initial data processing is sentiment labeling. The sentiment labeling process is done manually by one annotator. Positive labels are given to news that discusses government policies that have the potential to reduce TTP imports. Neutral labels are given to news that discuss government policies that do not have a direct impact on decreasing or increasing textile imports. Meanwhile, negative labels are given to news that discuss government policies that have the potential to increase textile imports. To check the reliability of the manual labeling that had been done, an inter-annotator agreement test was conducted using Cohen's Kappa by taking a 50% sample of the news data and relabeling it by a second annotator.

Feature Selection

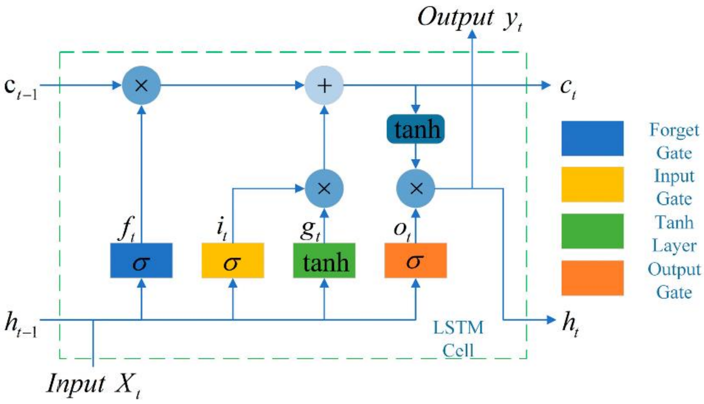
Feature selection is done to find out the most influential variables for forecasting textile import volume. Feature selection methods can improve model accuracy and can minimize system complexity (Apriliani & Nurmawati, 2024; Faiz et al., 2022). The feature selection process was conducted in two stages. First, a preliminary selection was applied specifically to the Google Trends (IGT) variables using correlation, retaining only those with a strong correlation ($|r| > 0.5$) with the target variable. Second, all variables were further analyzed using the Least Absolute Shrinkage and Selection Operator (LASSO) method. LASSO is a regression-based feature selection technique that has been widely used. The LASSO method modifies standard linear regression by applying a special penalty system (Nasution & Tamimi, 2024). This penalty works by changing the coefficients of less important variables to zero, so that the final model will only use variables that are truly influential. The LASSO method is able to produce models that are more accurate and easier to interpret because of its ability to eliminate variables or coefficients that do not have a significant relationship with the response variable (Pramanik et al., 2021).

Forecasting Model Building

In building a forecasting model, the data is divided into 80% training data and 20% testing data. This 80: 20 division has been empirically proven to be the best choice in many studies (Aisyah et al., 2021; Gholamy et al., 2018). The conventional statistical methods used in this research are ARIMA, ARIMAX, SARIMA, SARIMAX, and triple exponential smoothing (Holt-Winters).

ARIMA, ARIMAX, SARIMA, and SARIMAX model building is done through the auto.arima() function to identify the best model. The function returns the best fit based on the value of Akaike Information Criterion (AIC). ARIMA is suitable for linear time series data (Gifty & Yang Li, 2024), while ARIMAX includes exogenous variables to improve prediction accuracy (Amri et al., 2023). The Holt-Winters method is one of the most well-known forecasting techniques and is good at handling data that has a seasonal pattern, where the pattern can change over time (Lawton, 1998).

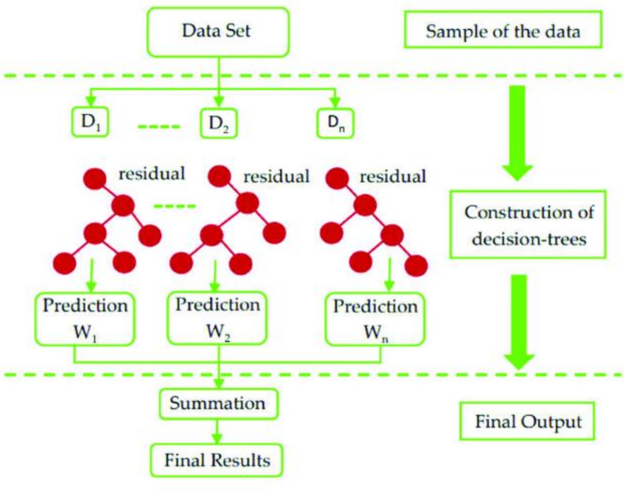
Further forecasting uses machine learning methods. The models that will be used at this stage are LSTM, and XGBoost. LSTM is a neural network method that is famous for its ability to handle long-term dependencies (Dave et al., 2021). LSTM performs better than other models in predicting nonlinear data (Geng et al., 2023). LSTM method is capable of handling time series data with nonlinear patterns and capturing long-term dependencies in data (Dave et al., 2021). Figure 2 is the architecture of the LSTM.



Source: Zhu et al., (2024).

Figure 2. LSTM Architecture

XGBoost is a scalable and flexible gradient- method, which uses a more regular boosting model formalization to control overfitting and thus provides better performance (Jiang et al., 2019). XGBoost is capable of capturing nonlinear relationships in data and has high scalability (Gifty & Yang Li, 2024). The structure of the XGBoost model is shown in Figure 3.



Source: Jan et al., (2023).

Figure 3. XGBoost Model Structure

Hybrid models such as ARIMA-LSTM are also used. ARIMA, while effective for linear data, often struggles when faced with non-linear patterns. On the other hand, LSTM, as a type of neural network, is capable of handling both linear and non-linear data, but requires a long training time and a complicated parameter selection process (Dave et al., 2021). To address these issues, a hybrid model approach is proposed. Combining the two in an ARIMA-LSTM hybrid model yields superior performance, effectively combining the strengths of both linear and nonlinear models (Wang et al., 2024). The flow of the hybrid ARIMA-LSTM method is shown in Figure 4.

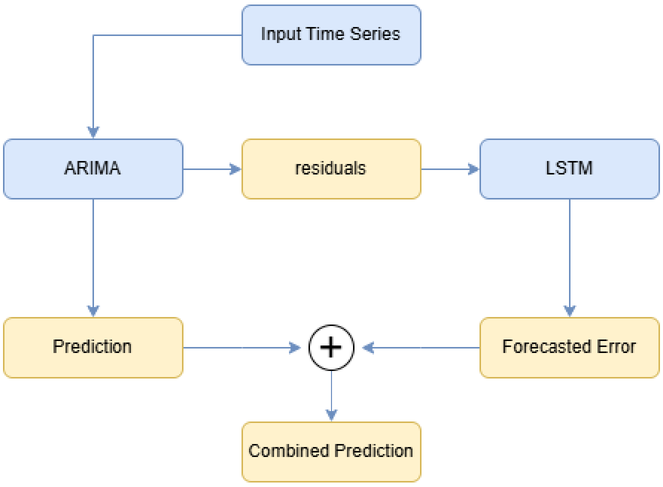


Figure 4. ARIMA-LSTM Flow

Evaluation of Forecasting Results

Model evaluation is carried out by looking at the results of the smallest RMSE, MAE, and MAPE values for each model from conventional statistical, machine learning, and hybrid methods. The formulas for RMSE, MAE, and MAPE values are as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \quad (2)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \quad (3)$$

Where, y_i indicates the true value, $\hat{y}_i$ indicates the estimated value, and *n* indicates the number of observations.

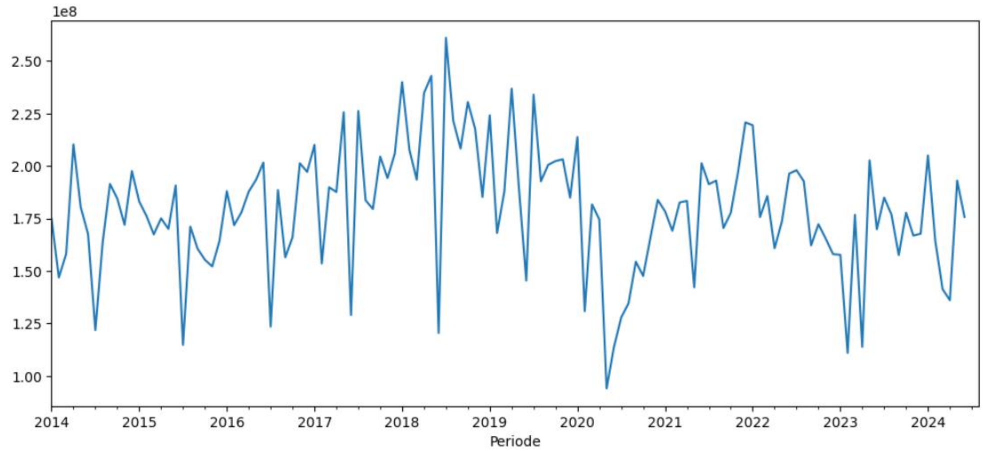
Forecasting Using the Best Model

After the best model has been obtained, the next step is to perform forecasting for the period July to October 2024. In this process, all exogenous variables are available up to October, except the textile production index which is only available until June 2024. The unavailability of this data is an obstacle in forecasting with exogenous variables. Therefore, to overcome this limitation, the textile production index data for July to October will be predicted first using the ARIMA method before being used in forecasting.

Results and Discussion

Data on the import volume of TTP in Indonesia from January 2014 to May 2024 has an average of 179,307.42 ton. The largest textile import volume value reached 261,078.08 ton, while the lowest import volume value reached 94,012.63 ton.

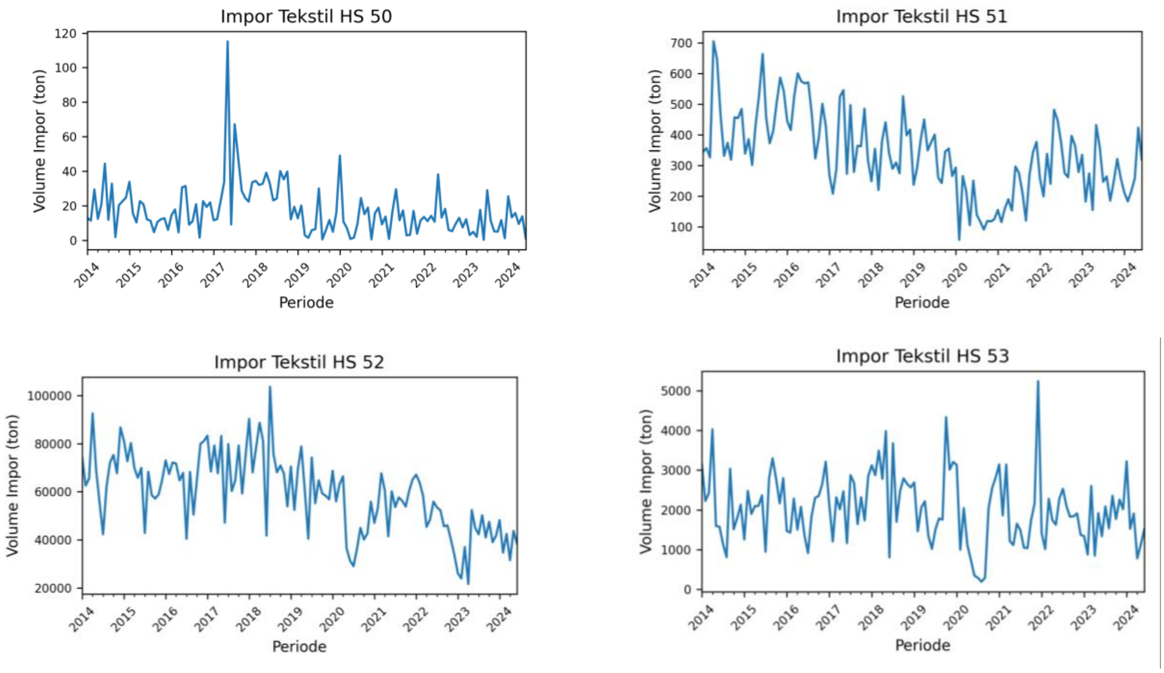
Figure 5 shows the development of Indonesia's textile import volume from 2014 to 2024. There is an upward trend that can be clearly seen from 2014 to mid-2019. Furthermore, there is a downward trend starting from mid-2019 until 2020. This is due to the unstable global economic conditions at the beginning of the Covid-19 pandemic, resulting in a drastic drop in demand for domestic and international textile goods (Arania et al., 2022). Starting in 2020, it can be seen that the data fluctuates but remains in a high trend. This situation is caused by the surge in demand for textile products related to handling Covid-19, namely personal protective equipment (PPE), such as masks, and protective clothing, which led the government to facilitate import regulations (Gondokesumo & Amir, 2022). There is a seasonal pattern in the data, namely a decrease in import volume that occurs in the middle of the year around June and July, especially in 2014-2019. Deputy for Production Statistics at BPS stated that textile imports are strongly influenced by seasonal factors, such as Eid al-Fitr (CNBC Indonesia, 2024).

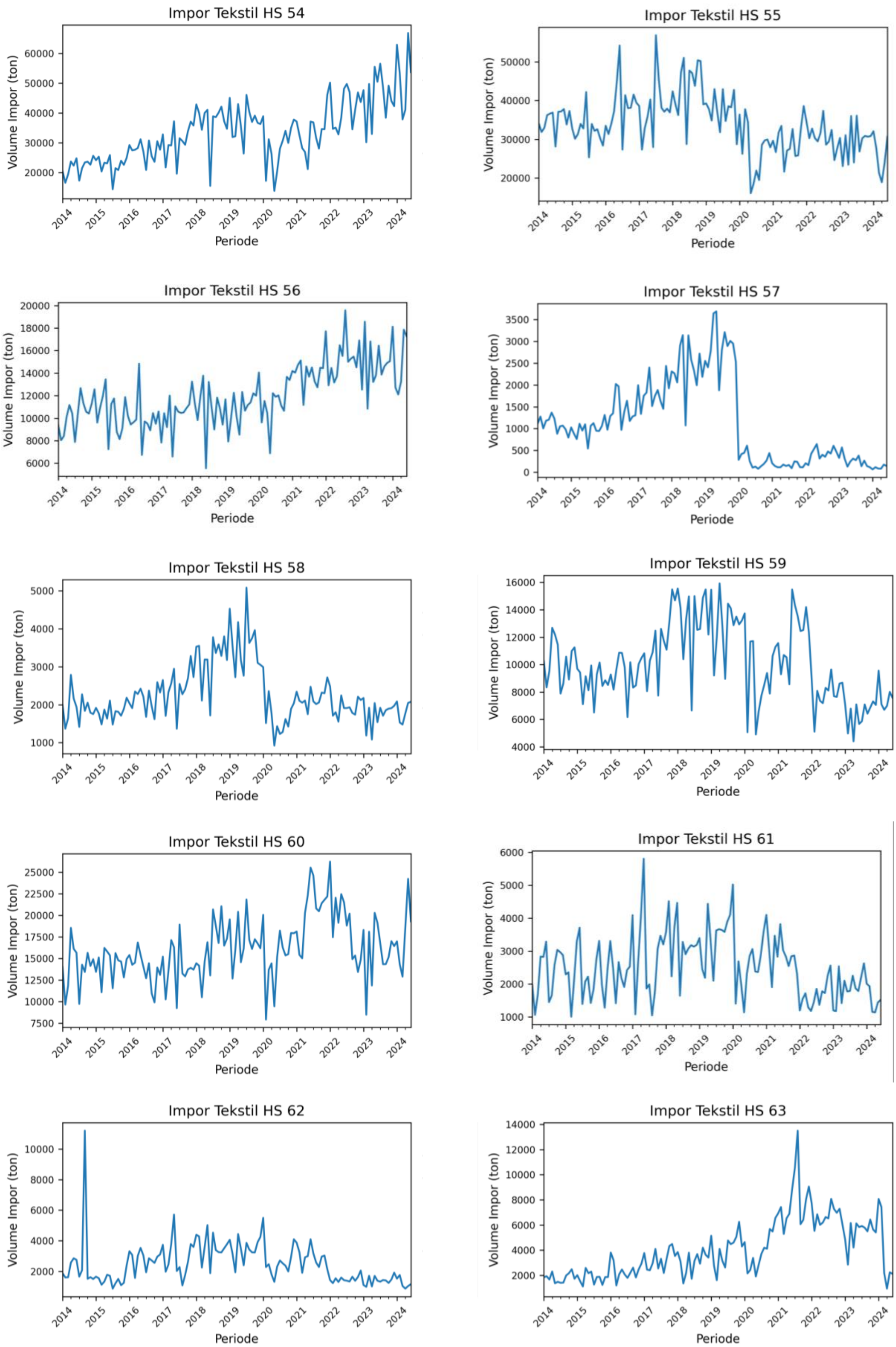


Source: BPS, processed.

Figure 5. Development of Textile Import Volume 2014-2024

Figure 6 shows the development of textile import volumes for each HS code from 50 to 63. According to Figure 6, the import volume of textile HS code 57 has declined sharply since 2021. This is due to the implementation of safeguard measures under MoF Regulation No. 10/PMK.010/2021, which imposed safeguard import duties (BMTP) on carpets and textile floor coverings. The volume of textile imports with HS 61 (knitted apparel) and HS 62 (non-knitted apparel) has declined significantly since the end of 2021. This aligns with the implementation of PMK No. 142/PMK.010/2021, which is a safeguard policy in the form of a Safeguard Import Duty (BMTP) targeting 134 HS codes for ready-made garments.





Source: BPS, processed.

Figure 6. Development of Textile Import Volume for each HS Code 2014-2024

Correlation Analysis

This analysis aims to identify which types of imported textile products are negatively correlated with textile labor. Understanding this relationship is crucial for determining which HS codes have a significant impact on the decline in domestic employment and can therefore form the basis for policy recommendations and feature selection in predictive modeling processes.

A correlation analysis was first conducted between the aggregate textile import volume for all HS codes and employment. The results of this analysis revealed that the aggregate textile import volume has a correlation of 0.48 with employment. This indicates that in aggregate, textile import volume is positively correlated with employment. However, the results of the correlation analysis in this study differ from Ribeiro's findings, which concluded that textile imports have a significant negative relationship with employment, where an increase in textile imports tends to reduce employment in the sector (Ribeiro, 2024). This discrepancy may be explained by the fact that the impact of imports varies depending on the type of product. Imported raw and semi-finished materials in Indonesia are needed to support domestic industrial production that cannot yet be fulfilled locally (Sangur et al., 2024). This aligns with the findings of Nurkomariyah and Vierke (2023) which states that Indonesia's garment industry heavily relies on imported inputs to sustain its export and production capacity. On the other hand, imports of certain goods such as used clothing tend to have a negative impact on the economy (Nazhifah et al., 2025).

Therefore, this study offers an innovation by conducting correlation analysis for each HS code of textile import volume, which has not been explored in previous studies. The results of the correlation analysis for each HS Code are shown in Table 1.

Table 1. Correlation Values between Textile and Textile Products Import and Labor

No.	HS Code	Correlation
1.	50	0.74
2.	51	0.34
3.	52	0.62
4.	53	0.37
5.	54	0.23
6.	55	0.75
7.	**56**	**-0.76**
8.	57	0.78
9.	58	0.48
10.	59	0.27
11.	**60**	**-0.60**
12.	61	0.25
13.	62	0.35
14.	**63**	**-0.61**

Source: BPS, processed.

In Table 1, it can be seen that not all HS codes of textile import volume are negatively correlated with textile business employment. HS codes of textile import volume that are negatively correlated include 56, 60, and 63. This indicates that when the import volume for HS codes 56, 60, and 63 increases, the number of textile business employment will decrease, and vice versa. HS code 56 covers wadding, felt, and nonwovens; specialty yarns; spun yarns, ropes, mines, cables, and articles made from these materials. Furthermore, HS code 60 refers to knitted or crocheted fabrics. Meanwhile, HS code 63 covers other finished textile goods; sets; used clothing and used textile goods; rags. The HS codes are then aggregated into variable Y.

Sentiment Labeling

The number of online news collected with the keyword "textile import" was 979 news. After initial data processing, 204 news articles were obtained. Next, the manual labeling process is carried out on the entire news. The results of news sentiment classification are in Table 2.

Based on the classification results in Table 2, there are 115 positive label news that discuss government policies that have the potential to reduce TTP imports, 2 neutral news that discuss government policies that have no direct impact on reducing or increasing TTP imports, and 87 negative label news given to news that discuss government policies that have the potential to increase TTP imports.

Table 2. Sentiment Classification Results

Sentiment	Total
Positive	115
Neutral	2
Negative	87

Source: Detik.com, processed.

To check the reliability of the manual labeling that had been done, an inter-annotator agreement test was conducted using Cohen's Kappa. The measurement results show that Cohen's Kappa value is 0.809. According to the interpretation put forward by Landis and Koch (1977), Cohen's Kappa values between 0.81 and 1.00 fall into the category of “Almost Perfect Agreement” or very high agreement (Landis & Koch, 1977). Thus, the labeling of this news data has a high level of consistency among annotators, and the results are suitable for use in further analysis processes.

Next, derived variables were created based on the labeling results for further analysis. These variables include the number of negative sentiment news items per month, the number of neutral sentiment news items per month, and the number of positive sentiment news items per month. Additionally, to determine the proportion of sentiment dominance in a given time period, the percentage of negative sentiment news items per month and the percentage of positive sentiment news items per month are also calculated. The percentage of negative sentiment is calculated by dividing the number of negatively labeled news articles in a given month by the total number of news articles in that month, then multiplying by 100. Similarly, the percentage of positive sentiment is calculated in the same way but using the number of positive news articles. These variables are used as exogenous indicators in the TTP import prediction model.

Feature Selection

First, a preliminary selection was applied specifically to the Google Trends (IGT) variables using Pearson correlation, retaining only those with a strong correlation ($|r| > 0.5$) with the target variable. This step aimed to identify keywords that best reflect the dynamics of TTP imports, which are known to be negatively correlated with labor. The correlation results are shown in Table 3.

Table 3. Correlation Values between Google Trends Index and Variable Y

No.	Keyword	Correlation
1.	Tekstil	0,07
2.	Pakaian	-0,15
3.	**Sutera**	**0,52**
4.	Sutra	-0,42
5.	Wol	0,09
6.	Kapas	0,24
7.	Serat tekstil	0,23
8.	Filamen	0,27
9.	Benang	0,18
10.	Karpet	-0,31
11.	Kain tenun	-0,02
12.	Tenun	-0,06
13.	Tenunan	0,11
14.	Kain tekstil	0,15
15.	Kain rajut	-0,05
16.	Kain rajutan	-0,30
17.	**Rajutan**	**-0,64**
18.	**Baju**	**-0,65**
19.	Impor pakaian	0,30
20.	Impor baju	-0,44
21.	Baju impor	-0,45
22.	Pakaian impor	0,30
23.	**Thrift**	**0,62**

Source: Google, processed.

Based on the correlation results, four keywords were found to have a sufficiently strong correlation (greater than ±0.5), namely sutera (silk), rajutan (knit), baju (clothes), and thrift. These keywords showed a significant relationship with TTP import volumes and were thus selected as input variables for the forecasting model. By incorporating keywords with strong correlations, the model is expected to more accurately capture public search trends that are closely linked to import fluctuations.

Second, all variables were further analyzed using the LASSO method. After the LASSO is performed, seven variables are obtained that have the most influence on textile imports in Indonesia, namely the Google Trends Index with the keywords "silk", "knit", "clothes", and "thrift", the rupiah exchange rate, the textile production index, and the percentage of the number of news with positive sentiment in that month. The coefficient results of the feature selection are listed in Table 4.

Table 4. Feature Selection Results

Variables	Coefficient
GTI thrift	4.269730x106
Textile production index	2.106746x106
Rupiah exchange rate	1.252430x106
GTI silk	9.602556x105
GTI knit	-6.015628x104
% positive	-3.068740x105
GTI clothes	-5.197194x105

Source: BPS, Google, and Detik.com, processed.

The coefficient of the feature selection results reflects the extent of the influence and direction of the relationship of each variable on the target variable (Apriliani & Nurmawati, 2024), namely the textile import volume. The greater the coefficient value, the greater the influence of the feature on changes in textile import volume. If a feature has a positive coefficient, it means that an increase in the variable will tend to increase the textile import volume. Conversely, if the coefficient is negative, then an increase in the variable will tend to decrease the textile import volume.

As shown in Table 4, the Google Trends Index (IGT) with the keyword “thrift” has a coefficient of 4.269730x106, which means that an increase in searches for the word “thrift” on Google is positively correlated with an increase in TTP import volume. This may reflect a trend toward the consumption of secondhand clothing, most of which is imported. Studies indicate that thrifting used clothing is in great demand by the public and has the potential to harm the industry and the environment (Sharky, 2023). Indotextile reported that in 2022, the volume of used clothing imports reached 26.22 tons with a value of USD 272,000, a 227.8% increase since 2021 (Indotextiles, 2023).

The IGT for the keyword “silk” also shows a positive influence, indicating that increased search interest in “silk” is positively correlated with increased imports. Silk is generally a luxury product and is widely imported from major producing countries such as China (Tempo, 2018). IGT with the keywords “knit” and “clothes” also has a significant influence on textile imports. This shows that Google search trends can influence textile imports.

According to the feature selection results shown in Table 4, The rupiah exchange rate variable has a positive and strong enough influence. This is in line with research (Mauliza & Andriyani, 2021; Tawaqal & Pujiyono, 2021) which states that the rupiah exchange rate variable has a positive and significant effect on the volume of textile imports. When the rupiah exchange rate strengthens, consumers tend to prefer to import textiles from abroad. This is due to the price of imported textiles which becomes more affordable compared to domestically produced textiles.

Based on the feature selection results in Table 4, the textile production index has a positive effect on textile import volume. It means that when textile production increases, the import volume will also increase. The results of this study are not in line with research conducted by Devinda et al. as well as the theory stated by Sukirno in Mauliza's research (Devinda et al., 2023; Mauliza & Andriyani, 2021). Both studies explain that an increase in domestic production can reduce imports. However, the results of this study show that despite the increase in textile production, it has not been able to significantly reduce the volume of imports. This condition occurs because the textile production capacity in Indonesia is still relatively low compared to the world's major textile producing countries (DPR RI, 2024; Tawaqal & Pujiyono, 2021). When the ability of domestic production is insufficient to meet domestic needs, imports remain a solution to cover the shortage.

In addition, referring to the feature selection results in Table 4, this study shows that the percentage of news with positive sentiment plays a significant role in negatively affecting the volume of textile imports. An increase in negative sentiment means that more news can reduce the volume of textile imports, which in turn leads to a decrease in imports.

Model Building

The construction of ARIMA, SARIMA, ARIMAX, SARIMAX models is done using auto_arima() in the pmdarima library to determine the best method. The exogenous variables used based on the results of feature selection include the rupiah exchange rate against the USD, textile production index, percentage of news with positive sentiment, Google Trends Index with the keywords "silk", "knit", "clothes”, and “thrift”.
The best models obtained are ARIMA (0,1,1), SARIMA (2,1,0) (1,0,0), ARIMAX (1,0,0), and SARIMAX (2,0,2) (1,0,0). The prediction results are visualized in a series of graphs that can be seen in Figure 7 to Figure 10.

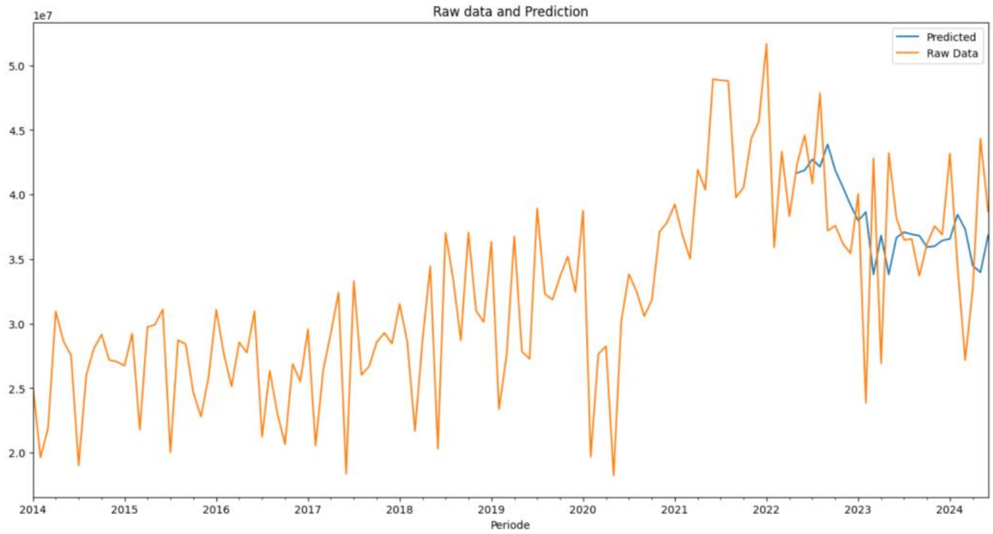


Figure 7. ARIMA (0,1,1) Prediction Results

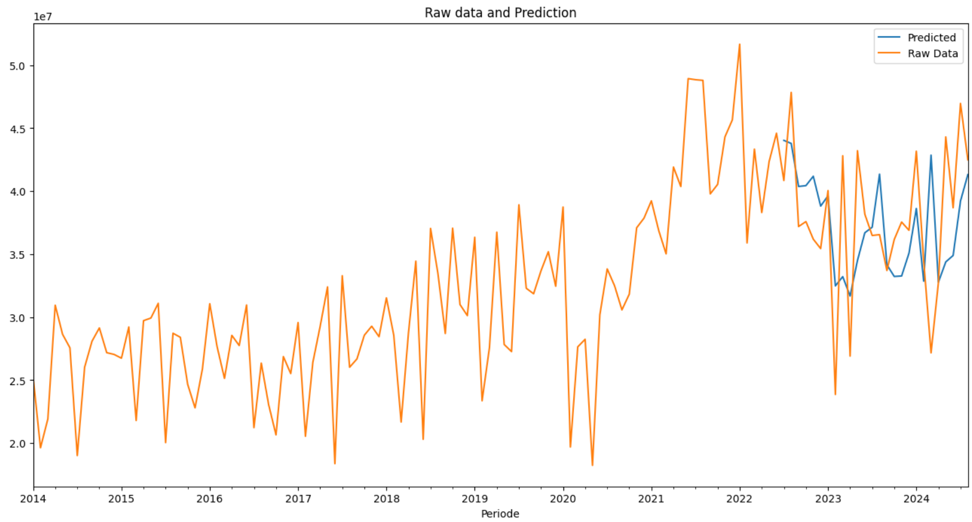


Figure 8. SARIMA(2,1,0) (1,0,0) Prediction Results

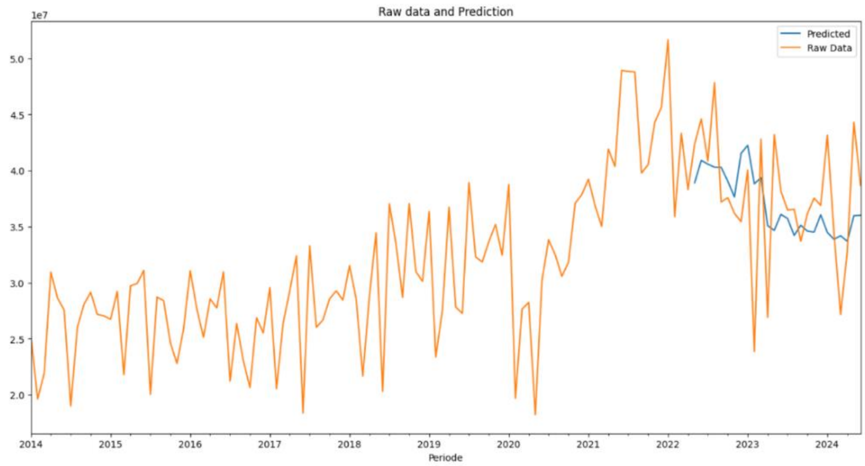


Figure 9. ARIMAX (1,0,0) Prediction Results

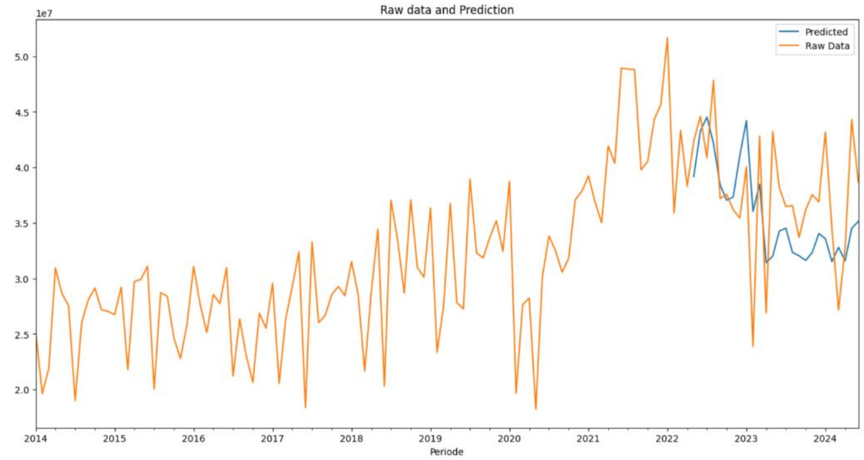


Figure 10. Prediction Results of SARIMAX(2,0,2)(1,0,0)

Furthermore, model building is carried out using the Holt-Winters method. The overall implementation results of the Holt-Winters model and its parameters are shown in Table 5.

Table 5. Holt Winters Model Results

Results		**Holt-Winters Method**
Smoothing parameters	α	0.2525
	β	0.0001
	γ	0.3289
Coefficient	ℓ	2.6107x107
	b	1.3717x105
	s0	3.071 x106
	s1	-4.283 x105
	s2	-3.2547x106
	s3	1.986x106
	s4	3.9139x106
	s5	-2.1045x106
	s6	2.9051x106
	s7	3.2658x105
	s8	9453.1892
	s9	-7.6435x105
	s10	-27498.675
	s11	1.7738x105

Source: BPS, processed.

The prediction results of the Holt-Winters model are shown in Figure 11.

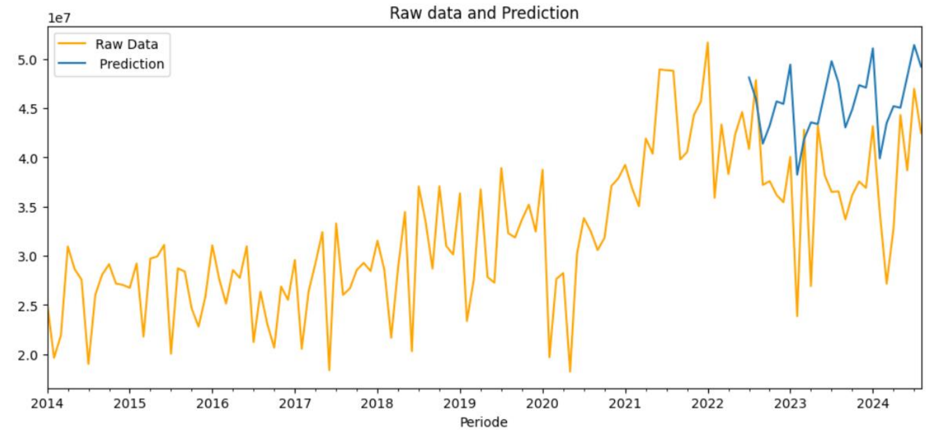


Figure 11. Holt-Winters Prediction Results

Model building with machine learning is done with LSTM and XGBoost methods. Model building is done by finding the most optimal parameters with hyperparameter tuning using gridsearch.

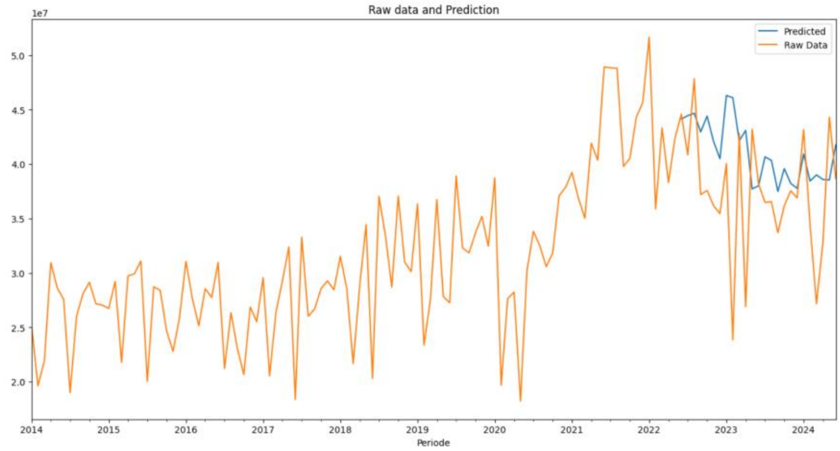


Figure 12. LSTM Prediction Results

The best LSTM model obtained is a model with the number of unit layers as many as 192; dropout rate of 0.1; learning rate of 0.01; batch size of 32; and number of epochs 100. Meanwhile, the best XGBoost model obtained is a model with the number of estimators as many as 100; with a maximum tree depth of 3; learning rate of 0.1; the number of gamma or the best parameter for pruning and regularization of lambda parameters as much as 0. The prediction results of LSTM and XGBoost are contained in a series of graphs that can be seen in Figure 12 and Figure 13.

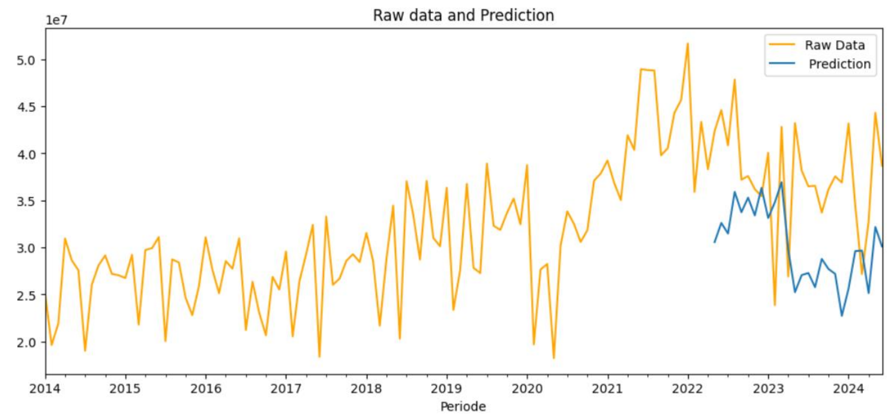


Figure 13. XGBoost Prediction Results

Next, the ARIMA-LSTM hybrid model is built. Modeling is done by building the ARIMA model first, then the residual results obtained are used to build the LSTM model. Furthermore, LSTM prediction results from ARIMA residual data will be combined with ARIMA prediction results to produce the final prediction output. The LSTM model was built with 32 neurons in the hidden layer, 2 hidden layers, and 1000 epochs. The model prediction results are shown in Figure 14.

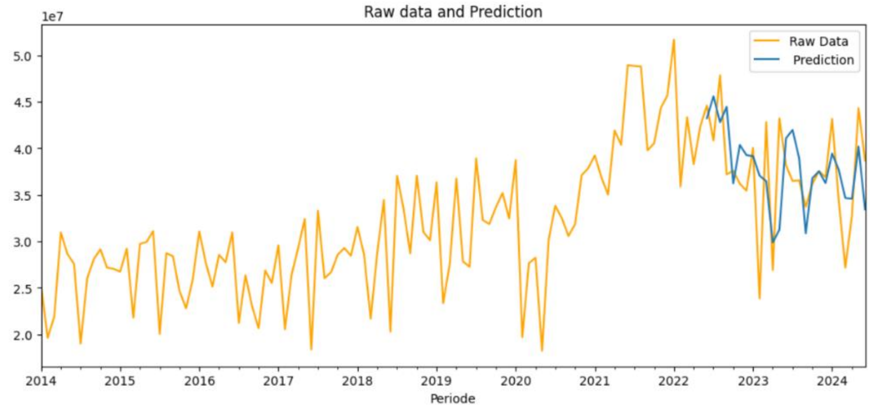


Figure 14. ARIMA-LSTM Prediction Results

Model Evaluation

Comparison of accuracy values based on RMSE, MAE, and MAPE for each model can be seen in Table 6.

Table 6. Model Accuracy Value

Methods	RMSE	MAE	MAPE
Without Exogenous Variables			
ARIMA	5953941.28	4529272.84	13.17%
SARIMA	5705557.04	4410748.98	12.39%
Holt-Winters	9341441.10	8242402.90	24.17%
ARIMA-LSTM	**5234564.20**	4147931.76	11.88%
Using Exogenous Variables			
ARIMAX	5339836.29	**4025370.02**	**11.60%**
SARIMAX	5406753.57	4453385.32	12.37%
LSTM	7175985.43	5251438.64	16.41%
XGBoost	9643542.21	8512904.38	22.37%

Source: BPS, Google, Detik.com, processed.

The best model obtained is the model with the smallest RMSE, MAE, and MAPE values. Based on the RMSE value, the ARIMA-LSTM model is better than other methods with the smallest RMSE value of 5234564.20. However, according to the model accuracy value in Tabel 6, overal the ARIMAX model is the best model with the smallest MAE and MAPE values of 4025370.02 and 11.60%, respectively. This shows that the use of exogenous variables, such as Google Trends Index and news sentiment can provide better prediction results.

Based on these results, the use of conventional statistical methods has superior performance compared to machine learning and hybrid methods. This is due to the need of machine learning and hybrid methods for large amounts of data to be optimally trained (Dhillon et al., 2022).

Forecasting Result

After obtaining the best model, the next step is to perform forecasting for the next few months, namely from July to October 2024. Data on the textile production index, one of the exogenous variables used, is not available for July to October so it will be predicted using the ARIMA method. The prediction results of the textile production index using the best model, ARIMA (1,1,1), are shown in Table 7.

Table 7. Prediction Results of Textile Production Index

Period	Prediction Results
Jul-2024	56.84
Aug-2024	56.56
Sept-2024	56.42
Oct-2024	56.35

Source: BPS, processed.

Once all exogenous variables for the period July to October 2024 are available, the forecasting process can be carried out. Forecasting is done using the best model obtained, namely ARIMAX (1,0,0). The results of the textile import volume forecasting are presented in Table 8, while the visualization of the forecasting results is shown in Figure 15.

Table 8. Forecasting Results of Textile Import Volume

Period	Forecasting Results
Jul-2024	37218805
Aug-2024	35998946
Sept-2024	36030147
Oct-2024	34749855
Total	143997753

Source: BPS, Google, Detik.com, processed.

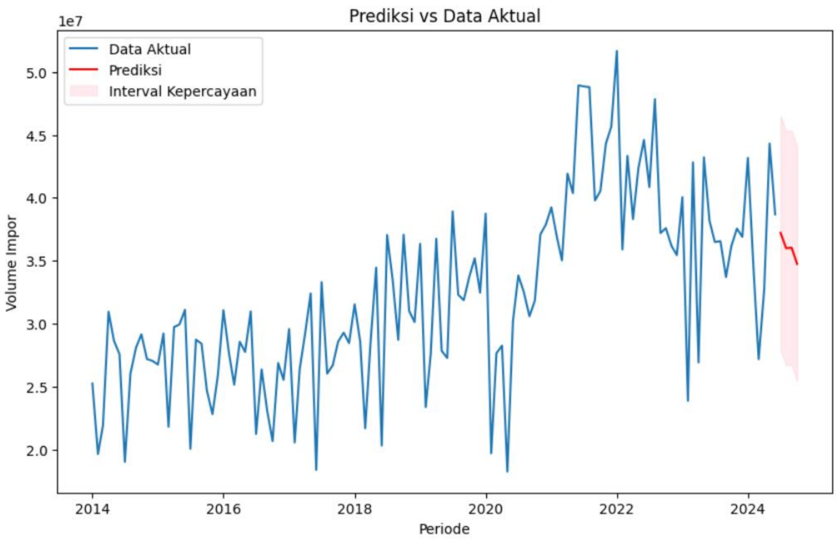


Figure 15. Prediction Results of Textile Import Volume

Based on the forecasts in Table 8 and Figure 15, Indonesia's textile import volume is projected to decline from 37.2 million kg in July 2024 to 34.7 million kg in October 2024. However, compared with the same period in the previous year (July–October 2023), this represents a 0.75% increase.

Historical trends show that textile import volumes tend to fluctuate in line with seasonal patterns and domestic demand dynamics, including the influence of Eid al-Fitr or the end of the year. In this context, the decline in the third quarter is part of an annual pattern.

Furthermore, geopolitical tensions, changes in export tariffs from major supplier countries (such as China, India, and Vietnam), and fluctuations in textile raw material prices in the international market can affect import prices and volumes. If supplier countries raise prices or restrict exports, a decline in Indonesian imports could occur not because of an increase in domestic capacity but because of global supply disruptions.

However, a decline in imports does not necessarily indicate a strengthening of domestic textile production. If domestic capacity, particularly for HS 56, 60, and 63 remains limited, unmet demand could result in rising prices or product scarcity. Therefore, a decline in import need to be accompanied by strong local subtitution (Nurkomariyah & Vierke, 2023). The government may consider implementing selective safeguard measures for specific subheadings like HS 56, 60, and 63 if future forecasts indicate a surge, while also incentivizing capacity expansion among domestic producers.

Importantly, since this research finds that the volume of textile imports is negatively correlated with employment in the textile industry, policymakers need to interpret the forecast as a labor market indicator. A decline in imports could create opportunities to increase domestic employment, but only if local industries are prepared to fill the supply gap. Monitoring labor absorption in the TTP sector and providing technical upskilling programs are necessary to optimize the labor benefits of this predicted trend.

It is also important to note that these forecasts rely partly on predicted values of the textile production index, which were generated using an ARIMA (1,1,1) model due to the unavailability of actual data. The use of such predicted input variables may introduce potential bias or uncertainty into the forecasting results.

Conclusions

The analysis shows that increased textile imports, particularly in HS 56 (nonwoven), HS 60 (knitted fabrics), and HS 63 (finished textile products), have a negative impact on employment in the textile, apparel, and footwear sector. This is reinforced by the wave of mass layoffs occurring in large companies, such as PT Sritex (HS 61–62), PT Delta Merlin (HS 60, 63), and PT Pismatex (HS 63), indicating that consumer demand is already being met by imported products. In other words, the domestic market has been substituted by imported goods, causing the domestic industry to lose competitiveness and reduce labor.

The decline in imports detected through forecasting does not necessarily indicate the recovery of the local industry. Without domestic production capacity readiness, the decline in imports will only trigger shortages and price increases. Therefore, import control must be accompanied by import substitution strategies and the strengthening of labor-intensive industries so that the positive effects on employment can be realized.

Moreover, the ARIMAX forecasting model can function as an early warning system for monitoring textile import trends. Leveraging Google Trends and news sentiment analysis presents a novel and proactive method for trade surveillance. This enables the government to respond to emerging public interest in certain products, especially those with high import potential, before trade surges occur.

Author Contributions

DIS: Conceptualization, Writing, Methodology, Data Processing; EN: Review, Manuscript Editing,

AI Writing Statement

During the preparation of this work authors used Grammarly in order to paraphrase and proofread the sentences. After using this service, the needed and take full responsibility for the content of the publication.

Conflicts of interest

The authors declare that there are no conflicts of interest related to the publication of this article. There are no financial, personal, or other relationships that could influence the objectivity of this research.

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