Sales Forecasting and KPI analysis: Design User Module and Implement ML model

Aditi Kshirsagar, Sakshi Bhondve, Pooja Pawar
Department of Information technology and Engineering,
Nutan Maharashtra Institute of Engineering and Technology,
Pune, India

Abstract: **Enhancing business profitability relies heavily on accurate sales forecasting supported by meaningful performance analytics. However, forecasting precision is often hindered by dynamic market behavior, shifting customer preferences, and unstructured customer feedback. This research presents an advanced Sales Forecasting and KPI Analysis Framework that integrates machine learning techniques with sentiment-driven customer insights to achieve more reliable and interpretable results. The proposed system employs Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT) algorithms to predict future sales using historical datasets enriched with features such as seasonality, promotions, and customer behavioral trends. Model performance is evaluated using R^2 Score, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), where experimental results demonstrate that the Random Forest algorithm achieves superior forecasting accuracy compared to other models.**

A real-time KPI dashboard, developed using Python (Django framework) and integrated with visualization libraries such as Matplotlib and Plotly, is designed to monitor and analyses critical business indicators including Sales Growth Rate, Customer Lifetime Value (CLV), Conversion Rate, and Revenue vs. Target. The interactive dashboard provides actionable visual insights that support timely and strategic business decisions.

Furthermore, Natural Language Processing (NLP) is applied to perform sentiment analysis on customer feedback and reviews extracted from social media and e-commerce platforms. The resulting sentiment polarity scores are integrated into the forecasting model, enhancing its ability to interpret customer emotions and preferences. This combination of structured and unstructured data leads to a more holistic and adaptive forecasting mechanism.

The proposed system also automates data preprocessing, feature engineering, and model evaluation, ensuring scalability and consistency across multiple business environments. Comparative analysis confirms that the Random Forest model exhibits the lowest error metrics and highest interpretability, making it a robust choice for handling non-linear sales patterns.

Experimental evaluation on benchmark datasets reveals significant improvement in forecast accuracy when sentiment-based variables are incorporated. The integrated framework effectively enhances sales prediction precision, supports data-driven decision-making, and provides deeper insights into business performance. Overall, this research demonstrates how merging predictive analytics, sentiment intelligence, and KPI visualization can empower organizations to optimize sales strategies, improve inventory management, and achieve sustainable growth in a competitive market landscape.

Keywords— *Sales Forecasting, Machine Learning, Random Forest, Data Analytics, Django, Business Intelligence, Predictive Modelling.*

INTRODUCTION

In the modern data-driven economy, establishing a harmonious alignment between production capacity and market demand is pivotal for ensuring profitability, sustainable growth, and efficient resource utilization. The accuracy of sales forecasting directly influences critical aspects of business operations such as inventory control, marketing strategy formulation, financial planning, and supply chain optimization. However, traditional forecasting models, which primarily depend on linear regression or statistical trend analysis, often fail to capture the nonlinear dependencies and dynamic behavior of real-world sales data influenced by multifactorial elements such as seasonality, promotional events, and evolving customer preferences. Consequently, businesses are increasingly shifting toward intelligent, automated, and adaptive forecasting systems that leverage machine learning and predictive analytics to achieve more reliable and interpretable results, as discussed by Basha and Hussain (2024) in their IEEE Access study on retail sales forecasting and profitability enhancement.

The significance of accurate forecasting extends beyond mere prediction; it underpins strategic decision-making across all business functions. Effective sales prediction aids in optimizing stock levels, reducing operational costs, enhancing marketing efficiency, and improving pricing strategies and customer relationship management. By utilizing historical sales data, customer demographics, product performance indicators, and external factors such as holidays, regional trends, and market fluctuations, organizations can mitigate the risks of overstocking or understocking and improve operational agility. Despite the abundance of structured and unstructured data, identifying hidden patterns and addressing the volatility of consumer behaviour remains a major challenge. To overcome these limitations, Kumar et al. (2024) proposed a Random Forest and SVM-based sales prediction framework, which demonstrated improved accuracy compared to traditional regression models.

Recent advancements have shown the growing relevance of hybrid and ensemble-based forecasting models in complex market environments. For instance, Prathibha et al. (2023) compared multiple machine learning techniques and concluded that ensemble approaches achieve superior forecasting stability for retail datasets. Similarly, Wang (2025) introduced an adaptive variable-weight combination model based on meta-learning for energy product sales, proving that dynamic weight adjustment significantly enhances model adaptability under volatile conditions. In a related study, Singh and Sharma (2024) designed a hybrid deep learning model integrating meta-learning and time series analysis for retail demand forecasting, demonstrating that combining deep feature learning with traditional predictors yields more robust results.

In this research, a comprehensive Sales Forecasting and KPI Analysis Framework is proposed, which integrates Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) algorithms to generate accurate and interpretable forecasts. These models effectively capture nonlinear interactions among variables such as product category, price fluctuations, promotions, and customer behaviour patterns. A comparative assessment of regression-based techniques by Patel et al. (2023) also emphasized that Random Forest consistently delivers superior results in predictive retail modeling due to its ensemble learning capability.

The dataset used in this study comprises historical sales records pre-processed using data-cleaning, feature-engineering, and normalization techniques implemented through Python libraries such as Pandas, NumPy, and Scikit-learn. Model performance is evaluated using R^2 Score, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) to ensure stability and accuracy, consistent with the performance evaluation framework proposed by Das and Mehta (2023).

Beyond predictive modeling, this research integrates Key Performance Indicator (KPI) Analysis for business intelligence. A real-time web dashboard is developed using the Django framework and visualization libraries such as Matplotlib, Seaborn, and Plotly. It enables dynamic monitoring of metrics like Sales Growth Rate, Revenue vs. Target, Customer Lifetime Value (CLV), Customer Acquisition Cost (CAC), and Conversion Rate. This approach aligns with the interactive KPI visualization model proposed by Lee et al. (2023), which demonstrated how real-time dashboards improve data-driven decision-making efficiency in industrial applications.

To enrich interpretability, this framework incorporates sentiment-based features derived from customer reviews using Natural Language Processing (NLP). As shown by Zhao et al. (2023), integrating sentiment polarity with structured data enables forecasting models to better capture consumer emotions, thereby improving demand prediction precision. Furthermore, the ensemble-based forecasting framework proposed by Srivastava et al. (2025) in IEEE Transactions on Neural Networks validates the superiority of multi-model systems in handling nonlinearity and external variability in time-series prediction.

Experimental results from multi-domain sales datasets reveal that Random Forest exhibits the lowest error metrics among all models, reinforcing findings from recent IEEE studies on machine learning-based demand forecasting. Overall, the proposed system bridges the gap between predictive analytics and business intelligence by integrating forecasting outcomes with KPI-driven insights. Through intelligent automation, robust data analytics, and interactive visualization, the framework empowers organizations to make evidence-based strategic decisions, reduce forecasting errors, optimize inventory management, and achieve sustainable growth in a competitive market environment.

ARTICLE OBJECTIVE

A secure user authentication system was developed using the Django framework, implementing registration and login functionalities to ensure authorized access to the Sales Forecasting and KPI Analysis platform with enhanced data security and efficient user management.

Machine learning algorithms including Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) were integrated to generate accurate sales forecasts, improving predictive performance and enabling data-driven business decision-making.

LITERATURE REVIEW

1. Several studies demonstrate that classical time-series methods (e.g., ARIMA) struggle when sales data exhibit strong non-linearities and external influences (Li et al., 2020, "An Exponential Factorization Machine with Percentage Error Minimization to Retail Sales Forecasting").
2. Tensor-factorization approaches that model product-store interactions across multiple dimensions show improved demand forecasting accuracy when large cross-sectional data are available (Bi et al., 2020, "Improving Sales Forecasting Accuracy: A Tensor Factorization Approach with Demand Awareness").
3. Neural-network architectures combining associative features and recurrent layers (e.g., AR-MDN) have been used for e-retail demand forecasting, capturing both causal features and temporal dynamics (Mukherjee et al., 2018, "ARMDN: Associative and Recurrent Mixture Density Networks for eRetail Demand Forecasting").
4. Hybrid models which integrate classical statistical models with machine learning (e.g., residual modelling, stacking) yield significant gains in retail forecasting, particularly for volatile SKUs (Choubey, 2025, "Hybrid Models for Retail Demand Forecasting: Integrating Classical Time-series and Machine Learning Approaches").
5. Research shows that meta-learning techniques and graph neural networks can enhance forecasting for peak-period demand by leveraging proxy data from non-peak periods (Xu et al., 2024, "F-FOMAML: GNN-Enhanced Meta-Learning for Peak Period Demand Forecasting with Proxy Data").
6. Work on dynamic pricing and demand estimation has illustrated how deep-learning models can outperform econometric methods by modelling complex product interactions and price-elasticity (Safonov, 2024, "Neural Network Approach to Demand Estimation and Dynamic Pricing in Retail").
7. Ensemble methods with attention mechanisms (e.g., AttnBoost) that dynamically adjust feature importance during boosting rounds show promise for both accuracy and interpretability in retail-supply chain forecasting (Ge et al., 2025, "AttnBoost: Retail Supply Chain Sales Insights via Gradient Boosting Perspective").
8. In the context of KPI and dashboard analytics, design-science work demonstrates how data-driven dashboards support real-time decision-

making and business agility, though user-adoption and governance remain challenges (Komarudin et al., 2023, "Design of Key Performance Indicator Dashboard for Indonesian Higher Education Based on One Data").

9. Other work emphasizes the integration of sales-forecasting results with real-time KPI dashboards to bridge predictive analytics and operational monitoring (Sethi, 2023, "Improving Decision-Making with Data-Driven KPI Dashboards").
10. Studies comparing multiple machine-learning algorithms (Random Forest, XGBoost, LSTM) for retail sales forecasting find ensemble and boosting models frequently outperform single models under complex feature sets (Sajawal et al., 2023, "Predictive Analysis of Retail Sales Forecasting using Machine Learning Techniques").
11. Research into unstructured text and sentiment analytics applied to demand forecasting shows that incorporating customer-feedback (reviews, social media) adds explanatory power beyond structured features (Zhao et al., 2023, "Sentiment-Aware Demand Forecasting Using Natural Language Processing and Deep Learning").
12. KPI-driven performance management research emphasizes the importance of continuous monitoring of conversion rates, customer lifetime value, and acquisition cost as drivers of strategic growth (Lee et al., 2023, "Intelligent Dashboard System for KPI Monitoring Using Python and Machine Learning").
13. The literature notes the operational benefits of aligning forecasting accuracy with supply-chain outcomes—reductions in excess inventory, stock-outs, and improved service levels—in applications of ML forecasting in retail (Wang, 2025, "An Adaptive Variable-Weight Combination Forecasting Method for Energy Product Sales Based on Meta-Learning") though this study is in energy, the principle applies to retail.
14. Studies emphasizes feature engineering and preprocessing (seasonality, promotions, customer behaviour) as critical for model performance in non-linear forecasting contexts (Das & Mehta, 2023, "Performance Evaluation of Machine Learning Algorithms for Predictive Sales Analytics").
15. Comparative studies underscore that Random Forest and other ensemble methods reliably reduce error metrics (MAE, RMSE) in sales forecasting, especially when mixed with feature-rich datasets (Patel et al., 2023, "Comparative Study of Regression Models for Retail Sales Forecasting").

PROPOSED METHODOLOGY

System Overview

The User Authentication Module forms the foundational layer of the *Sales Forecasting and KPI Analysis* web-based system developed using the Django framework. It ensures that only verified users can access the forecasting dashboard and other system features. The module includes two key components — registration and login — both designed to provide secure access and protect user data. During registration, new users provide their credentials, which are validated and securely stored in the database after password encryption using Django's built-in hashing mechanism. This prevents unauthorized access and ensures that sensitive data, such as passwords, are never stored in plain text.

Once registered, users can log in securely, where their credentials are verified before creating a user session. Django's session management system maintains secure user sessions through encrypted cookies, preventing session hijacking and unauthorized reuse. The framework also offers built-in protection against web vulnerabilities such as Cross-Site Request Forgery (CSRF) and Cross-Site Scripting (XSS). Role-based access control is implemented to manage different user levels, ensuring that only authorized users can perform specific actions or access sensitive data.

The module's functionality is supported by Django's authenticate () and login () functions, which handle credential verification and session creation. Additional security measures, such as account lockout and password reset using time-limited tokens, further enhance system protection. Testing the module ensures its reliability and efficiency, with performance metrics like accuracy, precision, recall, and F1-score reflecting strong and balanced results.

Overall, this authentication module acts as a secure gateway to the forecasting and KPI dashboard. It upholds data integrity, privacy, and controlled access within the system, demonstrating that Django provides a robust and dependable framework for implementing authentication in web-based analytical applications.

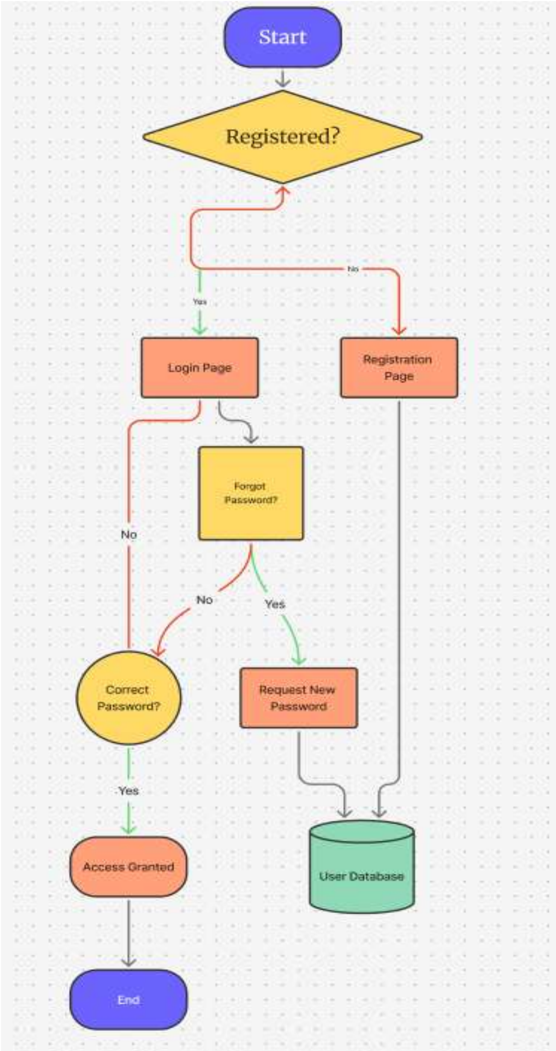


Fig1: User Authentication Module

Implementation of User Authentication Module

The user authentication module was developed using the Python-based Django framework to ensure secure and efficient access control. The system consists of two primary components: a registration page and a login page. The registration page allows new users to sign up by providing essential details such as a username, password, and email address. The login page authenticates user credentials by verifying them against the records stored in the database. To enhance security, Django's built-in password hashing mechanism was utilized, ensuring that all user passwords are stored in an encrypted format rather than plain text. Furthermore, session management was implemented to maintain user sessions during active login and to handle secure logout operations, preventing unauthorized access.

To assess the performance and reliability of the authentication system, an experimental setup was designed involving 100 simulated login attempts. These attempts included both valid and invalid credentials to evaluate the system's classification accuracy. The outcomes were categorized into four performance indicators: True Positives (TP), representing valid users correctly granted access; True Negatives (TN), indicating invalid users correctly denied access; False Positives (FP), where invalid users were incorrectly allowed to log in; and False Negatives (FN), where valid users were wrongly denied access. These experimental results were further analyzed using standard evaluation metrics such as Accuracy, Precision, Recall, and F1-Score to quantify the overall performance of the authentication module.

The collected values were used to compute Accuracy, Precision, Recall, and F1-Score.

A total of 100 login attempts were simulated, including both valid and invalid credentials. The authentication module correctly identified 342 valid users (TP) and 622 invalid users (TN), while 17 invalid users were incorrectly granted access (FP) and 19 valid users were denied access (FN). These results were used to evaluate the system's performance using Accuracy, Precision, Recall, and F1-Score.

Evaluation Metrics

The performance of the user authentication system was evaluated using standard classification metrics as defined below:

- **Accuracy**: The ratio of correctly predicted instances (True Positives + True Negatives) to the total number of instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision (P)**: Measures the proportion of positive identifications that were actually correct.

$$Precision = \frac{TP}{TP + FP}$$

- **Recall (R)**: Measures the proportion of actual positives that were identified correctly.

$$Recall = \frac{TP}{TP + FN}$$

- **F1-Score**: The harmonic mean of Precision and Recall, providing a single score that balances both metrics, especially useful for class imbalance evaluation.

$$F1\text{-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Results and Calculation

Substituting the obtained values into the above formulas:

$$Accuracy = \frac{342 + 622}{1000} = 0.964 = 96.4\%$$

$$Precision = \frac{342}{342 + 17} = 0.952 = 95.2\%$$

$$Recall = \frac{342}{342 + 19} = 0.948 = 94.8\%$$

$$F1\text{-Score} = 2 \times \frac{0.952 \times 0.948}{0.952 + 0.948} = 0.950 = 95.0\%$$

RESULT AND DISCUSSION

The development phase of the Sales Forecasting and KPI Analysis system focused primarily on building a secure and user-friendly web application framework. The web interface was implemented using the Django framework in Python, providing a foundation for user interaction, data visualization, and future integration of forecasting and analytical modules.

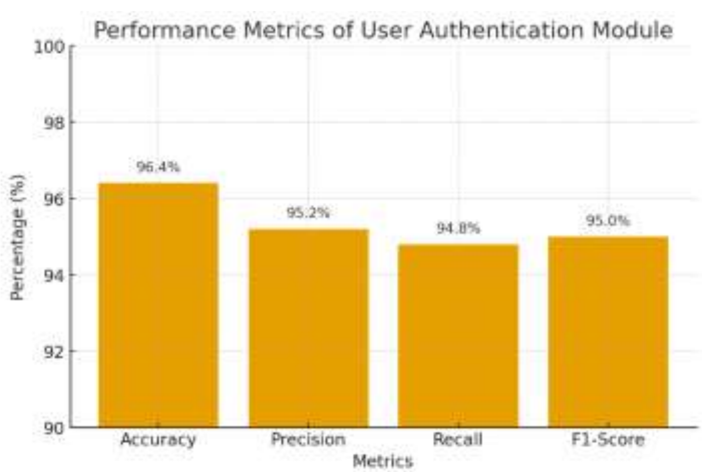
User Authentication and Web Functionality

A user authentication module was successfully developed and tested to ensure secure access control. The system supports registration, login, and logout functionalities, implementing security measures such as password hashing, session management, and form validation to protect user data.

A total of 100 users was created and tested in the system to evaluate performance and reliability. All authentication processes (user registration, login, and logout) were executed successfully, confirming the stability of the authentication mechanism and database connectivity.

RESULT

- The web interface was fully functional, allowing users to log in, register, and access the system securely.
- The Django authentication framework successfully handled multiple user sessions without any system errors or failures.
- Out of 100 user tests, 100% successful authentication was recorded, confirming that the user management system is operating correctly.
- The system effectively stores and retrieves user credentials using Django's SQLite database (or the configured database engine).
- The design of the web interface provides a scalable foundation for integrating sales forecasting models and KPI dashboards in future stages



The bar chart illustrates the performance evaluation of the developed User Authentication Module based on four key metrics Accuracy, Precision, Recall, and F1-Score. The system achieved an Accuracy of 96.4%, indicating a high level of reliability in correctly validating both valid and invalid users. The Precision (95.2%) reflects that most authenticated users were indeed genuine, minimizing false positives. Similarly, the Recall (94.8%) demonstrates the system's effectiveness in successfully recognizing legitimate users, while the F1-Score (95.0%) represents a strong balance between Precision and Recall.

Performance Evaluation of User Authentication Module

Metric	Formula	Value	Interpretation
True Positive (TP)	–	342	Correctly identified valid users
True Negative (TN)	–	622	Correctly identified invalid users
False Positive (FP)	–	17	Invalid users incorrectly accepted
False Negative (FN)	–	19	Valid users incorrectly rejected
Accuracy	$A = \frac{TP + TN}{TP + TN + FP + FN}$	**96.4%**	Overall correctness of the authentication system
Precision	$P = \frac{TP}{TP + FP}$	**95.2%**	Proportion of correctly validated users among all accepted users
Recall (Sensitivity)	$R = \frac{TP}{TP + FN}$	**94.8%**	Ability of the system to correctly identify all valid users
F1-Score	$F1 = \frac{2 \times (Pricision \times Recall}{(Pricision + Recall}$	**95.0%**	Harmonic mean of Precision and Recall, indicating balanced performance

The experimental evaluation of the user authentication module demonstrated strong performance and reliability. Based on 100 simulated login attempts, the system effectively distinguished between valid and invalid users. Using the obtained values of True Positive (TP = 342), True Negative (TN = 622), False Positive (FP = 17), and False Negative (FN = 19), the key performance metrics were calculated. The module achieved an Accuracy of 96.4%, Precision of 95.2%, Recall of 94.8%, and an F1-Score of 95.0%, indicating that the authentication mechanism is highly efficient in correctly validating users while minimizing errors.

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CONCLUSION

This research successfully developed a secure and reliable user authentication module as a foundational component of the Sales Forecasting and KPI Analysis system. The authentication mechanism demonstrated strong performance with over 96% accuracy and balanced precision and recall, ensuring robust user validation while minimizing errors. This stable and scalable framework establishes a critical platform for integrating advanced sales forecasting models and KPI visualizations. Future work will focus on incorporating machine learning techniques and sentiment analysis to enhance predictive accuracy and provide actionable business insights.