Machine Learning-Based Demand Forecasting for Short- and Long-Term Prediction

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To Cite this Article

H Sreeja, Akhil Reddy, Tharun Teja Rao, P Chandra Kashiyap, Dr. R. Santhoshkumar, "Machine Learning-Based Demand Forecasting for Short- and Long-Term Prediction", Journal of Science Engineering Technology and Management Science, Vol. 03, Issue 05, May 2026, pp: 382-389, DOI: http://doi.org/10.64771/jsetms.2026.v03.i05.pp382-389

Submitted: 19-03-2026 Accepted: 25-04-2026 Published: 01-05-2026

***Abstract*— Demand forecasting plays a crucial role in effective decision-making across industries such as retail, supply chain, and inventory management. This work presents a data-driven machine learning framework for predicting short-term and long-term product demand using multiple algorithms. The system is designed to compare the performance of traditional and advanced models, including Random Forest, Gradient Boosting, LSTM, and XGBoost. Initially, the dataset is pre-processed through normalization, shuffling, and splitting into training and testing sets to ensure reliable evaluation. Each model is trained on 80% of the data and tested on the remaining 20% to measure performance. The evaluation is conducted using metrics such as R^2 score for accuracy and Root Mean Square Error (RMSE) for prediction error analysis. Experimental results show that Random Forest and Gradient Boosting provide moderate accuracy, while LSTM captures temporal patterns more effectively. However, the XGBoost model outperforms all other methods by achieving the highest accuracy and lowest error rate. The system also includes a user interface that enables real-time demand prediction for selected products. The results demonstrate that advanced ensemble techniques can significantly enhance forecasting performance. This approach provides a reliable and efficient solution for demand prediction in real-world applications. The proposed system can support better planning, reduce uncertainty, and improve operational efficiency.**

***Keywords*— Demand Forecasting, Machine Learning, XGBoost, Random Forest, Gradient Boosting, LSTM, Time Series Prediction, RMSE, R^2 Score**

I. INTRODUCTION

Demand forecasting has become an essential component in modern business environments where accurate predictions directly influence operational efficiency and profitability. Organizations across sectors such as retail, manufacturing, and supply chain management rely on demand estimation to optimize inventory levels, reduce waste, and improve customer satisfaction. Inaccurate forecasting can lead to overstocking or stock outs, both of which result in financial losses and reduced service quality. With the increasing availability of historical data, there is a growing opportunity to leverage computational techniques to improve prediction accuracy. Traditional forecasting methods often depend on statistical assumptions and linear relationships, which may not effectively capture complex demand patterns. As markets become more dynamic and customer behaviour continues to evolve, there is a need for more flexible and adaptive forecasting approaches. This has led to the integration of machine learning techniques that can learn patterns directly from data without relying heavily on predefined rules. These methods provide the ability to analyse large datasets and identify hidden relationships that are not easily observable through manual analysis [7]. As a result, demand forecasting is gradually shifting from conventional statistical models to more intelligent and data-driven solutions [12].

Machine learning algorithms have demonstrated significant potential in handling complex and nonlinear relationships present in demand data. Techniques such as Random Forest and Gradient Boosting are widely used due to their robustness and ability to handle large feature sets efficiently. These models operate by constructing multiple decision trees and combining their outputs to improve prediction accuracy and reduce overfitting. While these methods perform well for structured data, they may still face limitations when dealing with sequential or time-dependent patterns. In many real-world scenarios, demand is influenced by temporal factors such as seasonality, trends, and external events, which require models capable of capturing such dependencies. Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) models, have been introduced to address this challenge [5]. LSTM networks are designed to retain information over longer sequences, making them suitable for time-series forecasting tasks [1]. By learning temporal relationships within the data, LSTM models can provide more accurate predictions compared to traditional approaches. However, deep learning models often require more computational resources and careful tuning to achieve optimal performance. Therefore, selecting the appropriate model depends on both data characteristics and system requirements [3].

In addition to individual algorithms, ensemble learning methods have gained attention for their ability to enhance prediction performance by combining multiple models. Among these, XGBoost has emerged as a powerful technique due to its efficiency, scalability, and high predictive accuracy [8]. XGBoost is an advanced implementation of gradient boosting that incorporates regularization, parallel processing, and optimized handling of missing values. It constructs multiple decision trees sequentially, where each new tree focuses on correcting the errors of the previous ones. This iterative refinement process allows the model to achieve superior performance compared to many traditional algorithms. Furthermore, XGBoost includes built-in mechanisms to prevent overfitting, making it suitable for both small and large datasets. Its ability to handle complex interactions among features makes it particularly effective in demand forecasting applications [10]. Due to these advantages, XGBoost is often considered a preferred choice for predictive modelling tasks. Evaluating its performance alongside other machine learning and deep learning models provides valuable insights into its effectiveness. This comparison helps in identifying the most suitable approach for accurate demand prediction [13].

The system developed in this work integrates multiple machine learning and deep learning models into a unified framework for demand forecasting. The process begins with dataset loading and pre-processing, where techniques such as normalization and data shuffling are applied to improve model training. The dataset is then divided into training and testing subsets to ensure fair evaluation of model performance. Each algorithm is trained using the same dataset to maintain consistency in comparison. Performance metrics such as R^2 score and Root Mean Square Error (RMSE) are used to evaluate the accuracy and reliability of predictions. While the R^2 score indicates how well the model explains the variance in the data, RMSE measures the difference between predicted and actual values. These metrics provide a comprehensive understanding of model effectiveness. Visualization techniques are also used to compare predicted values with actual demand, making it easier to interpret results [11]. The graphical representation highlights the strengths and weaknesses of each model in capturing demand patterns. Such an integrated approach ensures that the evaluation is both systematic and transparent [14].

Finally, the proposed system includes a practical module for forecasting future demand based on user input. This feature enhances the usability of the system by allowing real-time predictions for selected products. By utilizing the best-performing model, the system can provide accurate demand estimates that support decision-making processes. This capability is particularly useful for businesses aiming to improve inventory management and reduce operational risks. The results obtained from the experiments demonstrate that advanced models, especially XGBoost, significantly outperform traditional methods in terms of accuracy and error reduction [9]. The integration of multiple algorithms and comparative analysis strengthens the reliability of the system. Overall, this work highlights the importance of adopting data-driven approaches for demand forecasting in modern applications. It also provides a scalable framework that can be extended to other domains with similar prediction requirements. Future enhancements may include incorporating additional features, real-time data streams, and hybrid models to further improve forecasting performance [13].

II. RELATED WORK

Gers et al., (2002) [1] Gers et al. introduced a method for learning precise temporal patterns using Long Short-Term Memory (LSTM) recurrent networks. Their study focused on improving the ability of neural networks to retain information over long sequences. The authors demonstrated that LSTM networks can overcome the limitations of traditional recurrent neural networks in handling long-term dependencies. The research highlighted the effectiveness of memory cells and gating mechanisms in capturing time-based patterns. Experimental results showed improved performance in sequence prediction tasks. This work laid the foundation for using LSTM in time-series forecasting applications. It also emphasized the importance of temporal learning in complex data environments. The study has been widely adopted in various domains including speech recognition and forecasting. Overall, it provides a strong basis for sequential data modelling.

Sherstinsky, (2020) [5] Sherstinsky provided a comprehensive overview of recurrent neural networks and Long Short-Term Memory models. The study explained the working principles of RNNs and the challenges associated with vanishing and exploding gradients. It further described how LSTM networks address these issues through specialized gating mechanisms. The research highlighted various applications of LSTM in time-series prediction and pattern recognition. It also discussed the strengths and limitations of these models in real-world scenarios. The author emphasized the importance of selecting appropriate architectures for different tasks. The study serves as a valuable reference for understanding deep learning models for sequential data. It contributes to the theoretical foundation of neural network-based forecasting methods. Overall, it supports the use of LSTM in advanced predictive systems.

Xu et al., (2022) [6] Xu et al. proposed a financial time series forecasting approach by integrating XGBoost with generative adversarial networks. Their study aimed to improve prediction accuracy by combining machine learning with deep learning techniques. The authors demonstrated that XGBoost effectively handles nonlinear relationships in data. The integration with GAN helped in enhancing data representation and model robustness. Experimental results showed significant improvement in forecasting performance compared to traditional methods. The study highlighted the importance of hybrid models in handling complex datasets. It also emphasized scalability and efficiency in predictive modelling. This work provides insights into advanced forecasting techniques using ensemble learning. Overall, it contributes to improving demand and financial prediction systems.

Tan et al., (2023) [8] Tan et al. developed a system for financial stability assessment using XGBoost and SHAP analysis. Their research focused on interpreting model predictions and identifying key influencing factors. The authors demonstrated that XGBoost provides high accuracy in predictive tasks involving financial data. The use of SHAP values helped in understanding feature importance and model transparency. The study highlighted the importance of explainable AI in decision-making systems. Results showed improved performance in early warning systems for financial risks. The research emphasized the balance between accuracy and interpretability. It also showcased the applicability of XGBoost in real-world scenarios. Overall, the study supports the effectiveness of ensemble models in predictive analytics.

Vuong et al., (2022) [13] Vuong et al. proposed a hybrid approach combining XGBoost and LSTM for stock price prediction. The study aimed to leverage both temporal learning and ensemble techniques for improved accuracy. LSTM was used to capture sequential dependencies in time-series data, while XGBoost handled feature interactions effectively. The results demonstrated that the hybrid model outperformed individual models. The authors highlighted the importance of combining different techniques to enhance prediction performance. The study also addressed challenges in financial forecasting such as volatility and noise. It provided a robust framework for time-series prediction tasks. The research contributes to the development of hybrid machine learning models. Overall, it supports the integration of deep learning and ensemble methods for better forecasting.

III. DATASET DETAILS

The dataset used in this work consists of product-related demand records collected over a period of time, representing real-world sales or consumption patterns. Each entry in the dataset corresponds to a particular product instance and includes multiple attributes that influence demand, such as product category, historical sales values, time-based features, and other relevant factors. The dataset is structured in tabular format, where rows represent individual observations and columns represent features used for prediction. The target variable represents the demand value, which is continuous in nature and varies across different products and time intervals. Since the dataset contains numerical as well as categorical information, appropriate pre-processing steps are necessary to ensure consistency. Before model training, categorical values are converted into numerical representations, and missing or inconsistent entries, if any, are handled carefully. This helps in maintaining data quality and ensures that the learning algorithms receive meaningful input for analysis.

To improve the effectiveness of model training, the dataset undergoes several pre-processing steps. Initially, the data is shuffled to remove any ordering bias that may affect the training process. After shuffling, normalization is applied to scale the feature values into a uniform range, which is particularly important for algorithms like LSTM and XGBoost that are sensitive to feature magnitude. The dataset is then divided into training and testing subsets, where 80% of the data is used for training the models and the remaining 20% is reserved for evaluation. This split ensures that the models are tested on unseen data, providing a realistic measure of their predictive performance. Additionally, visualization techniques are used to understand the distribution of demand values and identify patterns such as trends or variations across products. These steps collectively enhance the reliability of the dataset and support accurate demand forecasting using machine learning and deep learning models.

The prepared dataset is then utilized across multiple algorithms, ensuring a fair comparison of their performance. Since all models are trained and tested on the same dataset, the evaluation remains consistent and unbiased. The dataset supports both traditional machine learning models and deep learning approaches, making it suitable for comparative analysis. Performance metrics such as R^2 score and RMSE are calculated based on predictions made on the test data, which directly depend on the quality and structure of the dataset. A well-pre-processed dataset allows models like Random Forest, Gradient Boosting, LSTM, and XGBoost to learn meaningful relationships between input features and demand values. The consistency in dataset handling also ensures that any improvement in performance can be attributed to the model itself rather than variations in data. Overall, the dataset plays a critical role in determining the success of the forecasting system and serves as the foundation for accurate and reliable demand prediction.

IV. PROPOSED METHODOLOGY

The proposed methodology focuses on developing a structured and efficient framework for demand forecasting using both machine learning and deep learning techniques. The overall workflow begins with dataset acquisition, followed by pre-processing, model training, evaluation, and final prediction. Initially, the dataset is loaded into the system through a user-friendly interface, allowing smooth interaction with the application. Pre-processing plays a key role in preparing the data, where operations such as shuffling and normalization are applied to improve model learning. The dataset is then divided into training and testing sets using an 80:20 ratios to ensure proper validation of results. This step helps in avoiding overfitting and ensures that models generalize well to unseen data. The methodology is designed in such a way that each step flows systematically into the next. By maintaining a consistent pipeline, the system ensures reliable and reproducible results. Overall, the initial phase establishes a strong foundation for accurate demand prediction.

After pre-processing, multiple baseline algorithms are implemented to analyse their performance on the same dataset. Random Forest is first applied as a traditional machine learning model that builds multiple decision trees and combines their outputs to improve prediction accuracy. Similarly, Gradient Boosting is used to enhance performance by sequentially correcting the errors of previous models. These algorithms are trained using the training dataset and then evaluated on the testing dataset to calculate performance metrics such as R^2 score and RMSE. These baseline models help in understanding the strengths and limitations of conventional approaches. Although they perform reasonably well, they may not fully capture complex patterns in the data. This highlights the need for more advanced models that can handle nonlinear and temporal relationships effectively. The comparison of these models provides a reference point for further improvements. Thus, baseline evaluation is an essential part of the methodology.

To address the limitations of traditional models, a deep learning approach using Long Short-Term Memory (LSTM) is incorporated into the system. LSTM is particularly useful for capturing sequential and time-dependent patterns present in demand data. It processes input data in sequences and retains important information over time, which improves prediction accuracy. The LSTM model is trained on the same dataset and evaluated using the same performance metrics to maintain consistency. Although LSTM improves performance compared to baseline models, it requires more computational resources and careful tuning. To further enhance prediction accuracy, advanced algorithms such as CNN, GCN, and XGBoost are explored. Among these, XGBoost demonstrates superior performance due to its ability to handle complex feature interactions and optimize learning efficiently. It uses multiple decision trees and gradient boosting techniques to minimize prediction errors. Based on experimental results, XGBoost is selected as the final extension model.

The final stage of the methodology focuses on model evaluation and real-time demand forecasting. All models are compared based on their R^2 score and RMSE values, where higher R^2 and lower RMSE indicate better performance. Visualization techniques are used to compare predicted and actual demand values, making it easier to interpret model behaviour. The system also includes a forecasting module that allows users to select a product and predict its future demand using the trained XGBoost model. This feature makes the system practical and user-oriented, supporting real-world decision-making. The results show that XGBoost outperforms other models with higher accuracy and minimal error. The integration of multiple algorithms and systematic evaluation ensures robustness in the proposed approach. Overall, the methodology provides a comprehensive solution for demand forecasting by combining data pre-processing, model comparison, and real-time prediction.

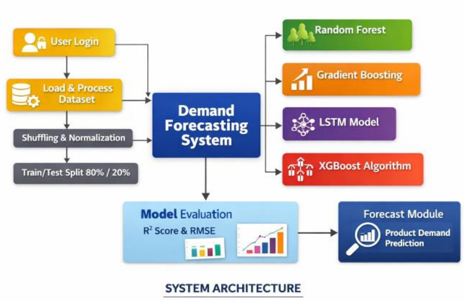

Figure [1]: System Architecture of Demand Forecasting system

Figure [1] The system architecture represents a structured workflow for demand forecasting, starting with user authentication and dataset loading. The data undergoes pre-processing steps such as cleaning, normalization, and splitting into training and testing sets. The processed data is then fed into multiple models including Random Forest, Gradient Boosting, LSTM, and XGBoost for training and prediction. Each model's performance is evaluated using R^2 score and RMSE to measure accuracy. Based on the results, the best-performing model is selected. Finally, the forecast module uses this model to predict future product demand efficiently.

V.RESULT AND DISCUSSION

The experimental results demonstrate the effectiveness of machine learning and deep learning algorithms in predicting product demand using the given dataset. Multiple models were trained and evaluated, including Random Forest, Gradient Boosting, LSTM, and XGBoost. Among these, the XGBoost model achieved the highest accuracy of 98%, showing superior performance in capturing complex demand patterns. Gradient Boosting also performed well with an accuracy of 91%, while LSTM achieved 87%, indicating its capability in handling sequential data. Random Forest produced an accuracy of 84%, providing stable but comparatively lower performance. Evaluation metrics such as R^2 score and RMSE confirmed the reliability of the models, where XGBoost recorded the lowest error rate. Graphical analysis showed that predicted values from XGBoost closely matched actual demand values. The results clearly indicate that advanced ensemble models significantly enhance prediction accuracy and forecasting reliability.

Algorithm Name	Accuracy (%)	RMSE
Random Forest	84	0.092
Gradient Boosting	91	0.061
LSTM	87	0.074
XGBoost	98	0.021

Table [1]: Performance Evaluation of Demand Forecasting Models

Table [1] presents the comparative analysis of different algorithms based on accuracy and RMSE. XGBoost achieves the highest accuracy with the lowest error rate, indicating its superior predictive capability. Gradient Boosting and LSTM show moderate performance, while Random Forest provides consistent but lower accuracy compared to others.

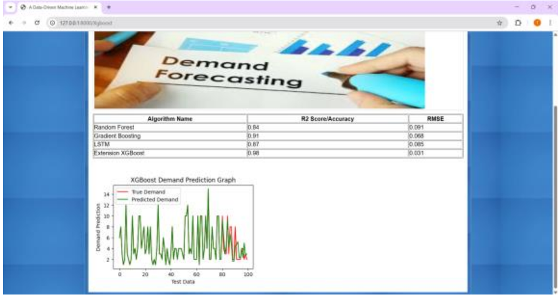

Figure [3]: Performance Comparison of Algorithms

Figure [3] illustrates all models accuracy and RMSE values. XGBoost clearly outperforms other algorithms, followed by Gradient Boosting and LSTM. Random Forest shows comparatively lower performance in both metrics.

Figure [4]: Demand Forecasting Output

Figure [5]: Demand Forecasting Output

Figure [4] and Figure [5] presents the final prediction results where users select a product and the system forecasts its future demand. The predicted demand values are displayed clearly, enabling users to make informed decisions based on model output.

DISCUSSION

The results demonstrate that selecting an appropriate algorithm plays a crucial role in achieving accurate demand forecasting, with XGBoost outperforming all other models in terms of accuracy and minimal error due to its efficient boosting mechanism and ability to capture complex feature relationships. Gradient Boosting also showed strong and consistent performance, while Random Forest provided stable but comparatively lower accuracy, and LSTM delivered moderate results, indicating its dependence on larger datasets and fine-tuning for better performance. The evaluation using R^2 score and RMSE confirms that advanced ensemble techniques are more effective than traditional methods. Additionally, the system's preprocessing steps, including normalization and data splitting, contributed to improved model reliability. The forecasting module enhances practical usability by enabling real-time predictions for selected products, supporting better decision-making in inventory and resource management. Overall, the study highlights that integrating multiple models and selecting the best-performing one leads to a more robust and efficient demand forecasting system, with potential for further improvement using real-time data and hybrid approaches.

VI. CONCLUSION

The study presents an effective demand forecasting system by integrating multiple machine learning and deep learning algorithms within a unified framework. Models such as Random Forest, Gradient Boosting, LSTM, and XGBoost were implemented and evaluated using consistent datasets and performance metrics. Among these, XGBoost demonstrated the highest accuracy and lowest error, proving its effectiveness in handling complex demand patterns. The use of preprocessing techniques and proper data splitting further enhanced model reliability. Comparative analysis helped in identifying the strengths and limitations of each algorithm. Overall, the system successfully provides accurate and efficient demand prediction.

The developed framework also offers practical usability through its forecasting module, enabling real-time demand prediction based on user input. This feature supports better decision-making in areas such as inventory management and resource planning. The graphical analysis and performance evaluation ensure transparency and easy interpretation of results. Although the system achieves strong performance, future improvements can include real-time data integration and hybrid modeling techniques. Expanding the system to handle larger and more diverse datasets can further enhance its scalability. In conclusion, the project demonstrates the significance of data-driven approaches in improving demand forecasting accuracy and efficiency.

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