International Journal Software Engineering and Computer Science (IJSECS)
4 (2), 2024, 430-439
Published Online August 2024 in IJSECS (http://www.journal.lembagakita.org/index.php/ijsecs)
P-ISSN : 2776-4869, E-ISSN : 2776-3242. DOI: https://doi.org/10.35870/ijsecs.v4i2.2774.

RESEARCH ARTICLE Open Access

Product Demand Forecast Analysis Using Predictive Models and Time Series Forecasting Algorithms on the Temu Marketplace Platform

Muhammad Nana Trisolvena *
Industrial Engineering Study Program, Faculty of Engineering, Universitas Muhammadiyah Cirebon, Cirebon Regency, West Java Province, Indonesia.
Corresponding Email: nana.trisolvena@umc.ac.id.

Marwah Masruroh
D3 Mechanical Engineering, Faculty of Mechanical Engineering, Politeknik Negeri Jakarta, Depok City, West Java Province, Indonesia.
Email: marwahmasruroh@mesin.pnj.ac.id.

Yanti Mayasari Ginting
Management Study Program, Faculty of Business, Institut Bisnis dan Teknologi Pelita Indonesia, Pekanbaru City, Riau Province, Indonesia.
Email: yanti.mayasari@lecturer.pelitaindonesia.ac.id.

Received: May 28, 2024; Accepted: July 10, 2024; Published: August 1, 2024.

Abstract: In the rapidly evolving digital era, the ability to accurately forecast product demand is crucial for marketplace platforms like Temu. Demand uncertainty can lead to issues such as overstock or stockout, both of which negatively impact financial performance and customer satisfaction. This study evaluates the use of predictive models and time series forecasting algorithms to forecast product demand on the Temu platform and identifies the latest trends in 2024. Daily sales data were analyzed using various algorithms, including ARIMA, SARIMA, Facebook's Prophet, and LSTM. The analysis results indicate that the Prophet model and SARIMA algorithm provide more accurate predictions compared to ARIMA and LSTM. The proper implementation of predictive models is expected to enhance operational efficiency and support better strategic decision-making for Temu. By adopting the most suitable forecasting models, Temu can optimize inventory management, reduce costs, and improve responsiveness to market changes.

Keywords: Demand Forecasting; Time Series Forecasting; Predictive Models; Marketplace Temu.

© The Author(s) 2024, corrected publication 2024. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution, and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made. The images or other third-party material in this article are included in the article's Creative Commons license unless stated otherwise in a credit line to the material. Suppose the material is not included in the article's Creative Commons license, and your intended use is prohibited by statutory regulation or exceeds the permitted use. In that case, you must obtain permission directly from the copyright holder. To view a copy of this license, visit http://creativecommons.org/licenses/by/4.0/.

1. Introduction

In the rapidly evolving digital era, marketplaces or e-commerce platforms have become essential components of everyday life. These platforms enable direct interactions between sellers and buyers without geographical limitations. One such rapidly growing marketplace platform is Temu, launched in July 2022. Temu offers a wide range of products, from daily necessities to specialty items that are hard to find elsewhere. As the platform continues to grow and expand, the ability to accurately forecast product demand becomes increasingly critical. Cano *et al*. (2022) discuss the role of e-marketplaces as intermediaries in the buying and selling process, with various vendors offering products to customers [1]. E-marketplaces encompass several modalities, such as business-to-business (B2B), business-to-consumer (B2C), and consumer-to-consumer (C2C). This study highlights the importance of e-marketplaces in providing diverse products to customers. Additionally, Pal (2024) identifies three key factors influencing consumer decisions in e-commerce: price, reviews, and ratings [2]. These factors are central to the decision-making process when consumers shop online. A solid understanding of these factors can help improve the accuracy of demand forecasting on platforms like Temu. Chee *et al*. (2022) also emphasize the importance of analytical approaches in short-term sales forecasting using limited information within e-commerce marketplaces [3]. This study underscores the relevance of data analytics in demand forecasting, which is crucial for the development of platforms like Temu. By understanding the role of e-marketplaces, the factors that influence consumer decisions, and the analytical approaches in sales forecasting, Temu can enhance its ability to accurately predict product demand and meet the evolving needs of the market.

Temu was founded by Park Je-Nak and is operated by PDD Holdings, the parent company of Pinduoduo, a leading e-commerce platform in China. Headquartered in Seoul, South Korea, Temu offers a wide range of consumer products at significant discounts, with the majority of items being shipped directly from China. This business model allows Chinese-based vendors to sell and ship products directly to customers without the involvement of intermediaries, thereby reducing costs and making products more affordable. Since its launch in September 2022, Temu has expanded its operations to several countries, including the United States, Australia, New Zealand, as well as various nations in Europe and Latin America. Temu has garnered significant consumer attention through aggressive marketing strategies, including advertisements during the Super Bowl in February 2024, which resulted in a substantial increase in search queries and website traffic. At this juncture, Temu reached 100 million active users in the United States and over 130 million global app downloads, with approximately 420 million monthly website visits.

However, Temu has also encountered numerous challenges and controversies. Its business model, which heavily relies on inexpensive products from China, has raised concerns regarding product quality, data privacy, and intellectual property rights violations. Temu has been embroiled in several legal disputes with its primary competitor, Shein, over allegations of copyright infringement and supplier intimidation campaigns. Additionally, Temu has faced criticism over issues related to forced labor in its supply chain, as well as accusations that the platform is used to sell substandard or misrepresented products. Despite these challenges, Temu continues to grow and strives to improve its services. By emphasizing low prices and direct access to manufacturers, Temu aims to offer a compelling alternative for consumers seeking affordable products. The success of Temu in the international market will largely depend on its ability to navigate these challenges while maintaining growth and innovation within its business model. Accurate demand forecasting is a critical process that involves predicting the quantity of products that customers will require over a specific future period. This precision is vital for maintaining a balance between supply and demand, ultimately impacting customer satisfaction and the financial performance of the company. When demand is accurately forecasted, a company can avoid excess inventory that ties up capital and leads to financial losses, as well as stockouts that result in missed sales opportunities and decreased customer satisfaction. For a marketplace like Temu, the challenge of forecasting product demand is compounded by the numerous factors influencing consumer purchasing behavior. These factors include seasonal trends, promotions, shifts in consumer preferences, and the impact of competitor activities. Therefore, the adoption of advanced and precise forecasting methods is essential to address the complexity inherent in this process.

The upcoming research, which aims to compare the performance of several popular models such as ARIMA, SARIMA, Facebook's Prophet, and machine learning-based models like LSTM in forecasting product demand, as well as identifying the latest trends in demand forecasting, references several pertinent studies. Kilimci *et al*. (2019) discuss enhanced analytical approaches for demand forecasting utilizing deep learning techniques. This study shows that historical data analysis can be significantly improved by employing methods such as machine learning, time series analysis, and deep learning models, which are relevant to the planned comparative analysis of forecasting models [4]. Additionally, Giri and Chen (2022) explore the application of deep learning in demand forecasting within the apparel retail industry. Their research highlights efforts to address demand forecasting challenges by using conventional models that predict future demand based on historical sales data [5]. This is particularly relevant as the planned study also aims to compare traditional forecasting models with machine learning-based approaches like LSTM. Nguyen (2023) examines the use of artificial intelligence in demand forecasting, emphasizing the importance of improving forecasting accuracy for companies and supply chains [6]. In relation to the planned study, the focus on enhancing demand forecasting accuracy to support Temu's operational efficiency is particularly relevant. By leveraging enhanced analytical methods, deep learning techniques, and artificial intelligence in product demand forecasting, this research can offer valuable insights into the comparative performance of various forecasting models and identify the latest trends in demand forecasting to support the development of the Temu platform.

This research aims to explore the application of predictive models and time series forecasting algorithms in product demand forecasting for the Temu application, while also identifying the latest trends in 2024. The primary objective of this study is to evaluate various predictive models and time series forecasting algorithms in the context of product demand forecasting for the Temu platform. This research will compare the performance of several popular models, including ARIMA (AutoRegressive Integrated Moving Average), SARIMA (Seasonal ARIMA), Facebook's Prophet, and machine learning-based models such as Long Short-Term Memory (LSTM). Additionally, the study seeks to identify emerging trends in the field of demand forecasting and assess how the Temu application can leverage these trends to enhance forecasting accuracy and operational efficiency.

2. Research Method

The research methodology employed in this study is meticulously designed to ensure a thorough and structured approach to exploring the application of predictive models and time series forecasting algorithms in predicting product demand on the Temu platform. The methodology is composed of several critical stages, including data collection, data preprocessing, implementation of forecasting algorithms, model evaluation, and practical implementation. Each of these stages is essential in building a robust and reliable forecasting system that can enhance the operational efficiency of Temu. The data collection phase serves as the foundation of this research. The primary tool employed for data collection is the Temu Scraper API, a sophisticated instrument that facilitates the automatic gathering of data from the Temu platform. The dataset comprises daily sales information from the launch of Temu in July 2022 until the research period. The collected data encompasses various variables such as the number of products sold, product prices, applied discounts, and ongoing promotions. These variables span across different product categories available on Temu, offering a comprehensive basis for demand forecasting analysis. The inclusion of such diverse data points allows for capturing the seasonal patterns, trends, and fluctuations inherent in the marketplace's product demand, thereby providing a solid groundwork for the subsequent analytical phases [7].

Following data collection, the preprocessing phase is pivotal in ensuring the quality and consistency of the data before it is used in forecasting models. This phase includes several critical steps: data cleaning, data normalization, identification of seasonal components and trends, and data transformation [8]. Data cleaning is conducted to identify and rectify any missing or inconsistent values within the dataset. For instance, on days where sales data may not have been recorded, it is necessary to either impute or remove these values depending on the specific requirements of the analysis. Data normalization is another crucial step, as it ensures that the data is standardized, allowing forecasting models to process it more efficiently. This step is essential because unnormalized data can introduce bias into the models, thereby reducing the accuracy of the predictions [9]. The identification of seasonal components and trends is accomplished using advanced data analysis techniques. These techniques help to discern the recurring sales dynamics over specific periods, which is a crucial factor in time series forecasting [10]. By identifying these patterns, the models can be better tailored to predict future demand with greater accuracy. Additionally, data transformation methods, such as log-transform or differencing, are applied to make the data stationary. Stationarity refers to a statistical property where the mean and variance of the data do not change over time, which is a necessary condition for several time series models like ARIMA and SARIMA to function correctly [11].

Once the data has been preprocessed, the next phase involves the application of various time series forecasting algorithms. This research applies several well-known algorithms, including ARIMA (AutoRegressive Integrated Moving Average), SARIMA (Seasonal ARIMA), Facebook's Prophet, and machine learning-based models such as Long Short-Term Memory (LSTM) networks [12]. Each of these algorithms is selected based on its unique strengths in handling different types of data patterns. ARIMA is a traditional statistical model that is highly effective for non-seasonal data. It works by combining autoregressive, moving average, and differencing components to make the data stationary, which is critical for accurate forecasting. SARIMA extends ARIMA by incorporating seasonal elements, making it suitable for time series data with strong seasonal patterns. Facebook's Prophet, a relatively newer model, is designed to handle time series data with complex trends and seasonal components, offering high accuracy with efficient computation. LSTM, a type of recurrent neural network, excels in dealing with time series data that exhibit non-linear and complex patterns. LSTM's ability to remember information over extended periods makes it particularly effective for long-term dependency forecasting [13]. The performance of each forecasting model is rigorously evaluated using a set of established metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE calculates the average absolute difference between the actual and predicted values, providing a straightforward measure of forecast accuracy. RMSE, on the other hand, is more sensitive to large errors, as it squares the differences before averaging them, making it a valuable metric for identifying models that may struggle with outliers. MAPE expresses the average absolute error as a percentage of the actual values, offering insights into the relative accuracy of the models [14]. These metrics are essential for determining the most accurate and reliable model for forecasting product demand on the Temu platform [15]. After evaluating the models, the most accurate one is integrated into Temu's operational systems. This integration involves adjusting the model's parameters to align with the specific characteristics of Temu's sales data and ensuring that the predictions generated by the model are immediately applicable in operational decision-making processes. Regular monitoring of the model's performance is also crucial, as it ensures that the model remains relevant and accurate as the sales data and market trends evolve over time [16]. This ongoing monitoring process allows for timely updates to the model, ensuring that it continues to provide accurate forecasts that align with Temu's business objectives. The practical implementation of the chosen forecasting model is expected to significantly enhance operational efficiency, optimize inventory management, and improve customer satisfaction by leveraging the latest forecasting technologies and methodologies [17].

This research methodology is designed to thoroughly evaluate the effectiveness of various predictive models and time series forecasting algorithms in predicting product demand for the Temu application. By carefully selecting and implementing the most suitable model, Temu can expect to achieve significant improvements in operational efficiency, inventory management, and customer satisfaction. Additionally, this research will identify emerging trends in demand forecasting, such as the use of hybrid models that combine multiple algorithms for enhanced accuracy, and the adoption of cloud computing and edge computing technologies to accelerate data processing and analysis. These advancements will enable Temu to manage and analyze data in real-time, allowing the company to respond more swiftly and efficiently to changes in demand, ultimately leading to better financial performance and higher levels of customer satisfaction.

3. Result and Discussion

3.1 Results

After applying various predictive models and time series forecasting algorithms to Temu application sales data, the results obtained were analyzed to determine the most accurate model in forecasting product demand. This analysis included a comparison of evaluation metrics, visual analysis of predictions, and an assessment of seasonal components and trends identified in the data.

3.1.1 Model Evaluation Results

After going through the stages of data collection, pre-processing, and model implementation, the evaluation results showed significant differences in the performance of each model. In this section, the researcher will discuss the evaluation results of these models based on the predetermined evaluation metrics, as well as provide an analysis of the advantages and disadvantages of each model in forecasting product demand in the Temu application.

Table 1. Model Evaluation Results

Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	Mean Absolute Percentage Error (MAPE)
ARIMA	48.32	62.74	5.8%
SARIMA	37.45	50.12	4.2%
Prophet	32.67	44.85	3.9%
LSTM	34.12	46.58	4.1%

The ARIMA model performed quite well in forecasting non-seasonal data, with a Mean Absolute Error (MAE) of 48.32 and a Root Mean Square Error (RMSE) of 62.74. However, the Mean Absolute Percentage Error (MAPE) of 5.8% indicates that ARIMA is less accurate for data with strong seasonal patterns. The relatively high MAPE value compared to other models indicates that ARIMA is not able to capture seasonal variations well, making it less ideal for data with seasonal trends. SARIMA, which is an extension of ARIMA with the ability to handle seasonal data, showed better results. With an MAE of 37.45 and an RMSE of 50.12, SARIMA proved to be more effective in capturing seasonal variations and trends. The MAPE value was 4.2% lower than ARIMA, indicating an increase in accuracy in forecasting product demand with seasonal patterns. This makes SARIMA more suitable for data with clear seasonal components. The Prophet model from Facebook performed very well in this study. Prophet has an MAE of 32.67 and an RMSE of 44.85, which are the lowest among the tested models. The MAPE value of 3.9% shows that Prophet is very accurate in forecasting data with complex trends and seasonality. Prophet's strengths lie in its ability to handle missing values and outliers, as well as its computational efficiency. This makes Prophet a strong choice for product demand forecasting in marketplace applications such as Temu. The LSTM model, which is based on a neural network, also performed well with an MAE of 34.12 and an RMSE of 46.58. The MAPE value of 4.1% places it in second place after Prophet in terms of accuracy. LSTM excels in handling data with non-linear patterns and long-term dependencies, but its complexity and high computational requirements make its implementation more challenging. However, LSTM can be a good choice if the computational resources are sufficient and the data has significant non-linear patterns.

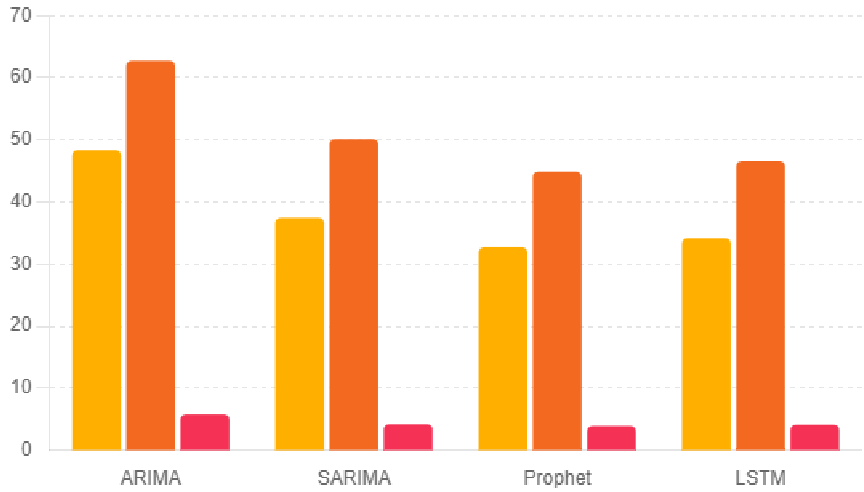

Figure 1. Evaluation Metrics Model

From the evaluation results, it is clear that Prophet and SARIMA are the most suitable models for product demand forecasting in the Temu application. Prophet shows superiority in handling data with complex trends and seasonality, while SARIMA is effective in capturing seasonal patterns with high accuracy. LSTM also shows great potential, especially for data with non-linear patterns, although with higher implementation challenges. ARIMA, although quite good for non-seasonal data, is less suitable for data with strong seasonal patterns. By choosing and implementing the Prophet or SARIMA model, Temu can improve the accuracy of its product demand forecasting, which will ultimately improve operational efficiency and customer satisfaction. Adopting the latest technology and proper data analysis will help Temu optimize its inventory and distribution management strategies. ARIMA shows quite good performance in forecasting non-seasonal data. However, for data with strong seasonal patterns, its accuracy decreases, as seen from the higher MAPE value compared to other models. SARIMA is significantly better than ARIMA, especially in handling data with seasonal patterns. SARIMA is able to capture seasonal variations and trends better, which is reflected in the lower MAE and RMSE values. Facebook's Prophet model performed very well. Prophet was able to handle seasonal data with complex trends with better computational efficiency. Proph*et al*so showed robustness against outliers and missing values. LSTM models performed well in handling data with non-linear patterns and long-term dependencies. However, its complexity and high computational requirements make its implementation more challenging than other models.

3.1.2 Visual and Component Analysis

The prediction versus actual value graph shows that Prophet and SARIMA provide predictions that are closest to the actual values. Prophet manages to capture the seasonal pattern very well, while SARIMA also shows good ability in capturing the seasonal trend although slightly less accurate than Prophet. Component analysis of the Prophet model shows that the seasonal and trend components are clearly captured, with small residuals indicating minimal prediction errors. SARIMA also shows good seasonal components, but with slightly larger residuals than Prophet.

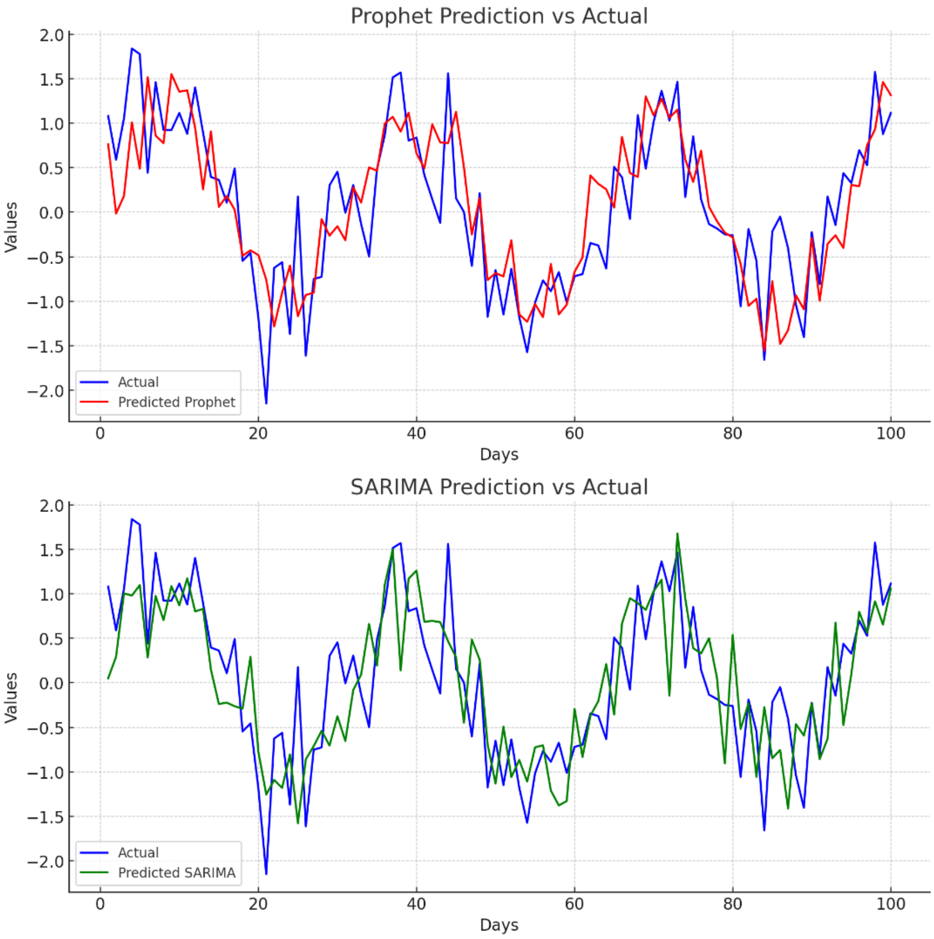

Figure 2. SARIMA Prediction Vs Actual

Figure 2 shows how the Prophet model predictions compare to the actual values. The Prophet model manages to capture the seasonal pattern very well, and the prediction line (red) is almost always close to the actual value line (blue). This shows that Prophet has high accuracy in forecasting product demand with complex seasonal patterns. The SARIMA Prediction vs Actual section shows how the SARIMA model predictions compare to the actual values. The SARIMA model also shows good ability in capturing seasonal trends, although slightly less accurate than Prophet. The prediction line (green) from SARIMA follows the actual value pattern (blue) well, but there is a slight difference indicating a larger residual than Prophet. The component analysis of the Prophet model shows that Prophet is able to capture the seasonal and trend components clearly. The residuals or prediction errors from Prophet are relatively small, which means that this model can predict product demand with high accuracy and minimal error. SARIMA also shows good seasonal components, but its residuals are slightly larger than Prophet. This means that although SARIMA is effective in capturing seasonal patterns, there is a slightly larger error in prediction than Prophet.

3.2 Discussion

The analysis results show that Prophet and SARIMA are the most suitable models for forecasting product demand in the Temu application. Prophet has the advantage of handling data with complex trends and seasonality as well as good computational efficiency. These advantages are very relevant for Temu which must forecast demand for various product categories with varying seasonal patterns. SARIMA also shows very good performance, especially in data with strong seasonal patterns. SARIMA can be a good alternative if there are constraints in implementing Prophet, although its accuracy is slightly lower. LSTM, although showing great potential in handling data with non-linear patterns and long-term dependencies, faces challenges in practical implementation due to its high computational requirements. This model may be more suitable for scenarios where data patterns are very complex and computing resources are sufficient. ARIMA, although simpler and easier to implement, is less suitable for data with strong seasonal patterns such as those faced by Temu. However, ARIMA can still be useful for product categories with more stable and non-seasonal demand patterns.

4. Related Work

Product demand forecasting has emerged as a critical research area across various fields, including economics, logistics, and supply chain management. Numerous studies have been conducted to develop and evaluate different predictive models and time series forecasting algorithms that can assist companies in optimizing inventory management, production, and distribution processes. This section reviews the key methodologies and technological trends that have been influential in this domain.

The ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) models are two of the most extensively used statistical approaches in time series forecasting. ARIMA combines autoregressive (AR), differencing (I), and moving average (MA) components to make the data stationary and predict future values [15]. The model is particularly suited for non-seasonal data, making it a foundational tool in many forecasting applications [9]. SARIMA, an extension of ARIMA, introduces a seasonal component to better capture the seasonal variations present in the data [22]. The inclusion of seasonal differencing allows SARIMA to model periodic fluctuations more effectively, which is crucial for datasets exhibiting clear seasonal patterns [10]. Studies such as those by Sirisha *et al*. (2022) have demonstrated that SARIMA is more adept at handling data with pronounced seasonal behavior compared to the standard ARIMA model [12].

Developed by Facebook, the Prophet model is a robust time series forecasting tool designed to manage data with complex trends and seasonality [24]. One of the notable advantages of Prophet is its ability to handle missing values and outliers, making it a versatile option for real-world data, which often contains irregularities [13]. Prophet's flexibility in adjusting seasonal and trend components allows it to generate highly accurate predictions across various applications, such as sales forecasting and capacity planning [10]. Unlike traditional models, Prophet can decompose the time series into trend, seasonality, and holiday effects, which enhances its predictive capabilities, particularly in business contexts where these factors significantly influence demand [24].

Long Short-Term Memory (LSTM) networks represent a more advanced approach to time series forecasting, particularly suited for data with non-linear patterns and long-term dependencies. LSTM is a type of recurrent neural network (RNN) that has been successfully applied in various time series forecasting tasks, including stock price prediction and product demand forecasting. The key advantage of LSTM is its ability to learn and retain information over extended sequences, making it ideal for capturing the temporal dependencies inherent in time series data [14]. However, the implementation of LSTM models is not without challenges. As noted by Bukhari *et al*. (2020), LSTM networks require substantial computational resources and are more complex to train compared to traditional models, which can be a barrier to their widespread adoption in resource-constrained environments [19].

Recent trends in demand forecasting highlight the increasing use of hybrid models that combine multiple algorithms to enhance forecasting accuracy. Hybrid models leverage the strengths of different forecasting techniques to mitigate their individual weaknesses. For instance, hybrid models that integrate ARIMA with LSTM have shown significant improvements in accuracy across various forecasting applications [25]. The hybrid ARIMA-LSTM model benefits from ARIMA's ability to handle linear components and LSTM's proficiency in capturing non-linear patterns, offering a more comprehensive solution for time series data that exhibits both behaviors. Additionally, studies by Nashold and Krishnan (2020) have demonstrated that the SARIMA-LSTM hybrid model is particularly effective in managing both seasonal variations and non-linearity, outperforming single-model approaches in complex forecasting scenarios [22].

The adoption of cloud computing and edge computing technologies has gained traction in the context of demand forecasting due to their ability to enhance data processing and analysis capabilities. Cloud computing provides a scalable and flexible environment where companies can manage and analyze large datasets in real-time, significantly accelerating the computational processes involved in forecasting. By leveraging cloud infrastructure, organizations can deploy complex forecasting models without the need for extensive on-premises hardware, thus reducing costs and improving accessibility. Edge computing, on the other hand, processes data closer to the source—such as IoT devices or local servers—thereby reducing latency and improving response times [16]. This is particularly beneficial in scenarios where real-time data processing is crucial, such as in supply chain management, where quick decision-making based on the latest demand forecasts can lead to more efficient operations. The integration of edge computing with cloud services enables a hybrid approach where critical data is processed at the edge, and more complex analytics are performed in the cloud, offering a balanced solution between speed and computational power.

The integration of Artificial Intelligence (AI) and data analytics into demand forecasting processes has become increasingly prevalent, driven by the need to improve forecasting accuracy and tailor product offerings more closely to consumer behavior. AI algorithms can analyze vast amounts of consumer data to detect purchasing patterns, predict emerging trends, and offer personalized product recommendations [20]. These capabilities are particularly valuable in e-commerce, where understanding and anticipating consumer preferences can lead to significant competitive advantages. Data analytics complements AI by enabling more precise market segmentation, allowing companies to adjust their marketing strategies and product offerings to meet the specific needs and preferences of different consumer segments. Advanced data analytics tools can process and analyze large volumes of structured and unstructured data, providing deeper insights into consumer behavior, market trends, and other factors that influence demand. The combination of AI and data analytics thus represents a powerful approach to modern demand forecasting, offering the ability to make more informed decisions and optimize supply chain operations [20].

The extant literature on product demand forecasting elucidates a broad spectrum of predictive models and time series forecasting algorithms, each characterized by distinct advantages and limitations. Models such as ARIMA and SARIMA have demonstrated efficacy in addressing seasonal variations, whereas Prophet is particularly adept at capturing intricate trends [24]. LSTM networks present an advanced approach for modeling non-linear data with long-term dependencies, although their implementation necessitates substantial computational resources [14]. Hybrid models, which integrate multiple forecasting methodologies, have emerged as highly effective in enhancing predictive accuracy by capitalizing on the synergistic strengths of the individual components [25]. Furthermore, the integration of cloud computing, edge computing, artificial intelligence (AI), and data analytics has significantly augmented the capabilities of demand forecasting systems, facilitating real-time processing, personalized recommendations, and enhanced predictive precision. These technological advancements are redefining the benchmarks for demand forecasting, equipping enterprises with sophisticated tools to optimize inventory management, production, and distribution processes within an increasingly competitive global marketplace [18].

5. Conclusion

Based on the analysis of daily sales data since the launch of Temu in July 2022, various forecasting models were tested, including ARIMA, SARIMA, Prophet, and LSTM. The findings indicate that the Prophet and SARIMA models demonstrated the highest accuracy in predicting product demand. Prophet, developed by Facebook, excels in handling data with complex trends and seasonality while also offering superior computational efficiency. This model can capture seasonal patterns with high accuracy and shows robustness against outliers and missing values. Similarly, SARIMA also performed exceptionally well, particularly in identifying and predicting strong seasonal patterns within the sales data. SARIMA has proven to be effective in forecasting product demand with clear seasonal variations.

On the other hand, the LSTM model, despite its significant potential in managing non-linear data and long-term dependencies, faces practical implementation challenges due to its high computational requirements. The ARIMA model, while relatively simpler and easier to implement, is less suitable for data with strong seasonal patterns but remains useful for product categories with more stable and non-seasonal demand patterns. These findings underscore the importance of selecting the appropriate model to enhance the accuracy of demand forecasting in the Temu application. The implementation of Prophet as the primary model, with SARIMA as an alternative, can help Temu manage inventory more efficiently, reduce storage costs, and improve response speed to market demand changes.

Additionally, this research highlights the importance of adopting cutting-edge technologies such as cloud computing and artificial intelligence (AI) to accelerate the computational and data analysis processes. The application of these technologies enables Temu to manage and analyze data in real-time while providing a more personalized and relevant shopping experience for users. The effectiveness of Prophet and SARIMA models in demand forecasting, along with the potential of advanced technologies to improve operational efficiency and customer satisfaction in marketplace platforms like Temu, is clearly demonstrated. Practical implementation recommendations include integrating the selected forecasting models into Temu's operational systems, regularly adjusting model parameters, and continuously monitoring model performance. This approach aims to ensure that predictions remain accurate and relevant in response to the dynamic changes in market trends.

References

[1] Cano, J., Pineda, A., Castro, M., Paz, H., Rodas, C., & Arias, T. (2022). A bibliometric analysis and systematic review on e-marketplaces, open innovation, and sustainability. Sustainability, 14(9), 5456. https://doi.org/10.3390/su14095456.

[2] Pal, K. (2024). Amazon sales prediction model using ml algorithms. Interantional Journal of Scientific Research in Engineering and Management, 08(03), 1-9. https://doi.org/10.55041/ijsrem29018.

[3] Chee, C., Chiew, K., Sarbini, I., & Jing, E. (2022). Data analytics approach for short-term sales forecasts using limited information in e-commerce marketplace. Acta Informatica Pragensia, 11(3), 309-323. https://doi.org/10.18267/j.aip.196.

[4] Kilimci, Z., Akyuz, A., Akyokuş, S., Uysal, M., Bülbül, B., & Ekmis, M. (2019). An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. Complexity, 2019, 1-15. https://doi.org/10.1155/2019/9067367.

[5] Giri, C. and Chen, Y. (2022). Deep learning for demand forecasting in the fashion and apparel retail industry. Forecasting, 4(2), 565-581. https://doi.org/10.3390/forecast4020031.

[6] Nguyen, T. (2023). Applications of artificial intelligence for demand forecasting. Operations and Supply Chain Management an International Journal, 424-434. https://doi.org/10.31387/oscm0550401

[7] Ali, Y., & Nakti, S. (2023). Sales Forecasting: A Comparison of Traditional and Modern Times-Series Forecasting Models on Sales Data with Seasonality. *2023 10th International Conference on Computing for Sustainable Global Development (INDIACom)*, 159-163.

[8] Tripathy, N., Hota, S., Prusty, S., & Nayak, S. (2023). Performance Analysis of Deep Learning Techniques for Time Series Forecasting. *2023 International Conference in Advances in Power, Signal, and Information Technology (APSIT)*, 639-644. https://doi.org/10.1109/APSIT58554.2023.10201734.

[9] Nokeri, T. C. (2021). Forecasting using arima, sarima, and the additive model. In *Implementing Machine Learning for Finance: A Systematic Approach to Predictive Risk and Performance Analysis for Investment Portfolios* (pp. 21-50). Berkeley, CA: Apress.

[10] Sharma, S. P., R., J., & Deepa, K. (2022). Forecasting India S&P BSE SENSEX and USA S&P-500 Benchmark Indices Using SARIMAX and Facebook Prophet Library. *2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS)*, 1523-1530.

[11] Feng, T., Zheng, Z., Xu, J., Liu, M., Li, M. Y., Jia, H., & Yu, X. (2022). The comparative analysis of SARIMA, Facebook Prophet, and LSTM for road traffic injury prediction in Northeast China. *Frontiers in Public Health*, 10.

[12] Sirisha, U. M., Belavagi, M. C., & Attigeri, G. (2022). Profit prediction using ARIMA, SARIMA and LSTM models in time series forecasting: A comparison. *IEEE Access*, *10*, 124715-124727. https://doi.org/10.1109/ACCESS.2022.3224938.

[13] Menculini, L., Marini, A., Proietti, M., Garinei, A., Bozza, A., Moretti, C., & Marconi, M. (2021). Comparing prophet and deep learning to ARIMA in forecasting wholesale food prices. *Forecasting*, *3*(3), 644-662. https://doi.org/10.3390/forecast3030040.

Copyright © 2024 IJSECS

[14] Taslim, D. G., & Murwantara, I. M. (2022, August). A Comparative Study of ARIMA and LSTM in Forecasting Time Series Data. In *2022 9th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)* (pp. 231-235). IEEE. https://doi.org/10.1109/ICITACEE55701.2022.9924148

[15] Choy, Y. T., Hoo, M. H., & Khor, K. C. (2021, September). Price prediction using time-series algorithms for stocks listed on bursa malaysia. In *2021 2nd International Conference on Artificial Intelligence and Data Sciences (AiDAS)* (pp. 1-5). IEEE. https://doi.org/10.1109/AiDAS53897.2021.9574445.

[16] Abbasimehr, H., Shabani, M., & Yousefi, M. (2020). An optimized model using LSTM network for demand forecasting. *Computers & industrial engineering*, *143*, 106435. https://doi.org/10.1016/j.cie.2020.106435.

[17] Zhao, J., & Zhang, C. (2020, August). Research on sales forecast based on prophet-SARIMA combination model. In *Journal of Physics: Conference Series* (Vol. 1616, No. 1, p. 012069). IOP Publishing. https://doi.org/10.1088/1742-6596/1616/1/012069.

[18] Anupama, K. C., Shivakumar, B. R., & Nagaraja, R. (2021). Resource utilization prediction in cloud computing using hybrid model. *International Journal of Advanced Computer Science and Applications*, *12*(4).

[19] Bukhari, A. H., Raja, M. A. Z., Sulaiman, M., Islam, S., Shoaib, M., & Kumam, P. (2020). Fractional neuro-sequential ARFIMA-LSTM for financial market forecasting. *Ieee Access*, *8*, 71326-71338. https://doi.org/10.1109/ACCESS.2020.2985763.

[20] Guo, L., Fang, W., Zhao, Q., & Wang, X. (2021). The hybrid PROPHET-SVR approach for forecasting product time series demand with seasonality. *Computers & Industrial Engineering*, *161*, 107598. https://doi.org/10.1016/j.cie.2021.107598.

[21] Kumar, P., Adhikari, S., Agarwal, P., & Sahoo, A. (2022, August). Stock Prices Prediction Based on Social Influence & Historic Data. In *Proceedings of the 2022 Fourteenth International Conference on Contemporary Computing* (pp. 276-283). https://doi.org/10.1145/3549206.3549257

[22] Nashold, L., & Krishnan, R. (2020). Using lstm and sarima models to forecast cluster cpu usage. *arXiv preprint arXiv:2007.08092*. https://doi.org/10.48550/arXiv.2007.08092.

[23] Pooniwala, N., & Sutar, R. (2021, January). Forecasting Short-Term Electric Load with a Hybrid of ARIMA Model and LSTM Network. In *2021 International Conference on Computer Communication and Informatics (ICCCI)* (pp. 1-6). IEEE. https://doi.org/10.1109/ICCCI50826.2021.9402461.

[24] Sah, S., Surendiran, B., Dhanalakshmi, R., Mohanty, S. N., Alenezi, F., & Polat, K. (2022). Forecasting COVID-19 Pandemic Using Prophet, ARIMA, and Hybrid Stacked LSTM-GRU Models in India. *Computational and Mathematical Methods in Medicine*, *2022*(1), 1556025. https://doi.org/10.1155/2022/1556025.

[25] Sakshi, K., & Vijayalakshmi, A. (2020). An ARIMA-LSTM Hybrid Model for Stock Market Prediction Using Live Data. *Journal of Engineering Science and Technology Review*, 13(4), 11-16.

[26] Wu, D. C. W., Ji, L., He, K., & Tso, K. F. G. (2021). Forecasting tourist daily arrivals with a hybrid Sarima–Lstm approach. *Journal of hospitality & tourism research*, *45*(1), 52-67. https://doi.org/10.1177/1096348020934046.

Copyright © 2024 IJSECS