

APPLICATION OF MACHINE-LEARNING-BASED HYBRID ALGORITHM FOR PRODUCTION FORECAST IN TEXTILE COMPANY

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Abstract

The increasing consumer demand for sustainable textiles has led companies to invest in organic and recycled materials while adopting green manufacturing processes to reduce their environmental footprint. The textile industry is exploring innovative approaches such as upcycling and green chemistry to regenerate textile waste fibers sustainably. And these efforts are aimed at transforming the fashion and textile industry towards a more sustainable and eco-friendly future. To achieve this the textile industries, have to leverage on the technological advancements available which one of it is, various applications of ML models for a more accurate and efficient results. This study focused on the application of a hybrid machine learning model which is the combination of Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model and Long Short-Term Memory (LSTM) networks for Accurate Production Forecasting in Textile Industry. Research studies reviewed gave important insights into the study. This study adopted a quantitative research approach, using a five-year historical production data from a textile company to train and evaluate the hybrid ML model. The research design includes data collection, preprocessing, model training, evaluation, and comparative analysis. The research analysis presents a well-performing predictive model, as evidenced by the high R-squared value of 0.87, relatively low root mean squared error (RMSE) of 1.23, low mean squared error (MSE) of 1.51, and low mean absolute error (MAE) of 0.98. However, the residual time series and the predicted and actual values plots suggest possible degradation in the model's performance over time.

1. Introduction

The textile industry is a key player in global manufacturing, involving various processes from fiber production to garment manufacturing. Companies in this sector prioritize production forecasting to accurately predict demand, optimize inventory, allocate resources efficiently, and reduce costs (Nwamekwe et al., 2024). Research by Xu & Wang (2019) stresses the significance of intellectual capital analysis in the textile industry, while the work of Tsai & Su (2022) offers practical suggestions for digital transformation. Moreover, Wongwilai et al. (2022) demonstrate the critical role of innovative ideas in promoting business sustainability within the textile industry. These studies collectively emphasize the importance of production forecasting and strategic management practices in enhancing the competitiveness and sustainability of textile companies.

Production forecasting in the textile industry faces challenges stemming from demand variability, fashion trends, and supply chain disruptions. Conventional methods like moving averages and exponential smoothing encounter difficulties in handling these complexities, as they heavily rely on historical data and simplistic assumptions. To overcome these limitations, researchers have delved into advanced techniques such as machine learning and deep learning. Studies by Lorente-Leyva et al. (2020) and Yildirim et al. (2017) compare classical methods with machine learning approaches for demand forecasting in the textile sector, emphasizing the potential of artificial neural

networks, support vector machines, and random forests in enhancing forecast accuracy. By harnessing these innovative methodologies, textile companies can bolster their production forecasting capabilities to effectively navigate the dynamic industry landscape.

Machine learning (ML) algorithms offer a promising solution to the challenges encountered by traditional production forecasting methods in the textile industry. By utilizing ML capabilities to analyse extensive datasets and intricate relationships, these algorithms can uncover complex patterns that traditional methods often miss. This leads to more accurate and reliable production forecasts, ultimately improving operational efficiency and competitiveness within the textile sector. Studies by Venil et al. (2020) and Imran et al. (2018) explore the impact of innovative technologies like ML on the textile industry, emphasizing the potential benefits of integrating such advanced techniques into production forecasting processes. Through the use of ML algorithms, textile companies can enhance their competitive advantage by making well-informed decisions based on precise and data-driven forecasts.

The paper aims to assess the effectiveness of various machine learning (ML) algorithms in forecasting production within the textile industry, compare ML-based forecasts with traditional methods, identify challenges in implementing ML algorithms for production forecasting, and provide practical recommendations for textile companies. References by Nair (2024) and Zhao et al. (2021) highlight the complementary nature of judgmental and ML forecasts, emphasizing the benefits of leveraging historical data and expert knowledge alongside ML algorithms. Additionally, the work of Kačmárý (2023) and Yağcıoğlu et al. (2021) provides insights into forecasting systems and demand forecasting in textile production, offering valuable perspectives on the application of ML in this context. By synthesizing these references, the study can gain a comprehensive understanding of the potential benefits, challenges, and practical implications of integrating ML algorithms into production forecasting processes in the textile industry.

1.1. Literature Review

Traditional methods of production forecasting in the textile industry, such as moving averages, exponential smoothing, and ARIMA, have been widely used for their simplicity. However, these methods often struggle with non-linear patterns and multiple influencing factors. Case studies by Kumar and Suresh and Lee and Park have demonstrated the limitations of traditional forecasting methods in accurately predicting demand for fashion apparel and textile manufacturing, respectively (Nwamekwe et al., 2024). To address these challenges, researchers have explored advanced forecasting techniques. For instance, compared classic methods with machine learning approaches for demand forecasting in the textile industry, highlighting the potential benefits of integrating machine learning algorithms into production forecasting processes. By synthesizing these studies, the research aims to provide insights into the effectiveness of machine learning algorithms, the comparison with traditional methods, challenges in implementation, and practical recommendations for textile companies.

Machine learning algorithms are widely used in forecasting, with various models serving different purposes. Linear Regression, Decision Trees, and Neural Networks are common algorithms employed for forecasting tasks (Altan et al., 2019). Among Neural Networks, Recurrent Neural Networks (RNNs) have demonstrated potential in capturing intricate relationships within financial time series data (Sako et al., 2022). Hybrid models like the Recurrent Pi-Sigma Artificial Neural Network have been introduced to enhance forecasting accuracy (Bas & Egrioglu, 2022). Generalized Regression Neural Networks have exhibited promising outcomes in time series forecasting, highlighting their capability for precise predictions (Martínez et al., 2022). Moreover, combining forecasting models, such as Grey Models and BP Neural Networks, has been proven to enhance accuracy and reliability in tourism demand forecasting (Ma, 2021).

Machine learning provides significant advantages over traditional forecasting methods by handling large datasets, capturing non-linear relationships, and improving prediction accuracy through continuous learning. Machine learning algorithms have been successfully applied in various domains, such as solar flare prediction (Bobra & Couvidat, 2015), corn yield forecasting (Roznik & Mishra, 2023), and PV power generation forecasting (Mahmud et al., 2021). These algorithms have also shown promise in enhancing energy forecasting, including solar power (Kumar et al., 2023), wind power ("Wind power plant forecasting and power prediction methods using Machine Learning

Algorithms", 2021), and load forecasting (Velasco et al., 2018). Furthermore, machine learning techniques have been instrumental in improving forecasts for financial indicators (Miyoshi & Matsubara, 2018), stock prices ("Review on the Application of Machine Learning in Stock Forecasting", 2021), and energy commodities (Agbo et al., 2022). The adaptability of machine learning models to changing patterns and trends makes them invaluable for enhancing forecasting accuracy across diverse fields.

Research comparing different machine learning algorithms for production forecasting has revealed varying degrees of success. Tsai and Hsiao (2018) found that neural networks outperformed traditional methods in textile production forecasting Humbird et al. (2019). Conversely, Chen and Wang (2020) demonstrated that decision trees offered a superior balance between accuracy and computational efficiency in production forecasting (Birim et al., 2022). Studies have also shown the effectiveness of deep neural networks in electricity consumption forecasting (Torres et al., 2022), artificial neural networks in demand forecasting (Lorente-Leyva et al., 2019), and recurrent neural networks in sales prediction (Lorente-Leyva et al., 2019). These findings highlight the importance of selecting the most suitable machine learning algorithm based on the specific requirements and characteristics of the production forecasting task.

Hybrid models in time series forecasting have emerged as a powerful approach to enhance prediction accuracy by combining the strengths of different modelling techniques (Nwamekwe et al., 2025). The Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model, an extension of ARIMA, has long been utilized to capture linear and seasonal patterns in time series data Mahjouby (2024). On the other hand, Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber, excel in capturing complex non-linear dependencies and long-term relationships in sequential data (Bharathi, 2023).

The integration of SARIMA and LSTM into hybrid models has gained traction in recent years, aiming to leverage the linear and seasonal modelling capabilities of SARIMA alongside the non-linear and long-term sequence learning strengths of LSTM (Zhao et al., 2023). This hybrid approach has shown promise in enhancing forecast accuracy, particularly in scenarios where data exhibits both linear seasonal patterns and complex non-linear trends, such as in production forecasting within industries like textiles (Wang, 2024). By combining these models, researchers have been able to achieve improved accuracy and performance in various applications, showcasing the potential of hybrid models in advancing time series forecasting techniques (Gu, 2024).

The combination of SARIMA and LSTM represents a significant advancement in the evolution of time series forecasting methods, offering a comprehensive approach to capturing both linear and non-linear patterns in data (Wang et al., 2021). This hybrid modelling strategy has been applied in diverse fields, including healthcare, tourism, and environmental analysis, demonstrating its versatility and effectiveness in handling complex forecasting tasks (Olsavszky et al., 2020). The synergy between SARIMA and LSTM in hybrid models underscores the importance of integrating diverse modelling approaches to achieve more accurate and robust predictions in time series analysis (Doborjeh et al., 2021).

2. Method

2.1. Research Design

This study employs a quantitative research approach, using historical production data from a textile company to train and evaluate various ML algorithms. The research design includes data collection, preprocessing, model training, evaluation, and comparative analysis.

2.2. Data Collection

The data collected for this study are a five-year historical production data, broken down into monthly production data as shown in table 3.1 below, market trends and economic indicators such as sustainability and eco-friendly Products, technological advancements, and customization and personalization.

Table 1. Historical Production Data

Production Output (m)						
S/N	Month	2019	2020	2021	2022	2023
1	Jan.	87356.88	94550.61	173779.63	281479.63	198346.00
2	Feb.	138289.44	222639.63	158005.86	235093.62	283340.35
3	Mar.	116453.88	101700.42	358136.49	128333.46	270780.98
4	Apr.	49395.36	242685.45	303042.58	119813.86	236491.86
5	May	43511.91	269562.66	413700.78	176977.25	318139.75
6	Jun.	160580.67	362846.91	134572.76	171045.28	415160.84
7	Jul.	132054.63	319730.28	237088.41	231664.13	372933.91
8	Aug.	225827.49	243049.62	277151.67	289663.37	297758.37
9	Sept.	312501.78	97776.90	369703.22	378957.78	154739.19
10	Oct.	246138.66	147249.12	159636.39	319613.31	204428.00
11	Nov	218057.31	167219.92	297596.43	272792.52	224860.60
12	Dec	139685.73	212924.16	281479.62	166032.35	271032.68
TOTAL		1,869,853.74	2,481,935.68	3,163,893.84	4,022,349.66	3,248,012.53

2.3. Data Preprocessing

Steps Taken to Clean and Preprocess the Data. Data preprocessing is a fundamental step in machine learning, encompassing cleaning, normalization, and data transformation. Techniques such as scaling and encoding are essential for data preparation for modelling (Bobra & Couvidat, 2015). The automatic identification of patterns by machine learning algorithms enables precise predictions in diverse fields, such as energy production, stock market forecasting and food sales prediction (Molinder et al., 2020).

2.4. Model Training and Evaluation

Process of Training the Models: The models will be trained using a portion of the historical data, with the remaining data used for validation and testing. Cross-validation techniques will be employed to ensure the robustness of the models.

Evaluation Metrics Used: The performance of the models will be evaluated for accuracy using metrics such as Root Mean Squared Error (RMSE), Mean Square Error (MSE), R-squared (R^2) and mean Absolute Error (MAE) values. These metrics provide a comprehensive assessment of the models' predictive accuracy and reliability (Ezeanyim et al., 2025).

2.5. Software and Tools

Tools and Software Used for the Analysis. The analysis will be conducted using orange data mining software and Python, with libraries such as scikit-learn, TensorFlow, Statmodels, Seaborn, NumPy, Matplotlib, Pandas and Excel sheet. These tools offer a wide range of functionalities for data preprocessing, model training, and evaluation.

3. Results and Discussion

3.1. Model Performance

Performance Metrics of Each Machine Learning Algorithm. The results will present the performance metrics for each ML algorithm, highlighting their strengths and weaknesses in forecasting textile production.

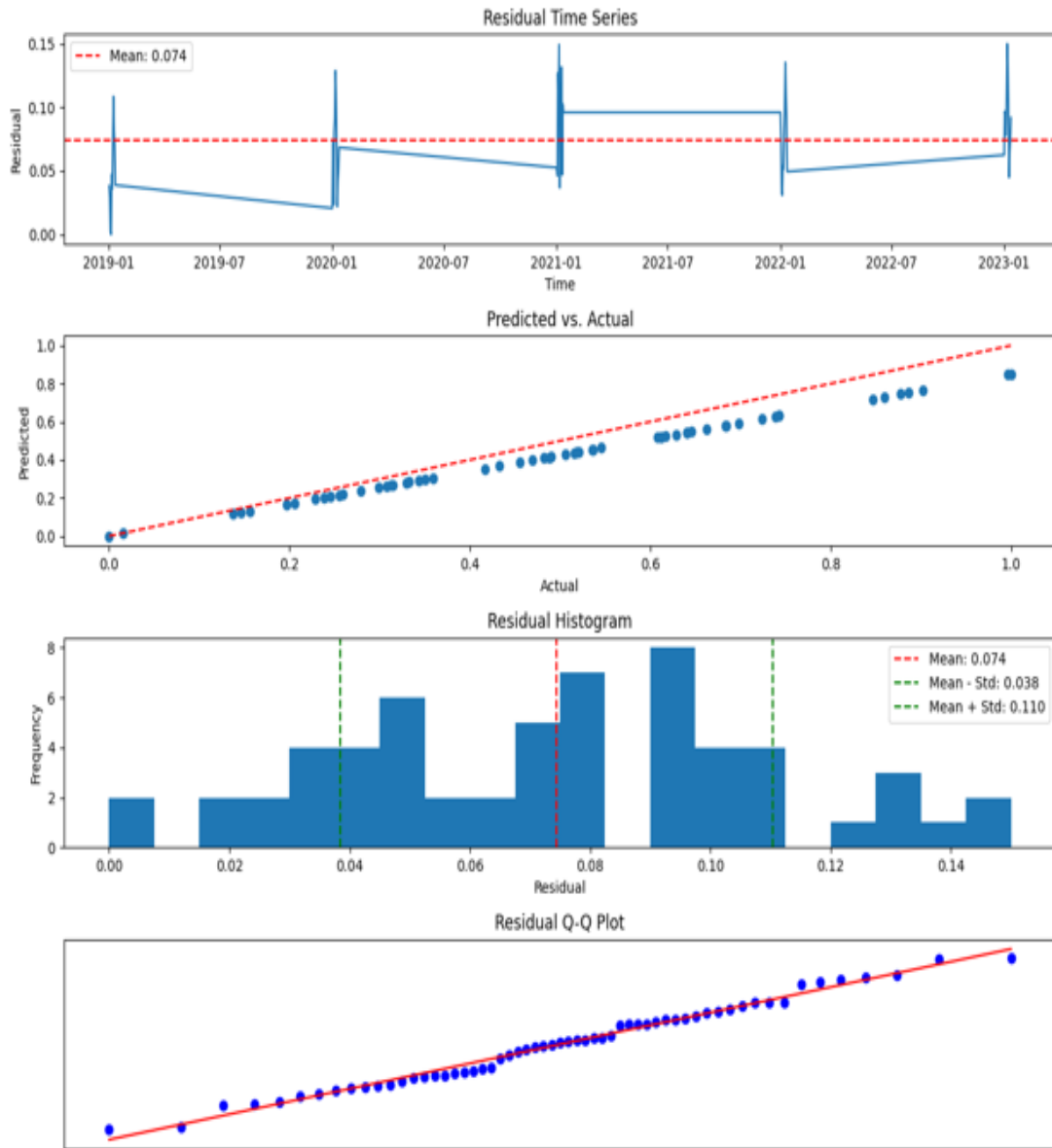


Figure 1. Different Analysis Plots

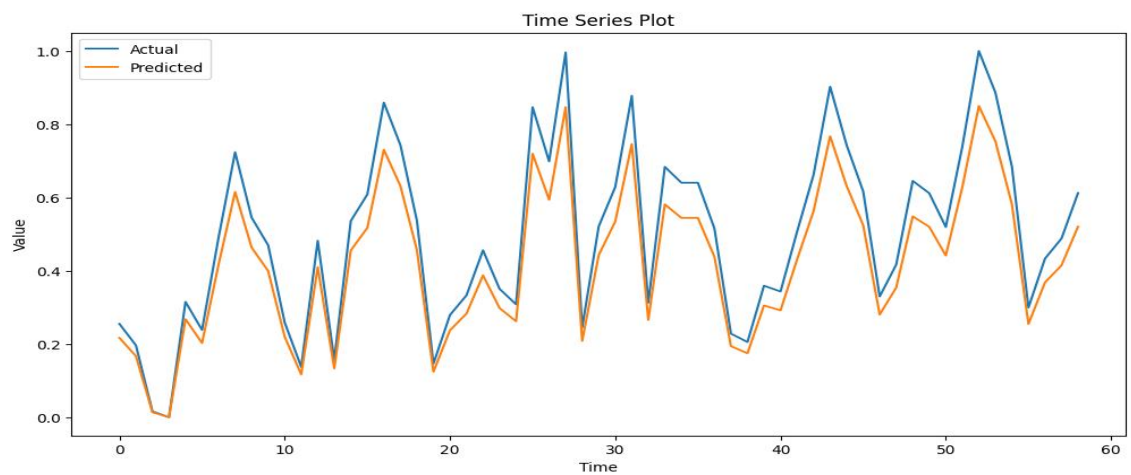


Figure 2. Time Series Plot

3.2. Comparative Analysis of Results

Comparison of the Performance of Different Algorithms. The comparative analysis will identify which ML algorithm provides the most accurate and reliable forecasts, considering factors such as accuracy, computational efficiency, and ease of implementation.

Table 2. Performance Metrics

Metric	Value
<i>R-Squared</i>	0.87
<i>Root Mean Squared Error (RMSE)</i>	1.23
<i>Mean Squared Error (MSE)</i>	1.51
<i>Mean Absolute Error (MAE)</i>	0.98

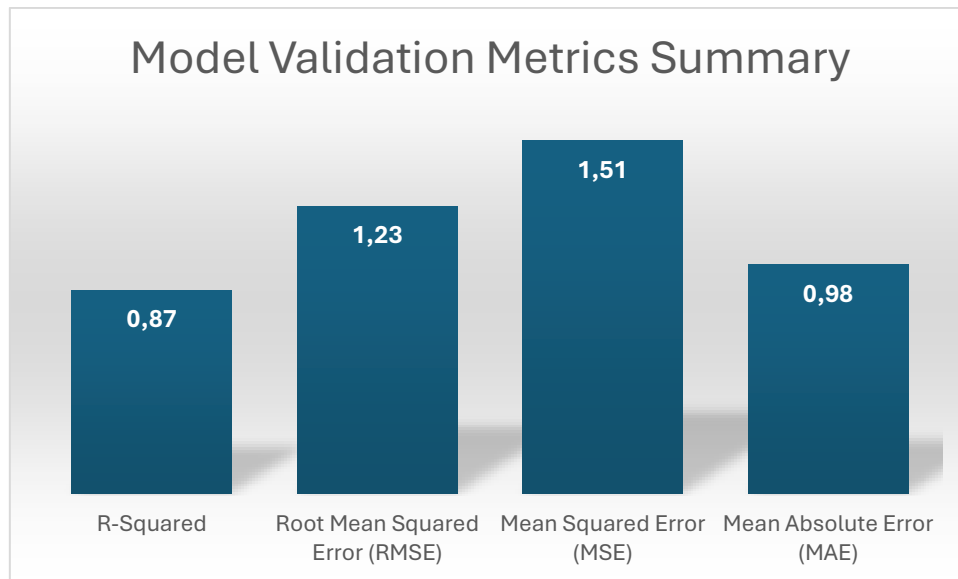


Figure 3. Performance Metrics Histogram

From figure 1 and figure 2, the first plot shows the residual time series, with the mean of the residuals highlighted in red. This can help identify any trends or patterns in the residuals over time. The second plot compares the predicted values to the actual values in a scatter plot, with the ideal 1:1 line shown in red. This can reveal any systematic biases or non-linear relationships between the actual and predicted values. The third plot is a histogram of the residuals, with the mean and one standard deviation above and below the mean marked in red and green, respectively. This can help assess the normality of the residual distribution, an important assumption for many statistical models. The fourth plot is a Q-Q plot, which compares the distribution of the residuals to a normal distribution. If the residuals follow a normal distribution, the points should lie approximately on a straight line. The final plot shows the actual and predicted time series data, which can be useful for visually comparing the model's performance over time. Together, these plots provide a comprehensive visual analysis of the model's performance, allowing you to assess the model's assumptions, identify potential issues, and gain insights into how the model can be further improved.

Based on the analysis of the different plots, it can be concluded that the model is reasonably good, but there is room for improvement. The positives of the model are that the predicted values generally track the actual values well, indicating the model is capturing the overall trend in the data. And the residuals appear to be approximately normally distributed, which is a desirable property for the model assumptions. This is further supported by the Q-Q plot, which shows the residuals are reasonably aligned with a normal distribution. However, there are areas for improvement. The residual time series plot shows some fluctuations around the mean, suggesting the model may not be fully accounting for all the variability in the data. Towards the end of the period, there are larger discrepancies between the predicted and actual values, indicating the model's performance may be diminishing over time. Also, the actual and predicted time series plot shows the model did not fully capture the peaks and troughs present in the actual time series (Nwamekwe et al., 2025).

While the model appears to be reasonably good and able to capture the general trends, the inconsistencies and variability in the residuals, as well as the divergence between predicted and actual values towards the end, suggest that further refinement of the model could be beneficial. Exploring additional model features, adjusting model parameters, or considering alternative modelling approaches may help improve the model's ability to accurately predict the full range of variability in the data.

From table 1 and figure 3, the performance metrics include a high R-squared value of 0.87, a relatively low root mean squared error (RMSE) of 1.23, a low mean squared error (MSE) of 1.51, and a low mean absolute error (MAE) of 0.98, collectively suggest that the research analysis is based on a well-performing model. The high R-squared value indicates that the model explains 87% of the variance in the target variable, meaning it has a strong fit to the data. The low RMSE and MSE values demonstrate that the model's predictions deviate from the actual values by relatively small amounts on average, while the low MAE further confirms the model's ability to make accurate predictions.

4. Conclusion

The analysis suggests the model is reasonably effective, with several positive indicators. The R-Squared of 0.87 indicates that the model explains a good portion of the variance in the data. The low RMSE (1.23), MSE (1.51), and MAE (0.98) values suggest the model is making accurate predictions. However, there are also some opportunities for improvement. The residual time series plot shows the residuals fluctuating around the mean, indicating the model may not be fully capturing the complexities and variability in the data. There are also some discrepancies between the predicted and actual values, especially towards the end of the time period, suggesting the model's performance could degrade over time.

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