Time-Series Forecasting of Product Sales Using Intelligence System: Evaluating XGBoost and LSTM Approaches

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***Abstract*—With the digital age, electronic products are one of the top product categories in global e-commerce with sales of over $922.5 billion in 2024. It's important to forecast the sales of electronic products accurately to make the right inventory, marketing, and business decisions. This paper presents a short-term sales forecasting model using historical transaction data of a fictional electronics store from September 2023 to September 2024. The dataset includes product categories, purchase quantities and time variables like date, week and month. After preprocessing and feature engineering methods like lag variables and moving averages, two models—Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM)—were used and compared. Results show XGBoost performed better than LSTM with MAE of 10.93 and R^2 of 0.65, while for LSTM, MAE was 14.39 and R^2 was 0.16. Results show tree-based model works well when structured feature inputs are used for retail short-term demand forecasting.**

Keywords—XGBoost, LSTM, sales forecasting, time series, electronic products

I. Introduction

In the era of digital transformation, electronic products have become the commodity with the highest demand in the global market. Shopify data reports show that electronic product sales reached $922.5 billion globally in 2024, making it the largest transaction category in e-commerce surpassing both fashion and food sectors [1]. This trend highlights the public's growing dependence on electronic devices such as smartphones, laptops, tablets, and other smart equipment in line with the increasing need for digital connectivity. The growth is further fueled by rapid technological advancements across various segments of society. Given this growing demand, the ability to accurately predict electronic product sales becomes increasingly important for industry players.

Sales forecasting models that can handle nonlinear sales trends are crucial to capturing complex demand patterns. The studies emphasize the role of knowledge-based databases and artificial intelligence (AI) in improving the accuracy of such models, especially when considering the nature of consumer behavior [2]. Reliable forecasts help companies make informed decisions in marketing, stock planning, and logistics. For instance, AI techniques have shown strong potential in analyzing and predicting sales trends, particularly in seasonal items, by learning from historical data patterns [3]

In addition to data modeling, it is also important to consider consumer behavior, particularly the influence of shopping patterns. For example, many online shoppers tend to make purchases during the weekend, taking advantage of their free time and the convenience of e-commerce platforms. This shift in behavior reflects a broader trend toward digital consumption of technology products. Reports show that a significant portion of online purchases up to 63% occur on Saturdays and Sundays, highlighting the need to incorporate temporal and seasonal patterns into forecasting models [4].

This research aims to develop a short-term predictive model for electronic product sales, focusing on a one-week forecast horizon. By leveraging time-based features and recent sales history, the model is expected to help improve operational efficiency and contribute to smarter inventory management. A comparative analysis of various techniques will also be conducted to determine the most suitable methods to improve forecasting accuracy [5].

II. Literature Review

A. Sales Forecasting: Concepts and Importance

One of the most important aspects of modern business intelligence is sales prediction [6]. It can be a complex problem, especially if there are missing data, outliers, or no data at all. Sales can be thought of as a time series. The primary disadvantage of using time series methods for sales forecasting is that they require historical data covering a significant period of time in order to capture seasonality. Secondly, sales data may contain a large number of outliers and missing data [7]. Sales forecasting is crucial for deciding on plant schedule and inventory replenishment [8].

B. Time Series Forecasting Techniques

One crucial aspect of forecasting is time series forecasting, which builds a model that describes the underlying relationship by gathering and analyzing historical records of the same variable. The autoregressive integrated moving average (ARIMA) model is one of the most significant and often applied time series models. The primary drawback of ARIMA models is their assumed linear shape, despite the fact that they are highly versatile in that they may represent a variety of time series types, including pure autoregressive (AR), pure moving average (MA), and mixed AR and MA (ARMA) series [9]. Recurrent neural networks (RNNs) and convolutional neural networks (CNNs), two traditional deep neural network models, have been developed and suggested in both recursive and direct multi-step ways. Accuracy, computational efficiency, generalizability, and resilience are evaluated in comparison to the Seasonal ARIMAX model. The gated 24-hour CNN model, which is executed in a direct multi-step fashion, outperforms all other deep learning techniques examined, increasing predicting accuracy by 22.6% when compared to the seasonal ARIMAX [10].

C. Long Short-Term Memory (LSTM) Networks in Time Series Forecasting

Recent studies shows the impact of Long Short-Term Memory (LSTM) networks in time series forecasting, especially because of their capacity to represent nonlinear patterns and long-term dependencies. Kim and Cho define that “LSTM showed superior prediction performance over the traditional time series model” in forecasting based on user-specific behavioral data [11]. Li et al. noted that “the LSTM neural network model has better prediction performance than traditional models and can effectively reflect the nonlinear growth characteristics of the forest” in the context of timber yield prediction [12]. In the agricultural, Yoo and Oh propose a “seasonal long short-term memory (SLSTM), which is a method for predicting the sales of agricultural products,” using calendar-based features such as week and month to enhance accuracy [13].

In retail forecasting, Ensafi et al. describe “a public dataset including the sales history of a retail store is investigated to forecast the sales of furniture” using LSTM among other machine learning models [3]. Lee and Lee integrate LSTM into a smart factory environment, where “the proposed LSTM-based forecasting model enhances decision-making in production processes” by enabling an accurate forecasting for manufacturing operations [14]. Karim et al. report that “the proposed LSTM model outperforms both ARIMA and GRU in terms of forecasting accuracy,” confirming its strength across traffic flow prediction tasks [15]. These studies confirm LSTM’s flexibility across diverse forecasting problems especially when enhanced by seasonal modeling, hybrid architectures or integration into decision-making systems.

D. XGBoost for Sales Prediction

Recent improvements in XGBoost-based sales prediction reveal its high performance across varied datasets. Pavlyshenko define that “using stacking techniques, we can improve the performance of predictive models for sales time series forecasting,” highlighting XGBoost as a strong base learner in ensemble structures [7]. Ensafi et al. demonstrate its application in retail, that “a public dataset including the sales history of a retail store is investigated to forecast the sales of furniture” using multiple machine learning algorithms, with XGBoost being the top performers [3].

Liang et al. present a “Bayesian optimized limit gradient boosting intelligent prediction model to train and predict the ordering data” and conclude that “making full use of machine learning models for prediction has higher accuracy and faster speed comparing to traditional prediction methods” [16]. Massaro et al. show that “the extreme gradient boosting (XGBoost) algorithm was applied in an industrial project as a supervised learning algorithm to predict product sales including promotion condition and a multiparametric analysis,” resulting in “an improvement of the prediction error, which decreases by about an order of magnitude” [17]. These studies validate XGBoost effectiveness in sales forecasting, particularly when combined with techniques like stacking and Bayesian optimization.

E. Comparative Studies Between Deep Learning and Tree-Based Models

Unlike traditional models, LSTM captures temporal dependencies directly, making such preprocessing unnecessary [18]. However, its ability to learn long-term dependencies may be affected by extreme trends or structural shifts. In contrast, XGBoost, a tree-based model, relies on direct feature interactions rather than sequential dependencies [19]. The findings demonstrated that XGBoost consistently outperformed LSTM across all evaluation metrics, achieving an R-squared value of 0.9508 for test data compared to LSTM’s 0.2005 [20].

F. Summary of Gaps and Research Opportunities

The rapid development of Artificial Intelligence (AI) with advanced machine learning algorithms has contributed to short-cycle agricultural product sales forecasting [21]. As for forecasting modeling, XGBoost performs well with structured data due to its unique tree-based structure. However, it often lacks flexibility in addressing time-series forecasting problems like short-cycle agricultural product sales. On the other side, RF captures nonlinear relationships or correlations within the time-series data. The results demonstrate that the combination of RF and XGBoost outperforms the others across the evaluation metrics, indicating superior forecasting capability in this field. Furthermore, the model costs less computational time, an additional advantage in short-term forecasting [22].

Here, there are still certain holes in the intelligence system used for product sales forecasting. First, this paper uses a different model. The Random Forest (RF) and XGBoost models were employed in the earlier study. LSTM and XGBoost will be used in this paper. The product that needs to be predicted comes in second. Sales of agricultural items were forecasted in the earlier study. The purpose of this article is to forecast sales of electronic goods. Therefore, the goal of this study is to close these gaps so that the model's accuracy and efficacy differ from those of the previous paper.

III. Methodology

A. Data Preparation and Preprocessing

The dataset used in this study consists of 20,000 sales transaction records from a fictional electronics company, spanning a one-year period from September 2023 to September 2024. It includes customer demographics, product information, and transactional details such as unit price, quantity, order status, and add-on purchases.

Before modeling, multiple preprocessing steps were performed to ensure data consistency and readiness. First, missing values were addressed, although the dataset was generated to be mostly complete — particularly ensuring that no null values existed in the customer ratings field. The "Purchase Date" field was converted to datetime format and used to generate time-based features such as day, week, month, and day of the week. The dataset was then sorted chronologically to preserve temporal relationships.

Additionally, categorical features such as "Product Type" were encoded using Label Encoding. One-hot encoding was applied to features like "Months" and "Day of the Week" to allow integration into machine learning models. To stabilize the time-series pattern and eliminate noise, data was grouped by date and product type, summing the total quantity sold per combination. Records were then filtered to remove rows that lacked the necessary lag or moving average information.

B. Descriptive and Exploratory Analysis

Exploratory data analysis is the next important step after the data preprocessing stage. Exploratory Data Analysis (EDA) is an important process to understand the structure, patterns, and important relationships of a data set, especially in product analysis. In this stage, visualization and examination of correlations between features are performed, as well as revealing trends that may impact model performance. Researchers using EDA can gather information about consumer behavior and product category performance through statistical summaries (bar charts and plots). This information helps in selecting the right features and helps in developing a robust predictive model. Therefore, EDA serves as a link between data processing and model development, ensuring that the training data is meaningful and contextual.

C. Feature Engineering and Selection

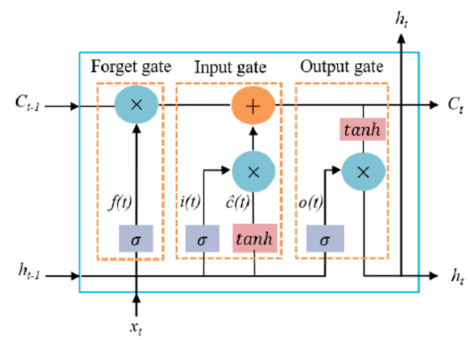
To better capture the temporal dynamics of sales patterns, lag features were generated for the previous seven days (lag_1 to lag_7) for each product type. A 7-day moving average was also included to provide smoothing and trend detection. These lag-based features allow machine learning models to recognize short-term demand trends based on recent sales history.

After encoding and transformation, the final feature set excluded direct identifiers like customer ID or product SKU to avoid overfitting. The selected features for modeling included lag values, moving averages, encoded product types, and time components such as month and weekday. This combination aimed to balance both recent temporal behavior and cyclic patterns (e.g., weekday vs. weekend sales). The target variable for this study was the daily quantity of units sold, and feature importance analysis was later used to validate the relevance of engineered attributes.

D. Model Development

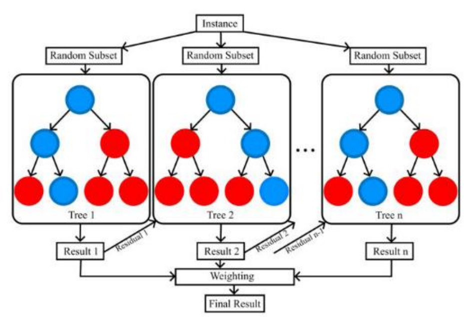
Two models were developed and evaluated: Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM). These models were selected based on their proven relevance and effectiveness in time series forecasting and tabular data modeling.

Figure 1. LSTM Architecture [23]



Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN). It works with sequential data over long stretches [24]. A diagram shows its design. The structure has memory cells and gates. A forget gate, an input gate as well as an output gate are those gates. They control information flow - these parts help LSTMs hold and update pertinent data through time. LSTMs perform well at jobs such as stock price prediction. For that, seeing time patterns matters [23].

Figure 2. XGBoost Architecture [25]



XGBoost (Extreme Gradient Boosting) is a powerful ensemble learning algorithm. It builds multiple decision trees in sequence to improve prediction accuracy. The diagram shows its architecture. Input data is passed through many decision trees. Each tree makes a prediction. These predictions are then averaged to create a final result. XGBoost uses gradient boosting where each tree learns to correct errors made by the previous ones. This method helps it perform well on structured data tasks like classification or regression problems.

For XGBoost, a regression model was implemented using 100 estimators and a learning rate of 0.1. The model was trained using the squared error objective, and performance was assessed on the test set using traditional regression metrics. Feature importance scores were extracted post-training to identify which features most contributed to predictions.

In parallel, an LSTM model was constructed using the same lag-based sequence format. The LSTM was trained on reshaped data, utilizing a two-layer architecture capable of learning sequential dependencies. Although LSTM is known for modeling temporal patterns, its performance in this setting is contingent on sufficient long-term data, which posed a challenge in this one-year dataset.

To simulate future forecasts, the XGBoost model was also used in a rolling prediction setup. Starting with the most recent observed data, forecasts were generated for the next 7 days by recursively feeding predicted values back as new lag inputs.

E. Evaluation and Model Comparison

The performance of both models was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2 Score). These metrics measure both the accuracy and reliability of model predictions.

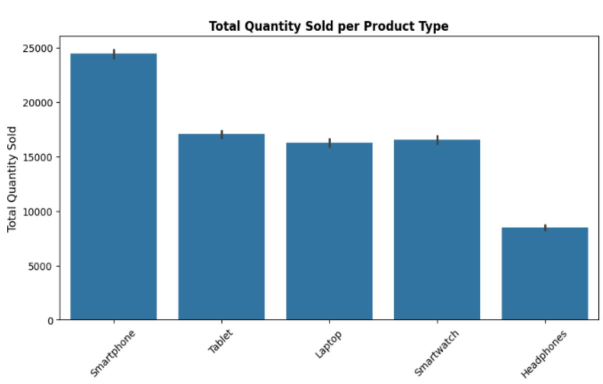
IV. RESULT AND DISCUSSION

A. Explaratory Data Analysis for Product Insight

The exploratory data analysis (EDA) revealed that smartphones consistently dominate total quantity sold across product types, followed by tablets and smartwatches. This trend is clearly visualized in the bar chart and supported numerically in the accompanying sales table, where smartphones reached 24,207 units sold, far exceeding the second-ranking tablets at 16,880.

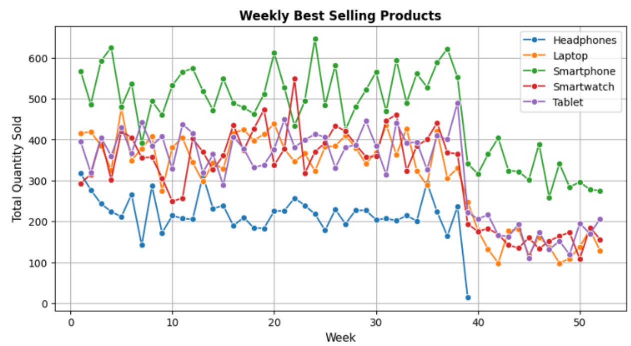
A bar chart visualization is provided to show the total quantity sold per product category to better understand consumer demand and product performance. A clear summary of the sales volume comparisons between many categories, including smartphones, tablets, laptops, smartwatches, and headphones, is given by this graphical representation. It is simpler to determine which products are most popular with customers and to get insights that aid in strategic decision making and sales planning.

Figure 3. Bar Chart Visualization



This line chart shows weekly sales of different product types throughout the year so you can see how products perform over time. Each line is a different product category - tablets, smartphones, laptops, smartwatches, headphones - and shows how each sold over a 52 week period. It's clear that some weeks smartphones sold the most. Others - tablets and headphones - had more gentle and steady trends. This temporal chart gives you insight into demand fluctuations, seasonality and promo effects.

Figure 4. Line Chart Visualization



B. Prediction Models

The figure 3 and figure 4 aligns closely with the results of the predictive modeling. The XGBoost model, which excelled in capturing temporal sales patterns through engineered features, accurately prioritized smartphones as the top-selling category. This observation reinforces that EDA, while primarily descriptive, plays a supportive role in predictive modeling, at least when it captures consistent behavioral patterns in the data.

These results demonstrate the advantage of XGBoost in handling tabular, engineered features derived from time-series data. The LSTM, while suited for sequence data, may require longer time spans and more granular input structures to reach competitive performance. A comparison of the two models is summarized on Table 1.

Table 1. Models Evaluation Result

Model	MAE	RMSE	R^2 Score
XGBoost	10.93	14.17	0.65
LSTM	14.39	17.16	0.16

According to the metrics, XGBoost is the best model. XGBoost has a MAE of 10.93, RMSE of 14.17 and the highest R^2 of 0.65. This means XGBoost is fairly accurate with a moderate error rate and is suitable for structured, tabular time-series forecasting. The second model, LSTM, has a MAE of 14.39, RMSE of 17.16 and a much lower R^2 of 0.16.

LSTM is designed to model sequential dependencies in time-series data but in this case it seems it needs a larger dataset or more granular temporal resolution to compete with XGBoost in forecasting aggregated sales.

The metric differences between the two models show that XGBoost is better at capturing short-term temporal trends and product-based seasonality especially when engineered features like lags and rolling averages are used. This is consistent with the earlier EDA findings where smartphones were the top selling product type and XGBoost was able to retain this trend in its output. Although both models are meaningful, XGBoost is more practical and better performing so it's the better choice for forecasting in structured retail datasets. Furthermore, a previous study by Champahom et al. supports this finding by demonstrating that XGBoost outperforms LSTM in forecasting tasks [20].

V. Conclusion

The exploratory data analysis (EDA) shows that smartphones are the clear winner across all product types, with tablets and smartwatches trailing behind. This is evident in the bar chart and further supported by the sales table which shows 24,207 smartphones sold vs 16,880 tablets. Clearly there is strong and consistent demand for smartphones as they are at the heart of daily communication, entertainment and productivity. The gap in sales volume means that forecasting models should weight smartphone trends more heavily as small errors in this category will have a bigger impact on business outcomes than lower selling products. These insights not only validate the importance of product specific forecasting but also help to align marketing and inventory strategies with consumer behaviour. So the EDA phase plays a key role in informing the feature engineering process and guiding model evaluation so the forecasting model stays grounded in real world sales.

For future work, we can add external factors like seasonality, promotions and social media sentiment which have a big impact on demand. We can also add inventory and logistics data to get a more complete view of the supply chain and more accurate and actionable forecasts. We can also explore the performance of deep learning models like LSTM against traditional time series models like ARIMA or even hybrid models that combine both. We can also segment customers based on demographics or purchase behavior to get more granularity and more personalized forecasts. And we can test the robustness of these models under sudden market shocks like economic downturns or major product launches.

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