ESP-JETA
ESP Journal of Engineering & Technology Advancements
ISSN: 2583-2646 / Volume 4 Issue 3 September 2024 / Page No: 189-199
Paper Id: JETA-V4I3P120 / Doi: 10.56472/25832646/JETA-V4I3P120

*Original Article*

# Leveraging ML for Business Forecasting in ERP-Enabled E-commerce Environments

**Anirudh Parupalli[1], Honie Kali[2]**
*[1,2] Independent Researcher*

Received Date: 28 July 2024 Revised Date: 02 September 2024 Accepted Date: 27 September 2024

***Abstract:*** *E-commerce platforms depend more and more on enterprise resource planning (ERP) tools to enhance decision-making and expedite processes. Accurate business forecasting in such ERP-enabled environments is critical for demand prediction and optimized inventory management. This paper presents a robust machine learning framework for business forecasting using the Brazilian Olist e-commerce dataset. The methodology incorporates comprehensive data preprocessing merging relational tables, removing irrelevant attributes, handling missing values, encoding categorical variables, min–max normalization, and temporal feature extraction related to delivery. Domain-specific feature engineering generates delivery accuracy metrics, product rating statistics. Class imbalance is addressed via SMOTE, and a stratified split is used for training and testing. Among four evaluated models Cat Boost, Convolutional neural network (CNN), Decision Tree, and K-Nearest Neighbors the Cat Boost classifier achieved superior accuracy of 97.62%, outperforming CNN (91.7%), Decision Tree (87.2%), and K-Nearest Neighbors (75%). These results demonstrate Cat Boost's strength in modelling heterogeneous data and complex feature interactions, confirming its scalability and practical effectiveness for accurate forecasting in dynamic ERP-integrated e-commerce platforms.*

***Keywords:*** *E-commerce, Enterprise Resource Planning (ERP), Business Forecasting, Cat Boost, Machine Learning.*

## I. INTRODUCTION

The rapid growth of global retail e-commerce has fundamentally changed the environment by offering businesses with access to a variety of marketplaces and allowing customers to browse and buy a huge selection of goods and services without being limited by geography [1][2]. As online transactions continue to surge, the amount of data produced by customer interactions has increased dramatically, posing both formidable potential and intricate difficulties for companies looking to comprehend, anticipate, and address changing consumer demands [3]. E-commerce, which encompasses a range of consumer-business interactions, digital payments, and online transactions, is using the Internet to purchase and sell products and services [4][5]. With purchasing habits shifting from conventional physical shopfronts to digital platforms, online product discovery has become a vital source of revenue [6][7][8]. While early online shopping heavily relied on general web search engines, recent trends indicate the increasing dominance of specialized e-commerce search engines and recommendation systems as the primary gateways to product exploration and purchasing decisions. These systems aim to replicate in-store experiences by aligning search results and product suggestions with customer intent, whether exploratory or goal-oriented [9].

Systems for enterprise resource planning (ERP) have emerged as a crucial component of contemporary corporate management [10][11], providing a single platform for managing and integrating key operations, including Supply chain, finance, human resources, and customer relationship management. By consolidating organizational data, ERP systems streamline workflows, improve coordination, and enhance operational efficiency [12][13][14]. However, traditional ERP solutions face limitations in dynamic and highly competitive business environments due to their dependence on static processes, extensive manual configuration, and limited adaptability to rapidly changing market conditions [15][16]. These restrictions frequently make it more difficult for e-commerce to react swiftly to changes in customer demand, interruptions in the supply chain, and new market possibilities [17][18].

Machine learning (ML) techniques to enhance business forecasting in ERP-enabled e-commerce environments. By integrating structured transactional data and unstructured customer feedback, AI-driven models such as Cat Boost, Convolutional neural network, Decision Tree, and K-Nearest Neighbors analyze complex patterns and relationships that traditional methods [19]. ML addresses this gap by transforming ERP systems from reactive record-keeping platforms into proactive forecasting engines. By leveraging both structured data, such as sales histories, transaction records, and inventory levels and unstructured data, such as customer reviews and search patterns, ML models can capture complex, non-linear patterns that traditional forecasting techniques overlook [20][21]. When applied in ERP-enabled e-commerce environments, ML enables more accurate demand predictions, dynamic inventory adjustments, and data-driven marketing strategies.

Moreover, techniques such as advanced feature engineering, natural language processing, and ensemble learning enhance model robustness against seasonal fluctuations, promotional events, and external market shifts.

### A. Motivation with Contribution

The fast growth of e-commerce has created a critical need for accurate business forecasting to support operational decision-making in ERP-enabled environments. Large-scale transactional data can exhibit complicated, non-linear patterns that are difficult for traditional statistical methods to describe, behavioral, and operational datasets, resulting in inefficiencies in demand planning, inventory control, and customer engagement. Using machine learning methods in conjunction with domain-specific feature engineering and thorough data preprocessing offers the potential to extract actionable insights from heterogeneous data sources. Furthermore, addressing challenges such as class imbalance, mixed data types, and integration of structured and unstructured features is essential for delivering reliable and scalable forecasting solutions that can be seamlessly incorporated into ERP systems. The main contributions of ERP enable E-commerce environment are as follows:

- A comprehensive and reproducible ML-based forecasting framework tailored for ERP-supported e-commerce systems, integrating heterogeneous data sources into a unified pipeline.
- Utilized the publicly available Brazilian Olist e-commerce dataset, encompassing transactional, product, customer, delivery, and review data, to ensure transparency and replicability of results.
- Applied min–max normalization and one-hot encoding within a structured Column Transformer to efficiently handle heterogeneous numerical and categorical features, ensuring consistent scaling and representation. Class imbalance was mitigated using SMOTE on the training set.
- Conducted an extensive comparative analysis of Cat Boost against established classifiers (CNN, Decision Tree, and KNN), exhibiting exceptional performance as measured by recall, accuracy, precision, and F1-score.
- A reproducible end-to-end pipeline, enabling seamless integration into ERP-supported e-commerce platforms and adaptable to diverse retail forecasting contexts.

### B. Significance and Novelty

This study is significant as it presents a robust, scalable, and data-driven ML framework specifically designed for business forecasting in ERP-enabled e-commerce environments, a critical requirement for optimizing demand planning, inventory management, and customer engagement. The integration of an end-to-end pipeline that incorporates efficient data preparation is what makes it innovative, heterogeneous feature handling through a structured Column Transformer, class imbalance mitigation using SMOTE, and comprehensive evaluation of multiple classifiers on the Brazilian Olist e-commerce dataset. Unlike many studies that rely solely on numerical sales data or a single predictive model, this work incorporates domain-specific engineered features such as delivery accuracy, RFM metrics, and product rating statistics, to capture both quantitative and qualitative business factors. The comparative analysis demonstrates the Cat Boost model's higher performance while offering CNN, Decision Tree, and K-Nearest Neighbors benchmark results, guaranteeing useful flexibility for ERP-integrated systems in the real world. The inclusion of exploratory data analysis further enhances the framework by uncovering actionable insights into sales patterns and customer behavior, addressing the need for robust and adaptable forecasting solutions in dynamic online retail environments.

### C. Structure of Paper

The following structure of the paper: Section II provides the literature review of ERP enabling e-commerce using ML, Section III discusses the proposed methodology with each phase of this system design, Section IV evaluates the results of proposed models, comparison, discussion, and last Section V provides the conclusion of this work with future work.

## II. LITERATURE REVIEW

This section discusses the literature review on ERP enabling e e-commerce environment using machine learning for business forecasting. Table I provides a summary of the literature reviews discussed below:

Madhav et al. (2023) ERP, or enterprise resource planning, refers to systems that combine predictive analytics and ML, which are essential to modern companies, to improve sales projections using publicly accessible sales data. Z-score normalization and feature selection are used in preprocessing to provide consistent, high-quality data that is prepared for analysis. With a 99.34% R2 score, an 11.64 MAE, and an RMSE of 13.57, the SVM LSTM model outperforms other models, indicating its ability to assess a variety of trends and patterns in the sales data set. The existence of significant bias and noisy signals during the volatile period, affects the algorithm's performance when other inputs are added to the program, such as holidays, promotions, and economic signals. The LSTM model exhibits strong correlation throughout the extended durations of the time series [22].

Azad (2023) e-commerce sector, such as end users' purchase intentions, top management needs to know precisely that E-commerce owners find it challenging to completely comprehend black-box output because of distorted training data, incorrect input, and unforeseen biases picked up during system creation, even for the developers. The black-box system decided to display no willingness to purchase for a specific client using training data. Explainable artificial intelligence is becoming more concerned with elucidating the categorization methods and processes that underlie the ultimate predictions and feature recommendations resulting from GDPR data regulation [23].

***Table 1 : Comparative Analysis of Recent Studies on Machine Learning-Driven Forecasting In ERP-Supported E-Commerce Systems***

| Author & Year | Dataset | Methodology | Key Findings | Advantages | Limitations | Future Work |
|---|---|---|---|---|---|---|
| Madhav et al. (2023) | Public sales dataset | Z-score normalization, feature selection, LSTM, SVM | LSTM achieved $R^2$ = 99.34%, MAE = 11.64, RMSE = 13.57; strong ability to detect long-term trends | High predictive accuracy; effective handling of time series trends | Performance drops in volatile periods due to bias and noise | Include more contextual features (holidays, promotions, economic indicators) to improve stability |
| Azad (2023) | E-commerce transaction data | Black-box ML system analysis; focus on explainable AI (XAI) under GDPR | Highlights difficulty in understanding black-box predictions due to biased/skewed training data | Addresses GDPR compliance and transparency | Lack of interpretability in black-box models; susceptible to input errors and biases | Develop interpretable ML frameworks with clear feature–decision links |
| Wangkiat & Polprasert (2023) | Olist dataset | Feature engineering (delivery duration, avg. product rating), Random Forest, Logistic Regression | RF achieved best recall: 0.43 (Low), 0.33 (Average/Good); key features: mean & SD of product rating | Identifies main drivers of satisfaction; uses explainable features | Limited recall performance; classification accuracy not reported | Improve recall with hybrid/ensemble models; consider more behavioural features |
| Petroșanu et al. (2022) | Olist dataset | Prediction based on categories with a Directed Acyclic Graph Neural Network (DAGNN) | $R^2$ = 0.94; low RMSE; scalable and adaptable forecasting | Strong generalization across categories; efficient processing | Complex model architecture; higher computational demand | Apply to other e-commerce datasets; integrate external economic/seasonal data |
| Diamantaras et al. (2021) | Web server log data | LSTM for real-time shopping intent prediction | Achieved 98% accuracy in classifying browsing, cart abandonment, and purch ase | Real-time prediction; enhances personalization and conversion | Dependent on quality of log data; may not adapt to sudden user behaviour shifts | Incorporate cross-session behaviour; extend to multi-platform analysis |
| Kulshrestha & Saini (2020) | Olist dataset | ML-based sales forecasting | Achieved 96.3% accuracy; outperformed traditional forecasting | Supports ERP-enabled decision-making; robust performance | Accuracy may vary with seasonality and market changes | Integrate with automated ERP workflows; enhance adaptability to market shifts |

Wangkiat and Polprasert (2023) ML to forecast the customer happiness rating based on the sales data gathered by the Brazilian online retailer Olist. Customer satisfaction scores are divided into four categories: provide a feature engineering technique that generates the average product assessment score and delivery length, which are the main attributes of the ML model. One of the main elements influencing a customer's happiness rating is low product ratings based on previous purchases. Logistic Regression (LR) and Random Forest (RF). Furthermore, for the Low, Average, and Good classes, RF attains the highest recall of 0.43, 0.33, and 0.33, respectively. The two features having the highest feature relevance are the product rating's mean and SD, which are 0.313 and 0.087, respectively [24].

Petroșanu et al. (2022) propose, dynamic forecasting method based on a DL architecture called a Directed Acyclic Graph Neural Network (DAGNN). The model is intended to give owners of e-commerce sites a scalable and extremely accurate forecasting tool that can anticipate sales of goods by category up to three months ahead of time. Leveraging a dynamically incremental construction of the DAGNN architecture, the proposed method ensures strong generalization capabilities and adaptability across different business contexts. The Olist dataset, which is freely accessible on Kaggle, was used to train and assess the model, which contains detailed transaction and product category data. Experimental results demonstrate that the method achieves high forecasting accuracy, with an $R^2$ score of 0.94 and low RMSE values, while maintaining efficient processing times [25].

Diamantaras et al. (2021) an LSTM-based model to leverage web server log data to forecast e-commerce customers' purchasing intent in real-time. Sessions were categorized as browsing, cart abandonment, or purchase. The model achieved 98% accuracy, outperforming traditional methods. These forecasts improve conversion rates in ERP-integrated e-commerce platforms by enabling proactive incentives and personalized experiences [26].

Kulshrestha and Saini (2020) Prediction of business growth remains a critical aspect of the e-commerce market, where online vendors rely on intelligent forecasting to manage their inventories and meet customer demand effectively. Traditional forecasting methods often fall short in delivering reliable and accurate sales predictions, limiting their utility in fast-paced ERP-enabled environments. The Olist dataset from Kaggle, which contains comprehensive transactional data, is the real-world e-commerce dataset to which ML techniques are used in this study. The proposed ML-based forecasting model achieved an accuracy of 96.3%, significantly outperforming traditional methods. This enhanced predictive capability enables business organizations to make data-driven choices and maximize sales and supply chain tactics [27].

Recent studies have demonstrated that integrating machine learning into ERP-enabled e-commerce platforms can significantly enhance business forecasting accuracy. Combining sophisticated models like LSTM with preprocessing methods like Z-score normalization and feature selection has achieved exceptionally high predictive performance, with strong capabilities in capturing long-term trends in sales data. However, performance degradation in volatile periods highlights the necessity of include extra contextual factors like advertising, vacations, and economic indicators. The issue of interpretability in complex black-box models has also been emphasized, particularly in light of data regulations, driving the adoption of explainable AI techniques to address biases and improve transparency. Feature engineering approaches, including the derivation of delivery duration and product rating metrics, have been shown to improve customer satisfaction prediction, while deep learning architectures Sales projections by category are scalable and very accurate thanks to technologies like Directed Acyclic Graph Neural Networks. Real-time intent prediction using sequential models on web interaction data has enabled personalized engagement strategies, and machine learning–driven forecasting applied to large-scale transactional datasets has consistently outperformed traditional methods, supporting data-driven inventory optimization and supply chain management in fast-paced e-commerce environments.

## III. METHODOLOGY

The approach, shown in Figure 1, builds a machine learning framework for improved forecasting in ERP-supported online retail contexts using the Brazilian Olist e-commerce dataset. The process begins with consolidating multiple raw data tables, removing irrelevant identifiers, handling missing values through deletion or imputation, and encoding categorical variables using one-hot encoding. Datetime fields are parsed to extract delivery-related metrics such as shipping duration and delivery accuracy. Feature engineering then generates RFM measures, product rating statistics, and numerical variables, which are scaled via min–max normalization to ensure uniform feature ranges. SMOTE is used to resolve class imbalance on the training set. In order to enable robust model assessment, the dataset is stratified into training and testing groups. The efficiency of the main prediction model, a Cat Boost classifier, is evaluated using a variety of methods, including K-Nearest Neighbors, CNN, and Decision Tree. The completed pipeline is saved for potential future usage and ERP system connectivity when the most effective approach has been identified by computing evaluation criteria such as F1-score, recall, accuracy, and precision.

**A. Data Collection**

The Brazilian e-commerce site Olist Shops contributes the data for this study to Kaggle. It encompasses information from around 100,000 transactions conducted between 2016 and 2018, facilitating an in-depth review of various elements such as order progress, payment methods, shipping efficiency, pricing strategies, customer demographics, product details, and feedback. Additionally, a geocoding dataset maps Brazilian postal codes to their geographic coordinates. Orders may consist of multiple products, each potentially fulfilled by different sources. Some of the visualizations are given below:

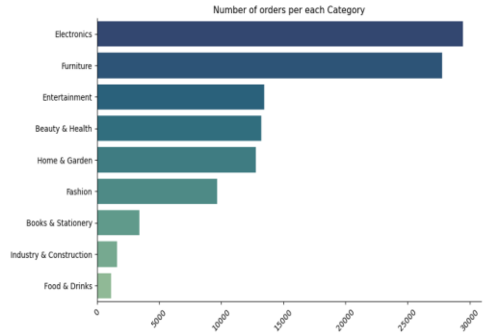


***Figure 1 : Number of Orders Per Category***

This horizontal bar chart illustrates order volume distribution across product categories in an e-commerce environment in Figure 1. Electronics and Furniture demonstrate the highest transaction frequencies, followed by Entertainment, Beauty & Health, and Home & Garden categories with moderate volumes. Fashion, Books & Stationery, Industry & Construction, and Food & Drinks exhibit lower order densities, providing insights for demand forecasting and inventory management optimization strategies.

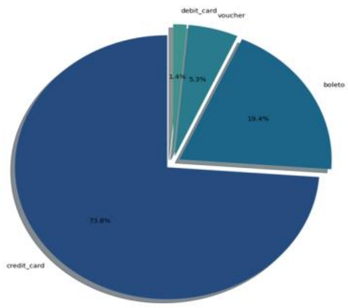


***Figure 2: Payment Type***

This pie chart presents payment method distribution in an e-commerce transaction dataset in Figure 2. Credit card payments dominate with 74.8% market share, followed by boleto payments at 19.4%. Debit card and voucher methods represent smaller segments at 4.1% and 1.7% respectively. The visualization demonstrates clear consumer preference hierarchies for digital payment gateway optimization and financial analytics implementation.

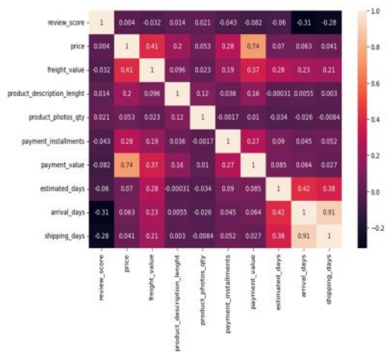


***Figure 3: Relation Pattern of Column***

This correlation matrix heatmap analyzes feature relationships in an e-commerce dataset using Pearson correlation coefficients in Figure 3. The visualization employs a colour gradient from dark blue (-1.0) to white (0.0) to red (+1.0) to represent correlation strengths. Notable strong positive correlations include arrival days and shipping days (0.91), while review score shows negative correlations with freight value (-0.32) and estimated days (-0.31). This analysis facilitates feature selection and multicollinearity detection for predictive modelling applications.

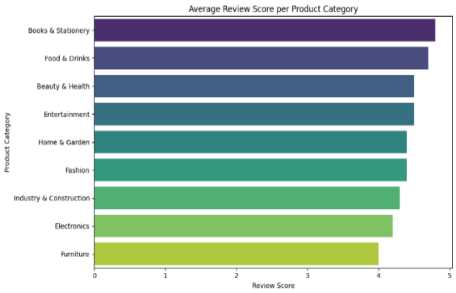


***Figure 4 : Average Review Score Per Product Category***

The average review scores for each product category on an e-commerce platform are displayed in this horizontal bar chart in Figure 4. The categories of food and drink and beauty and health have the greatest customer satisfaction ratings, followed by books and stationery. Entertainment, Home & Garden, Fashion, and Industry & Construction demonstrate moderate performance levels. Electronics and Furniture exhibit the lowest average review scores, indicating potential quality or service improvement opportunities for customer experience optimization strategies.

### B. Data Preprocessing

Data preprocessing involved e-commerce dataset, removing irrelevant columns, and handling missing values through deletion or imputation. Features were separated into numerical, categorical, and textual types, followed by one-hot encoding for categorical data, normalization for numerical data, and product ratings were created, while SMOTE was applied to address class imbalance. Finally, to ensure clean and balanced input for training, an 80:20 stratified split was used to divide the dataset into sets for testing and training. Key steps in data preprocessing include:

- Missing value: Missing values happen when a variable in a particular observation has no data recorded for it, which can distort analysis and model performance imputing values using statistical methods like mean.
- One hot encoding: A categorical variable's categories are individually transformed into distinct binary columns using one-hot encoding, allowing machine learning algorithms to process non-numeric data without implying any ordinal relationship between categories.
- Dropping Irrelevant Columns: Dropping irrelevant columns involves removing fields like IDs, redundant attributes, or metadata that do not contribute to model learning, which helps reduce noise, memory usage, and processing time.
- Datetime parsing & delivery features: Datetime parsing & delivery features refer to transforming raw date strings into datetime objects and deriving useful time-based metrics such as shipping duration, delivery delays, or seasonal patterns to improve predictive power.

### C. Feature Engineering

The effectiveness of ML models, the features analyzed to extract additional information and produce new features. Feature engineering entails converting raw data to adapt the data into formats suitable for machine learning algorithms [28]. This essential step can enhance modelling accuracy and result in improved outcomes. In the online retail industry, this included deriving delivery-related characteristics like shipment duration and delivery accuracy (the discrepancy between the predicted and actual delivery date), as well as RFM features (Recency, Frequency, Monetary) to capture customer purchasing behavior. The timeliness of delivery significantly affects customer satisfaction. A new metric, termed delivery accuracy, evaluates the difference between the actual and expected delivery dates.

### D. Feature Scaling with Normalization

Feature scaling is the process of transforming numerical features so they share a common scale, avoiding the dominance of characteristics with wider ranges in model training techniques such as Normalization scaling values between 0 and 1. Ensure that distance-based algorithms like Cat Boost scaling can also improve convergence speed in optimization and reduce bias toward high-magnitude features.

The Min Max Normalization formula is Equation (1).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

Where x = is the initial value, $x_{min}$ and $x_{max}$ are the feature's minimum and maximum values, respectively, and $x'$ is the normalised value in the interval [0,1].

### E. Class imbalance using Synthetic Minority Over-sampling Technique(SMOTE)

The e-commerce dataset's target variable was unbalanced, with noticeably fewer samples in some classes, hence SMOTE was used to address class imbalance. The thesis addressed this by using SMOTE within the ML pipeline to generate artificial samples created by interpolating between the minority classes' closest neighbors [29]. This balanced the dataset, improved model learning for underrepresented classes, and helped achieve better recall and overall performance compared to using the raw imbalanced data.

### F. Data Splitting

In order to splitting a dataset into several subsets, often training and testing sets, allows to assess how well a model performs on unknown data. Stratified sampling was used in the thesis to divide the data in an 80:20 ratio while maintaining the intended class distribution in both sets, guaranteeing an impartial and trustworthy performance evaluation.

### G. Classification Equation of Cat Boost Model in E Commerce Environment

The terms "boosting" and "categorical" are the history behind the moniker "CatBoost." This popular open-source ML method was created by Yandex using R and Python. The main learners in the Gradient-Boosting Decision Tree (GBDT) system CatBoost are symmetric decision trees. Because it has a high accuracy rate, supports class variables, and has fewer parameters, it is ideal for processing class-type data efficiently and fairly. Additionally. It reduces the likelihood of overfitting by mitigating gradient bias and prediction shift [30]. The label means are also employed as the node splitting criterion for the decision tree and are sometimes known as greedy target variable statistics the following is:

$$\hat{x}_k^i = \frac{\sum_{j=1}^{p-1}[x_{j,k}=x_{i,k}]\cdot y_i}{\sum_{j=1}^{n}[x_{j,k}=x_{i,k}]} \tag{2}$$

This approach's clear flaw is that, in Equation (2), features generally provide more information than labels. To avoid conditional bias, which may arise if the distributions and data structures of the training and test datasets change, the average of the labels must accurately reflect the features. A priori distribution parameters are often used to reduce the impact of noise and low-frequency category-type data on the data distribution in order to enhance greedy TS (target-based statistics). The following is the Equation (3) for this enhancement:

$$\hat{x}_k^i = \frac{\sum_{j=1}^{p-1}\left[x_{\delta_{j,k}}=x_{\delta_{p,k}}\right]\cdot y_i + a.p}{\sum_{j=1}^{p-1}\left[x_{\delta_{j,k}}=x_{\delta_{p,k}}\right]+a} \tag{3}$$

where $a$ typically indicates a greater weight coefficient than 0 in Equation (3), and $p$ $is$ the additional previous component. The prior probability of affirmative cases is the prior term in classification issues. To further enhance the model's expressiveness, the algorithm dynamically adds category characteristics to new features in a simultaneous and incremental manner. The Cat Boost method could be able to extract more information to completely enhance the model expression since the vast bulk of the dataset on blueberry ecological appropriateness is categorized.

### H. Performance Matrix

The confusion matrix of the suggested model in Figure 5 supplied the F1-score, recall, accuracy, and precision that were utilized to evaluate performance. False Positives (FP) and False Negatives (FN) show inaccurate classifications, whereas True Positives (TP) and True Negatives (TN) show accurate predictions. The model's capacity to predict demand in ERP-enabled e-commerce is evaluated using these measures.

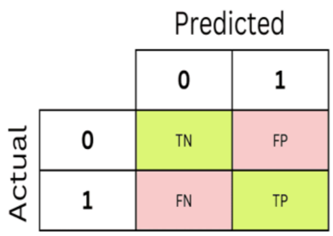


***Figure 5 : Confusion Matrix***

*a) Accuracy*

Accuracy is a metric that counts how many accurate predictions were produced in the dataset out of all the input values. Precision refers to the classifier's accuracy in the following Equation (4).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{4}$$

*b) Precision*

This measure indicates the number of the projected favorable circumstances turn out positive, indicating the model's accuracy in positive predictions is described in below Equation (5):

$$Precision = \frac{TP}{TP+FR} \times 100 \qquad (5)$$

*c) Recall*

This measure captures how well the model identifies all actual positive cases, highlighting its effectiveness in detecting positivesare described in Equation (6):

$$Recall = \frac{TP}{TP+FN} \times 100 \qquad (6)$$

*d) F1 Score*

This metric balances precision and recall by computing the harmonics they imply, giving an exhaustive evaluation of the model's functionality, taking into account both positive and negative prediction errors, are described in Equation (7):

$$F1 - score = \frac{2 \times recall \times precision}{recall + precision} \qquad (7)$$

*e) ROC Curve*

The efficiency of the suggested models are evaluated using the area under the curve (AUC) and the receiver operating characteristic (ROC) curve. A classification model's accuracy across all classification thresholds is represented graphically by the ROC curve. The true positive rate (R) and false positive rate (R) are used to display this curve.

## IV. RESULTS AND DISCUSSION

This section presents the experimental result analysis for business forecasting in ERP-enabled e-commerce settings using the Brazilian Olist e-commerce dataset, assessing model performance with significant measures such as the F1-score for classification tests, recall, accuracy, and precision. Programming using Python and its required libraries, such as scikit-learn, Cat Boost, pandas, NumPy, and seaborn, and matplotlib, the implementation was completed in a Jupiter Notebook environment on Google Colab. The experiments were executed on a computational setup capable of efficiently handling the training of ensemble classifiers. In addition to the recommended Cat Boost model, the analysis compares the performance of three other models: K-Nearest Neighbors, CNN, and Decision Tree. The following results provide detailed insights into the forecasting performance, supporting the efficiency of the suggested method for ERP integration enables accurate and scalable decision-making in e-commerce systems.

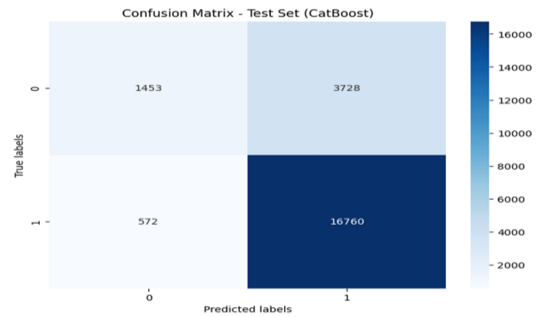


***Figure 6 : Confusion Matrix of Cat Boost Classifier***

This confusion matrix from a Cat Boost model demonstrates robust binary classification performance for predictive analytics in integrated enterprise commerce platforms in Figure 6. The algorithm achieved strong accuracy with 16,760 TP and 1,453 TN, while minimizing errors at 572 FN and 3,728 FP. This validates the model's effectiveness for automated demand forecasting, inventory optimization, and data-driven decision support in digital business ecosystems.

***Table 2 : Proposed Models Performance on ERP Enable E-Commerce on Brazilian Olist E- Commerce Dataset***

| Measure | Cat Boost |
|---|---|
| Accuracy | 97.62 |
| Precision | 97.32 |
| Recall | 98.66 |
| F1-score | 96.78 |

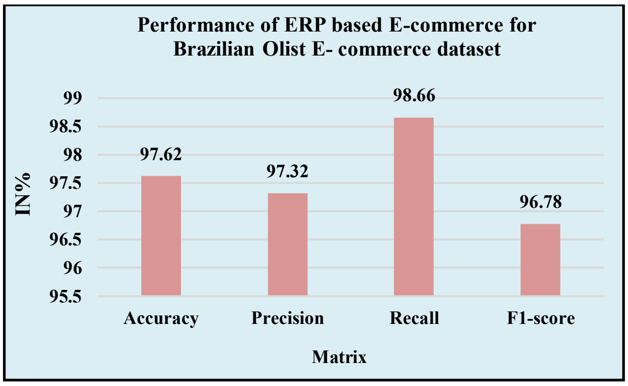


*Figure 7: Comparison of Model Performance Metrics*

Table II and Figure 7 present the Brazilian Olist e-commerce dataset to assess the effectiveness of the recommended Cat Boost classifier for business forecasting in ERP-enabled e-commerce. The model's results were 97.62% accuracy, 97.32% precision, 98.66% recall, and 96.78% F1-score. These results demonstrate that Cat Boost delivers high predictive accuracy while effectively capturing relevant patterns in the data, ensuring a strong balance between correctly identifying target outcomes and minimizing false predictions. Such performance confirms its suitability as a robust and reliable forecasting model within ERP-integrated e-commerce environments.

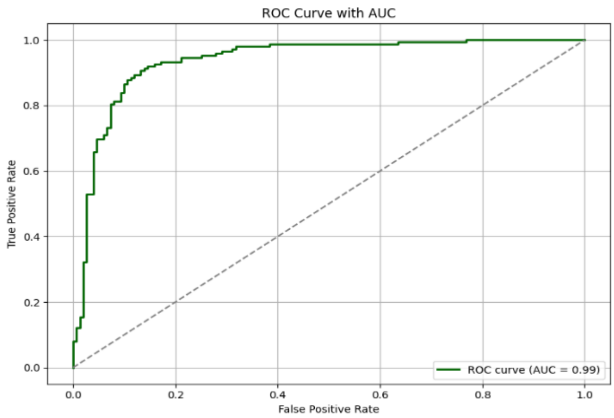


*Figure 8 : Roc Curve of Proposed Model*

This ROC curve demonstrates exceptional model performance with an AUC of 0.99, indicating near-perfect classification capability for enterprise analytics applications in Figure 8. This outstanding discriminatory power validates the machine learning model's reliability for automated business intelligence, risk assessment, and predictive decision-making in data-driven commercial environments.

The proposed approach leveraging machine learning models, particularly Cat Boost, offers significant advantages in delivering high-accuracy business forecasting within ERP-enabled e-commerce environments. Its ability to effectively balance prediction precision and recall ensures reliable demand estimation, optimized inventory management, and enhanced customer satisfaction, which are critical for competitive online retail operations. Compared to traditional models like KNN and Decision Trees, ensemble models such as Cat Boost and CNN demonstrate superior performance through their robust handling of class imbalance, complex feature interactions, and diverse consumer behavior patterns. This robustness is evidenced by Cat Boost achieving the highest accuracy of 97.62% on the Brazilian Olist dataset, significantly outperforming alternative approaches. This study is innovative in that it utilizes specific performance measures to compare and evaluate several well-tuned models, thereby selecting the most effective forecasting technique. Additionally, integrating these models into an end-to-end pipeline emphasizes scalability and real-world applicability, addressing challenges such as heterogeneous data processing, imbalanced classes, and dynamic demand shifts. This research not only confirms the efficacy of ensemble methods but also highlights the practical impact of deploying such advanced ML frameworks to enhance ERP-supported e-commerce forecasting with higher trust, adaptability, and operational efficiency.

**A. Discussion**

The comparative analysis for business forecasting in ERP-enabled e-commerce environments, as presented in Table III, highlights the accuracy-based performance of four distinct machine learning models. With an accuracy of 97.62%, Cat Boost outperformed the others, showcasing its exceptional ability to handle diverse data and intricate feature interactions. CNN and Decision Tree followed with accuracies of 91.7% and 87.2% respectively, showing moderate predictive strength, while K-Nearest Neighbors recorded the lowest accuracy at 75%, indicating its limited suitability for this forecasting task. These results clearly show that tree-based ensemble methods, particularly Cat Boost, outperform other approaches for structured e-commerce data, because of their resilience, adaptability, and effectiveness in managing diverse feature types within ERP-integrated forecasting systems.

***Table 3 : Comparison between All Proposed Model and Existing Models for E Commerce Environment Using Machine Learning***

| Measure | Accuracy |
|---|---|
| Cat Boost | 97.62 |
| CNN[31] | 91.7 |
| Decision tree[32] | 87.2 |
| KNN[33] | 75 |

The proposed ensemble of four machine learning models demonstrates strong performance in business forecasting for ERP-enabled e-commerce environments, with the Cat Boost classifier achieving the highest accuracy of 97.62%, followed by CNN at 91.7% , Decision Tree at 87.2%, and KNN at 75%. By leveraging diverse algorithmic approaches, including tree-based ensemble methods and instance-based learning, the models effectively capture complex patterns in sales, delivery, and customer behaviour data to enable precise demand prediction and inventory optimization. The superior performance of tree-based ensemble methods highlights their effectiveness in handling heterogeneous e-commerce datasets, addressing class imbalance, and modelling intricate feature interactions. However, potential challenges include adapting to rapidly changing market dynamics and ensuring computational effectiveness for predicting in near real time. Overall, this multi-model framework provides ERP-integrated e-commerce platforms with robust and reliable tools for improving business decision-making while maintaining high predictive accuracy.

## V. CONCLUSION AND FUTURE WORK

The effectiveness of ML techniques, particularly the Cat Boost classifier, for accurate business forecasting within ERP-enabled e-commerce environments. By leveraging a comprehensive preprocessing pipeline and domain-specific feature engineering on the Brazilian Olist dataset, the proposed framework successfully addresses challenges such as data heterogeneity, class imbalance, and complex feature interactions, resulting in superior predictive performance compared to conventional models, including CNN, DT, and KNN. These results underscore the critical role of advanced ML models in enhancing demand prediction, inventory control, and overall decision-making processes, thereby supporting e-commerce businesses in achieving operational efficiency and customer satisfaction. Future work may explore how ERP's real-time data streams are integrated with e-commerce platforms to enable dynamic forecasting capabilities, thereby enhancing responsiveness to market fluctuations. Additionally, expanding the framework to incorporate deep learning architectures, such as LSTM or Transformer models, could further improve forecasting accuracy by recognizing the sequential patterns and temporal connections present in transactional and consumer activity data. Exploring explainability methods for ML models would also be valuable to increase transparency and trust in automated forecasts among business stakeholders. Moreover, extending the dataset scope to multiple geographic regions and various e-commerce sectors could validate the model's generalizability and robustness, providing a holistic forecasting approach that aligns closely with strategic business planning and enhances competitive advantage in rapidly evolving e-commerce markets.

## VI. REFERENCES

[1] M. Sun, K. Grondys, N. Hajiyev, and P. Zhukov, "Improving the E-Commerce Business Model in a Sustainable Environment," Sustainability, vol. 13, no. 22, Nov. 2021, doi: 10.3390/su132212667.

[2] V. Verma, "Big Data and Cloud Databases Revolutionizing Business Intelligence," TIJER – Int. Res. J., vol. 9, no. 1, 2022.

[3] G. Modalavalasa and H. Kali, "Exploring Big Data Role in Modern Business Strategies: A Survey with Techniques and Tools," Int. J. Adv. Res. Sci. Commun. Technol., vol. 3, no. 3, pp. 431–441, Jan. 2023, doi: 10.48175/IJARSCT-11900B.

[4] A. Andonov, G. P. Dimitrov, and V. Totev, "Impact of E-commerce on Business Performance," TEM J., pp. 1558–1564, Nov. 2021, doi: 10.18421/TEM104-09.

[5] A. Octavia, S. Indrawijaya, Y. Sriayudha, Heriberta, H. Hasbullah, and Asrini, "Impact on e-commerce adoption on entrepreneurial orientation and market orientation in business performance of SMEs," Asian Econ. Financ. Rev., 2020, doi: 10.18488/journal.aefr.2020.105.516.525.

[6] X. Zhang, F. Guo, T. Chen, L. Pan, G. Beliakov, and J. Wu, "A Brief Survey of Machine Learning and Deep Learning Techniques for E-Commerce Research," J. Theor. Appl. Electron. Commer. Res., vol. 18, no. 4, pp. 2188–2216, 2023, doi: 10.3390/jtaer18040110.

[7] F. Fernández-Bonilla, C. Gijón, and B. De la Vega, "E-commerce in Spain: Determining factors and the importance of the e-trust," Telecomm. Policy, 2022, doi: 10.1016/j.telpol.2021.102280.

[8] S. S. S. Neeli, "Ensuring Data Quality: A Critical Aspect of Business Intelligence Success," Int. J. Lead. Res. Publ., vol. 2, no. 9, 2021.

[9] V. Verma, "Security Compliance and Risk Management in AI-Driven Financial Transactions," Int. J. Eng. Sci. Math., vol. 12, no. 7, pp. 1–15, 2023.

[10] B. Li, "Research and development of e-commerce ERP system based on artificial intelligence technology," Int. J. Knowledge-Based Dev., vol. 13, no. 2–4, pp. 327–343, 2023, doi: 10.1504/IJKBD.2023.133333.

[11] V. K. Singh, D. Pathak, and P. Gupta, "Integrating Artificial Intelligence and Machine Learning into Healthcare ERP Systems: A Framework for Oracle Cloud and Beyond," ESP J. Eng. Technol. Adv., vol. 3, no. 2, pp. 171–178, 2023, doi: 10.56472/25832646/JETA-V3I6P114.

[12] M. Tsagkias, T. H. King, S. Kallumadi, V. Murdock, and M. de Rijke, "Challenges and research opportunities in eCommerce search and recommendations," ACM SIGIR Forum, vol. 54, no. 1, pp. 1–23, Jun. 2021, doi: 10.1145/3451964.3451966.

[13] S. S. S. Neeli, "The Significance of NoSQL Databases: Strategic Business Approaches and Management Techniques," J. Adv. Dev. Res., vol. 10, no. 1, 2019.

[14] V. Shah, "Managing Security and Privacy in Cloud Frameworks: A Risk with Compliance Perspective for Enterprises," Int. J. Curr. Eng. Technol., vol. 12, no. 06, pp. 1–13, 2022, doi: 10.14741/ijcet/v.12.6.16.

[15] H. Narne, "AI and Machine Learning in Enterprise Resource Planning: Empowering Automation, Performance, and Insightful Analytics," Int. J. Res. Anal. Rev., vol. 9, no. 1, pp. 284–288, 2022.

[16] Y. Wang and Y. Shi, "Analysis on the integration of ERP and e-commerce," in AIP Conference Proceedings, 2017. doi: 10.1063/1.4992954.

[17] M. Godavari and B. S. Prakash, "Next-Generation AI-Powered Automation for Streamlining Business Processes and Improving Operational Efficiency," J. Comput. Technol., vol. 12, no. 12, 2023.

[18] V. Varma, "Data Analytics for Predictive Maintenance for Business Intelligence for Operational Efficiency," Asian J. Comput. Sci. Eng., vol. 7, no. 4, pp. 1–7, 2022.

[19] R. E. Bawack, S. F. Wamba, K. D. A. Carillo, and S. Akter, "Artificial intelligence in E-Commerce: a bibliometric study and literature review," Electron. Mark., 2022, doi: 10.1007/s12525-022-00537-z.

[20] H. Pallathadka, E. H. Ramirez-Asis, T. P. Loli-Poma, K. Kaliyaperumal, R. J. M. Ventayen, and M. Naved, "Applications of artificial intelligence in business management, e-commerce and finance," Mater. Today Proc., vol. 80, pp. 2610–2613, 2023, doi: 10.1016/j.matpr.2021.06.419.

[21] A. R. Bilipelli, "End-to-End Predictive Analytics Pipeline of Sales Forecasting in Python for Business Decision Support Systems," Int. J. Curr. Eng. Technol., vol. 12, no. 6, pp. 819–827, 2022.

[22] K. M. Jha et al., "Optimising Sales Forecasts in ERP Systems Using Machine Learning and Predictive Analytics," J. Contemp. Educ. Theory Artif. Intell., 2023, doi: 10.47991/2023/JCETAI-104.

[23] S. Azad, "Exploring customer behavior and enhanced revenue generation in e-commerce using interpretable and explainable artificial intelligence," IET Conf. Proc., vol. 2023, no. 5, pp. 324–332, Jul. 2023, doi: 10.1049/icp.2023.1511.

[24] P. Wangkiat and C. Polprasert, "Machine Learning Approach to Predict E-commerce Customer Satisfaction Score," in 2023 8th International Conference on Business and Industrial Research (ICBIR), IEEE, May 2023, pp. 1176–1181. doi: 10.1109/ICBIR57571.2023.10147542.

[25] D.-M. Petroșanu, A. Pîrjan, G. Căruţaşu, A. Tăbușcă, D.-L. Zirra, and A. Perju-Mitran, "E-Commerce Sales Revenues Forecasting by Means of Dynamically Designing, Developing and Validating a Directed Acyclic Graph (DAG) Network for Deep Learning," Electronics, vol. 11, no. 18, 2022, doi: 10.3390/electronics11182940.

[26] K. Diamantaras, M. Salampasis, A. Katsalis, and K. Christantonis, "Predicting shopping intent of e-commerce users using LSTM recurrent neural networks," Proc. 10th Int. Conf. Data Sci. Technol. Appl. DATA 2021, no. Data, pp. 252–259, 2021, doi: 10.5220/0010554102520259.

[27] S. Kulshrestha and M. L. Saini, "Study for the Prediction of E-Commerce Business Market Growth using Machine Learning Algorithm," in 2020 5th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE), IEEE, Dec. 2020, pp. 1–6. doi: 10.1109/ICRAIE51050.2020.9358275.

[28] D. Tolstoy, E. R. Nordman, S. M. Hånell, and N. Özbek, "The development of international e-commerce in retail SMEs: An effectuation perspective," J. World Bus., vol. 56, no. 3, Apr. 2021, doi: 10.1016/j.jwb.2020.101165.

[29] K. Siau and J. Messersmith, "Enabling Technologies for E-Commerce and Erp Integration.," Quarterly Journal of Electronic Commerce. 2002.

[30] T. Mazzarol, "SMEs engagement with e-commerce, e-business and e-marketing," Small Enterp. Res., vol. 22, no. 1, pp. 79–90, Jan. 2015, doi: 10.1080/13215906.2015.1018400.

[31] N. A. Hakami and H. A. H. Mahmoud, "Deep Learning Analysis for Reviews in Arabic E-Commerce Sites to Detect Consumer Behavior towards Sustainability," Sustainability, vol. 14, no. 19, Oct. 2022, doi: 10.3390/su141912860.

[32] A. N. Wong and B. P. Marikannan, "Optimising e-commerce customer satisfaction with machine learning," J. Phys. Conf. Ser., vol. 1712, no. 1, 2020, doi: 10.1088/1742-6596/1712/1/012044.

[33] B. Kumar, S. Roy, A. Sinha, C. Iwendi, and Ľ. Strážovská, "E-Commerce Website Usability Analysis Using the Association Rule Mining and Machine Learning Algorithm," Mathematics, vol. 11, no. 1, Dec. 2022, doi: 10.3390/math11010025.