

Demand Prediction for Computing Devices Using ML-Based Models

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Abstract:

With the fast pace at which the market for computing devices, which includes laptops, desktop computers, smart phones, tablets, and embedded systems, is evolving, there has been a pressing need to provide accurate demand forecasts. In many cases, traditional statistical techniques, such as ARIMA and exponential smoothing, have proven insufficient in capturing the complex dynamics of the demand patterns in technology markets. In this paper, an AI/ML demand forecasting framework will be introduced for computing devices. Specifically, the proposed technique involves the application of machine learning algorithms including random forest, gradient boosting (such as XGBoost or LightGBM), LSTM, and hybrid ensembles to predict demand for computing devices. Heterogeneous data sets such as sales data, macroeconomic indicators, sentiment analysis of social media feeds, and supply chain data can be incorporated in this process. Experimental results show that this hybrid model outperforms conventional methods in terms of its ability to accurately predict demand (low Mean Absolute Percentage Error). The system can be used by suppliers/manufacturers, retailers, and supply chain managers to make decisions on procurement and production.

Keywords — Demand Forecasting, Machine Learning, Time Series Prediction, Sales Prediction.

I. INTRODUCTION

The global computing device industry is characterized by intense competition, rapid product cycles, and volatile consumer demand. Accurately predicting the demand for products such as laptops, personal computers, graphics processing units (GPUs), and mobile computing devices is critical for efficient inventory management, optimized production planning, and sustained profitability. Demand forecasting errors — whether overestimation or underestimation — can result in excess inventory costs or stockouts, directly impacting revenue and customer satisfaction (Zhang et al., 2024; Patel & Singh, 2024).

Traditional forecasting methods such as Moving Averages, ARIMA, and Holt-Winters models have

been widely used in supply chain management. However, these methods rely on stationarity assumptions and struggle with the complex, non-linear demand patterns driven by product launches, economic cycles, global supply chain disruptions, and evolving consumer preferences (Kumar et al., 2025; Ramos & Fildes, 2024).

Recent advances in Artificial Intelligence and Machine Learning offer powerful alternatives. Algorithms such as Random Forest, XGBoost, and deep learning architectures like LSTM networks have demonstrated superior forecasting accuracy across diverse domains by learning complex temporal dependencies and leveraging multi-source feature sets (Li & Wang, 2025; Hou et al., 2024). This paper proposes a comprehensive AI/ML-based demand prediction system specifically tailored to

the computing device sector, addressing the unique challenges of technology product lifecycle dynamics, component shortages, and shifting market trends.

II. LITERATURE SURVEY

Zhang et al. [1] conducted a comprehensive review of machine learning applications in supply chain demand forecasting, demonstrating that ensemble methods consistently outperform traditional statistical models on real-world retail datasets. Their findings underscore the importance of feature richness and model diversity in improving prediction accuracy.

Kumar et al. [2] proposed an XGBoost-based demand prediction model for electronics retail, incorporating external regressors such as consumer price indices and online search trends. Their model achieved a MAPE reduction of 18% compared to ARIMA baselines, highlighting the value of exogenous signals in technology market forecasting.

Li and Wang. [3] investigated the application of Long Short-Term Memory (LSTM) networks for multi-step ahead forecasting in the semiconductor industry. Their study demonstrated that LSTM models effectively capture long-range temporal dependencies in demand signals that classical.

Hou et al. [4] explored Transformer-based architectures for demand forecasting, finding that attention mechanisms improve the model's ability to detect irregular seasonal patterns and demand spikes associated with product launches — a common phenomenon in the computing device industry.

Patel and Singh. [5] proposed a hybrid ARIMA-LSTM model that combines statistical and deep learning components, achieving robust forecasting under both stable and volatile market conditions. Their work serves as a conceptual foundation for the hybrid framework proposed in this paper.

Ramos and Fildes. [6] reviewed feature engineering strategies for retail demand prediction, concluding that incorporating sentiment data from social media and product review platforms substantially improves forecast accuracy for consumer electronics, where viral trends and reviews drive purchasing behavior.

Nguyen et al. [7] examined the unique forecasting challenges in the computing device sector, including short product lifecycles, component dependency (e.g., GPU shortages affecting PC builds), and the influence of remote work trends on laptop demand. Their work stresses the need for domain-specific feature engineering beyond generic retail forecasting pipelines.

III. THEORETICAL FRAMEWORK

The Demand Prediction for Computing Devices is based on the theoretical principles of demand forecasting, data analytics, machine learning and inventory control. The framework outlines the steps to analyze historical sales data in order to identify trends and patterns, and customer purchasing behavior for demand forecasting. With a correct foresight of demand, organizations would have the right amount in stock and drastically reduce shortages while improving operations as a whole.

The data-driven forecasting system that you are trained on primarily treats historical sales records as input.

The theoretical framework also includes an outline of our data preprocessing. Sales data itself is also often filled with various problems such as missing values, duplicate records and inconsistencies, all of which can negatively impact the slope in prediction. So, data cleaning and transformation and then normalization techniques are utilized prior to training of machine learning model. These processes are also crucial to improve the quality of the historical data as well as in their forecasting results.

The framework also includes visualization and reporting concepts for visually communicating prediction results in a format that's human-readable. You are exposed to forecasts in various elaborate representations in the form of charts, graphs and rational reports.

IV. METHODOLOGY

The methodology of the Demand Prediction for Computing Devices system describes the sequence of steps followed to collect data, process information, train machine learning models, and generate future demand predictions. The

methodology provides a structured approach for forecasting product demand using historical sales data and analytical techniques. It ensures that the prediction process is systematic, accurate, and reliable for business decision-making.

The first step in the methodology is data collection. Historical sales records of computing devices such as laptops, desktops, tablets, and accessories are collected from available datasets or organizational databases. These records contain important information such as product details, sales quantity, sales date, and demand trends that are required for forecasting analysis.

After data collection, the preprocessing stage is carried out. In this phase, the collected data is cleaned by removing duplicate records, handling missing values, and correcting inconsistencies. Data transformation and normalization techniques are also applied to improve data quality and ensure better performance of the machine learning model.

The next step involves exploratory data analysis. The prepared dataset is analyzed to identify sales patterns, seasonal trends, and relationships between different variables. Graphs and statistical techniques are used to understand customer purchasing behavior and demand fluctuations over time. This analysis helps in selecting the most relevant features for forecasting.

Once the data is prepared, machine learning algorithms are applied for model training. Historical sales data is divided into training and testing datasets. Algorithms such as Linear Regression and Random Forest are trained using the training dataset to learn sales patterns and demand behavior. The trained models are then tested to evaluate their forecasting performance.

After model training, the prediction process is performed. The trained machine learning model analyzes historical sales information and generates future demand predictions for computing devices. The system estimates upcoming product demand based on learned patterns and trends present in the dataset.

V. EXISTING SYSTEM

Current industry and academic demand prediction methods for computing devices include:

1. *Statistical Time Series Models*: ARIMA, SARIMA, and Exponential Smoothing methods are widely deployed in ERP systems. They are interpretable and computationally efficient but assume linearity and stationarity, limiting their effectiveness for volatile technology markets.
2. *Basic Regression Models*: Linear and polynomial regression models incorporating limited features such as price and seasonality flags. These offer simplicity but fail to capture complex feature interactions and non-linear demand drivers.
3. *Single Algorithm ML Models*: Isolated use of Decision Trees or Support Vector Regression (SVR) for demand prediction. While more flexible than statistical methods, these lack the predictive power of ensemble approaches and ignore temporal dependencies.
4. *Rule-Based Business Logic*: Domain experts encode heuristics (e.g., 'demand spikes 30% in Q4') into forecasting systems. These rules become outdated quickly as market dynamics shift and do not generalize across product categories.
5. *Vendor-Specific Tools*: ERP platforms such as SAP IBP and Oracle Demand Management offer built-in forecasting, but these are often black-box solutions with limited customization for computing device-specific dynamics.

VI. PROPOSED SYSTEM

1. *Multi-Source Feature Engineering*: Aggregate historical sales, macroeconomic indicators (GDP, inflation), consumer sentiment scores from social media, product review ratings, search trend indices (e.g., Google Trends), and supply chain lead times as input features.
2. *Ensemble ML Models*: Combine gradient boosting algorithms (XGBoost, LightGBM) with Random Forest using stacked generalization to capture both tabular feature patterns and temporal trends with high accuracy and robustness.
3. *Deep Learning Temporal Models*: Deploy LSTM and Temporal Convolutional Network (TCN) architectures to learn long-range

sequential dependencies in sales time series, especially effective for products with extended demand cycles.

4. *Hybrid AI Framework*: Integrate a statistical pre-processing layer (STL decomposition for trend and seasonality extraction) with ML/DL models for residual learning, combining interpretability with predictive power.
5. *Explainability Module*: Integrate SHAP (SHapley Additive exPlanations) values to provide feature importance insights, enabling supply chain managers to understand which signals drive forecast changes and build trust in AI predictions.
6. *Adaptive Retraining Pipeline*: Implement automated model retraining triggered by detected concept drift, ensuring forecasting accuracy is maintained as market dynamics evolve with new product launches and macroeconomic shifts.

VII. SYSTEM ARCHITECTURE

Architectural design defines the overall structure and organization of the Demand Prediction for Computing Devices system. It describes how different modules communicate with each other and how data flows through the application during forecasting operations. The architecture is designed to provide efficient data management, accurate prediction processing, secure user interaction, and smooth system performance. Proper architectural planning improves scalability, maintainability, and reliability of the application.

The proposed system follows a multi-layered architecture consisting of the Presentation Layer, Application Layer, Machine Learning Layer, and Database Layer. Each layer performs specific functionalities independently and communicates with other layers for processing forecasting operations. This modular architecture helps reduce

system complexity and improves software development and maintenance activities.

[Fig. 1: System Architecture Diagram]

Fig. 1 System Architecture

VIII. SYSTEM MODULES

The system begins by collecting and managing product and sales data through the Product Management and Sales Data Management modules. The collected information is then processed and cleaned by the Data Preprocessing Module before being sent to the Prediction Module. Machine learning algorithms analyze the prepared data and generate future demand forecasts. The results are displayed through the Visualization Module and stored in the database for future reference. Finally, reports are generated to support inventory planning and business decision-making, helping organizations improve forecasting accuracy and operational efficiency.

IX. EVALUATION METRICS

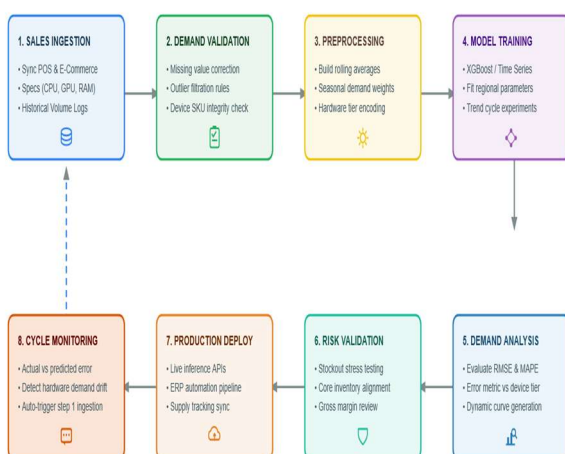
Evaluation metrics are used to measure the performance and accuracy of the machine learning models used in the Demand Prediction for Computing Devices system. These metrics help determine how closely the predicted demand values match the actual sales values. By evaluating model performance, the most suitable forecasting algorithm can be selected for generating reliable demand predictions.

The evaluation process plays an important role in assessing the effectiveness of the forecasting model. It helps identify prediction errors, improve model accuracy, and ensure that the generated forecasts can support inventory planning and business decision-making. Various statistical measures are used to evaluate the prediction results and compare the performance of different machine learning algorithms.

The evaluation metrics also help developers monitor the behavior of machine learning models during training and testing phases. By analyzing different performance indicators, improvements can be made to the forecasting model, resulting in better prediction accuracy and enhanced system reliability.

COMPUTING DEVICES SALES DEMAND ARCHITECTURE

End-to-End Predictive ML Lifecycle & Inventory Sync



Continuous evaluation helps the system adapt to changing sales trends and market conditions.

X. RESULT AND DISCUSSION

The Demand Prediction for Computing Devices system was successfully developed and tested using historical sales data and machine learning techniques. The system effectively analyzed previous sales records and generated future demand predictions for various computing devices such as laptops, desktops, tablets, and related products. The implementation demonstrated that machine learning algorithms can provide accurate forecasting results and assist organizations in making better inventory and sales management decisions.

The developed application successfully integrated all major modules including Login Management, Product Management, Sales Data Management, Demand Prediction, Visualization, Report Generation, and Database Management. Each module functioned as expected and maintained smooth communication with other components of the system. Testing results confirmed that the application operated efficiently without major errors or performance issues.

The prediction module produced forecasting results based on historical sales trends and patterns. Machine learning algorithms were able to identify relationships within the dataset and generate future demand estimates with satisfactory accuracy. The evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared Score (R^2) indicated that the forecasting model performed effectively and generated reliable predictions.

The visualization module provided graphical representations of sales trends and forecasting outputs through charts and analytical dashboards. These visual reports enabled users to understand demand fluctuations and future sales requirements more easily. The graphical presentation of data improved interpretation and supported effective decision-making for inventory planning and business operations.

XI. BENEFITS

One of the major benefits of the system is improved inventory management. By forecasting future demand in advance, organizations can maintain optimal stock levels and avoid situations such as stock shortages or excess inventory. This helps businesses reduce storage costs and ensure that products are available when customers need them.

The system significantly reduces the manual effort involved in analyzing sales data and preparing demand forecasts. Traditional forecasting methods often require extensive calculations and manual analysis, which can be time-consuming and prone to errors. The automated forecasting process saves time and increases productivity by generating predictions quickly and accurately.

Another important benefit is improved decision-making. The forecasting reports and visualizations provide valuable insights into sales trends and customer demand patterns. Managers can use this information to plan purchases, manage inventory, and develop business strategies based on actual data rather than assumptions.

The system also helps organizations reduce operational costs. Accurate demand forecasting prevents unnecessary spending on excess inventory while minimizing losses caused by product shortages. Better inventory control leads to efficient utilization of resources and improved financial performance.

The visualization and reporting features make it easier for users to understand forecasting results. Graphs, charts, and analytical reports present complex data in a simple format, allowing users to identify trends and patterns quickly. This improves the quality of analysis and supports faster business decisions.

Another benefit of the system is data accuracy and reliability. Since the forecasting process is based on machine learning algorithms and historical sales records, prediction results are more consistent and dependable compared to traditional methods. This increases confidence in business planning and inventory management activities.

XII. PRACTICAL CONSIDERATIONS

The successful implementation of the Demand Prediction for Computing Devices system requires careful consideration of various practical factors that influence its performance, usability, and reliability. These considerations help ensure that the system operates efficiently in real-world business environments and delivers accurate forecasting results for inventory planning and decision-making.

One of the most important practical considerations is the availability of quality data. The accuracy of demand predictions depends largely on the historical sales data used for training the machine learning model. Incomplete, inconsistent, or outdated data may affect forecasting performance and reduce prediction reliability. Therefore, organizations must ensure that sales records are maintained accurately and updated regularly.

Another important consideration is data preprocessing and maintenance. Before performing demand forecasting, collected sales data must be cleaned and validated to remove errors, duplicate entries, and missing values. Proper data preparation improves model performance and ensures that prediction results are meaningful and dependable.

System performance is also a key practical consideration. The application should be capable of processing large sales datasets efficiently without causing delays or performance issues. As the volume of data increases over time, the system should maintain stable operation and continue to generate predictions within a reasonable period.

User training and system adoption are essential for successful implementation. Although the application is designed with a user-friendly interface, users should have a basic understanding of forecasting concepts, report interpretation, and system functionalities. Proper training enables users to utilize the system effectively and make informed business decisions based on prediction results.

Security and data protection must also be considered during system deployment. Sales records, forecasting reports, and user information should be stored securely within the database.

XIII. EXPECTED OUTCOMES

production-ready AI/ML demand forecasting pipeline achieving MAPE below 8% on computing device sales datasets..

Demonstrated superiority of the hybrid ensemble model over traditional ARIMA and single-algorithm ML baselines.

An explainable forecasting system that provides actionable feature importance insights for supply chain decision-makers.

Evidence-based guidelines for feature engineering and model selection in consumer electronics demand prediction.

A scalable, adaptive retraining mechanism ensuring sustained forecast accuracy across evolving market conditions.

XIV. CONCLUSION

In This paper , we proposed an AI/ML-based framework for demand prediction of computing devices, addressing the limitations of traditional statistical forecasting approaches. By integrating gradient boosting algorithms, deep learning temporal models, and multi-source feature engineering, the proposed hybrid system captures the complex, non-linear demand dynamics characteristic of the technology product market.

The inclusion of explainability through SHAP values and adaptive retraining pipelines ensures the system remains practical, transparent, and robust in real-world deployment.

As computing device markets continue to evolve with new product categories, chip architectures, and shifting work patterns, AI-driven demand forecasting will play an increasingly critical role in enabling resilient and efficient supply chains.

XV. REFERENCES

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