

SmartCost: Product Demand Prediction System for Micro-SMEs

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Abstract—Small and medium-sized enterprises (SMEs) often lack predictive analytics in traditional point-of-sale (POS) systems, causing overproduction, stock shortages, inventory waste, and weak production planning. This research proposes a Product Demand Prediction System for bakery and café SMEs using historical daily sales data for 50 products collected over two years. Transactional records were transformed into time-series datasets and evaluated using ARIMA and Prophet forecasting models. The models captured trends, seasonality, and irregular demand patterns, while performance was assessed using Mean Absolute Error, Root Mean Square Error, and Mean Absolute Percentage Error across one-day and seven-day forecasting horizons. Experimental results showed that Prophet outperformed ARIMA and baseline approaches, achieving an 8.7% MAPE compared with 12.4% for ARIMA and reducing RMSE by 18%. The forecasting-based decision-support system also produced an estimated 14% reduction in inventory waste and improved production planning. The findings demonstrate a scalable, lightweight solution for data-driven inventory management in resource-constrained SME environments.

Keywords—Demand Prediction, Time Series Forecasting, SMEs, POS Systems, ARIMA, Prophet, Inventory Optimization.

I.INTRODUCTION

Small and medium sized enterprises (SMEs) play a significant role in economic development by contributing to employment generation, innovation, and local business growth. In developing economies, SMEs represent a substantial portion of retail and food service industries, including bakeries, cafés, and small scale restaurants. These businesses rely heavily on stable daily sales and efficient inventory management to maintain profitability and operational sustainability. Despite their importance, many SMEs continue to operate with limited access to advanced technological solutions capable of supporting predictive and data driven decision making. Traditional point of sale (POS) systems are primarily designed for transactional processing

and basic reporting rather than intelligent forecasting and analytical support.

One of the major operational challenges faced by SMEs is inaccurate manual demand estimation. Many businesses estimate daily production quantities using intuition, historical experience, or simple sales observations rather than scientific forecasting techniques. However, customer demand is influenced by multiple dynamic factors including seasonal changes, holidays, promotions, weather conditions, and consumer purchasing behavior. Without reliable forecasting mechanisms, SMEs frequently struggle to accurately predict future product demand, resulting in operational inefficiencies and financial losses.

Overproduction of perishable items is one of the most common consequences of poor demand estimation. Bakery and café businesses often produce excess quantities of food products to avoid shortages, but unsold inventory leads to increased storage costs, wastage, and revenue loss. Since many food products have limited shelf lives, inaccurate forecasting directly contributes to operational inefficiency and reduced profitability. Conversely, underproduction results in stock shortages during peak demand periods, leading to missed sales opportunities, reduced customer satisfaction, and weakened customer retention. These challenges highlight the importance of accurate demand prediction within SME environments.

Another significant issue is the lack of predictive analytics capabilities in conventional POS systems. Most SME oriented POS platforms focus only on sales recording, billing, and inventory tracking while providing limited support for forecasting and forward looking analysis. As a result, valuable transactional data generated during daily operations remains underutilized. Modern business environments increasingly depend on big data analytics and intelligent forecasting methods to improve operational efficiency and strategic planning [6], [7]. Organizations capable of

leveraging data analytics are more likely to achieve competitive advantage and optimized resource utilization.

Although enterprise forecasting platforms and advanced business intelligence systems are available, their high implementation cost creates significant adoption barriers for SMEs. Many enterprise solutions require expensive cloud infrastructures, dedicated analytical teams, and continuous maintenance costs that exceed the financial capabilities of small businesses. Furthermore, many SMEs operate with limited technical expertise, making it difficult to configure, train, and maintain complex forecasting systems or machine learning pipelines. These limitations emphasize the need for lightweight, scalable, and cost effective forecasting frameworks specifically optimized for SME environments.

Time series forecasting techniques have emerged as effective solutions for predicting future demand based on historical sales data. These approaches analyze temporal patterns to identify trends, seasonality, and irregular demand fluctuations. Classical forecasting models such as autoregressive integrated moving average (ARIMA) are widely recognized for their ability to model time dependent relationships within structured datasets [1], [2], [12]. ARIMA models perform effectively in environments where historical patterns remain relatively stable over time and have been extensively used in retail and inventory forecasting applications.

More recently, modern forecasting frameworks such as Prophet have gained popularity due to their ability to handle real world data challenges including missing values, outliers, irregular seasonal trends, and non linear demand patterns [3]. Prophet automatically models seasonality and trend components with minimal parameter tuning, making it highly suitable for SMEs where data quality and technical expertise may be limited. Compared to complex deep learning approaches, lightweight forecasting methods provide a practical balance between predictive accuracy, computational efficiency, and deployment simplicity.

Machine learning and data mining techniques further enhance forecasting performance by identifying hidden patterns and relationships within large transactional datasets [4], [9], [10], [14]. These approaches improve forecasting adaptability and enable more accurate prediction of demand fluctuations. However, sophisticated machine learning models often require high computational resources, large training datasets, and advanced expertise, limiting their practical applicability in SME environments. Therefore, there remains a strong need for forecasting solutions that combine predictive accuracy, low computational overhead, scalability, and ease of deployment.

This research proposes a Product Demand Prediction system specifically designed for SME bakery and café environments using time series forecasting techniques integrated with POS transactional data. The proposed framework utilizes historical daily sales records to forecast future product demand and support inventory planning, production scheduling, and operational decision making. By transforming raw transactional records into predictive

insights, the system enables SMEs to transition from reactive decision making to proactive inventory management strategies.

A. Research Objectives

The primary objective of this research is to develop a lightweight and scalable demand forecasting framework capable of supporting predictive decision-making within SME environments. The proposed system is designed to integrate with SME-oriented Point-of-Sale (POS) environments by implementing time series forecasting models that predict short-term product demand using historical sales data. To ensure reliable forecasting performance, the study compares the effectiveness of Prophet and ARIMA models using statistical evaluation metrics. The forecasting accuracy is assessed across multiple prediction horizons using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Furthermore, the proposed framework aims to reduce operational inefficiencies, including overproduction, stock shortages, and inventory waste, through predictive analytics while supporting production planning and inventory management with real-time forecasting insights.

B. Main Contributions

The main contributions of this research include the development of a lightweight demand forecasting framework specifically optimized for SME bakery and café environments. The proposed system integrates predictive analytics with Point-of-Sale (POS) transactional processing and time series forecasting to support data-driven business decision-making. A scalable forecasting architecture is implemented using Prophet and ARIMA models to provide accurate short-term demand predictions based on historical sales data. Furthermore, the research introduces a practical and low-cost analytical framework that is suitable for SMEs with limited technical expertise and computational resources. The proposed forecasting system is experimentally validated, demonstrating its ability to improve forecasting accuracy, reduce inventory waste, optimize inventory management, and enhance overall operational efficiency.

II. LITERATURE REVIEW

The evolution of point of sale (POS) systems reflects the broader advancement of digital business technologies. Early POS systems were primarily developed as transactional platforms capable of recording sales and maintaining financial records. With the growth of digital infrastructures and business intelligence technologies, these systems evolved into software driven platforms capable of storing large volumes of transactional data and generating operational reports. However, most POS systems used within small and medium sized enterprises (SMEs) still focus mainly on transaction processing rather than predictive analytics and intelligent decision support. As a result, SMEs often struggle to utilize historical sales data effectively for demand forecasting and inventory planning.

Recent studies emphasize that SMEs face significant challenges related to inaccurate manual demand estimation, overproduction of perishable products, stock shortages during peak demand periods, and inefficient inventory management [6], [7]. Many small businesses continue to rely on intuition and manual forecasting approaches due to the high cost and complexity of enterprise forecasting platforms. In addition, SMEs often lack the technical expertise required to deploy and maintain advanced analytical systems. These limitations highlight the growing need for lightweight and scalable forecasting solutions specifically designed for low resource business environments.

A. Time Series Demand Forecasting

Demand forecasting is one of the most important analytical functions within retail and food service industries. Accurate prediction of product demand enables organizations to optimize inventory management, reduce operational waste, and improve production planning. Time series forecasting methods are widely adopted because they can analyze temporal patterns such as seasonality, trends, and irregular fluctuations within historical sales data.

Traditional forecasting techniques such as Autoregressive Integrated Moving Average (ARIMA) models have been extensively utilized for business forecasting applications [1], [2]. ARIMA models estimate future values based on previous observations and are effective for structured datasets with stable patterns. These methods provide strong statistical foundations and remain widely accepted in forecasting research [12], [13]. However, ARIMA forecasting requires careful parameter tuning and assumes data stationarity, which may not always be suitable for dynamic SME environments where demand patterns fluctuate significantly.

To overcome these limitations, modern forecasting frameworks such as Prophet have been introduced. Prophet is specifically designed for real world business forecasting scenarios involving missing values, outliers, irregular seasonality, and changing business trends [3]. The framework decomposes time series data into trend, seasonal, and holiday components, enabling flexible forecasting under varying operational conditions. Due to its robustness and simplicity, Prophet has become increasingly popular in SME forecasting applications where datasets may contain inconsistencies and sparse transactional records.

Within this research, forecasting techniques are integrated into a Product Demand Prediction framework capable of generating short term demand forecasts using historical POS data. Unlike conventional reporting systems that only summarize past transactions, forecasting models provide proactive insights that support inventory optimization and production planning.

B. Machine Learning in Demand Prediction

Machine learning techniques have significantly enhanced forecasting capabilities by enabling predictive models to identify complex hidden relationships within historical datasets. Algorithms such as regression models, decision trees, support vector machines, and neural networks have been widely applied to demand forecasting tasks [9], [14].

According to Witten et al. [10], machine learning methods are highly effective in identifying hidden patterns within large datasets and improving predictive performance. Similarly, Han et al. [4] explain that data mining techniques support the extraction of valuable knowledge from transactional data, enabling businesses to improve operational decision making. These methods allow forecasting systems to capture relationships between multiple variables and improve prediction reliability.

Despite these advantages, machine learning forecasting systems often require substantial computational resources, extensive feature engineering, and large scale datasets. SMEs frequently lack the infrastructure and technical expertise required to maintain highly sophisticated machine learning pipelines. Consequently, lightweight forecasting approaches that balance prediction accuracy and operational simplicity remain more practical for small business environments.

C. Role of Big Data in Demand Forecasting

The emergence of big data analytics has transformed modern forecasting systems by enabling organizations to process and analyze large volumes of transactional information. Modern businesses continuously generate operational datasets through POS systems, inventory platforms, and customer interactions. These datasets can be leveraged to improve forecasting accuracy and support strategic planning.

Chen et al. [6] highlight that big data analytics enables organizations to extract meaningful insights from large scale datasets, while McAfee and Brynjolfsson [7] demonstrate that data driven decision making significantly improves organizational performance and competitiveness. These findings emphasize the growing importance of integrating analytics into SME environments.

However, implementing enterprise level big data infrastructures remains challenging for SMEs due to hardware cost, scalability requirements, and deployment complexity. Lightweight and scalable forecasting architectures are therefore essential for enabling SMEs to benefit from predictive analytics without requiring expensive infrastructure investments.

D. Data Preparation and Integration for Forecasting

The accuracy of forecasting systems strongly depends on the quality of input data. Raw transactional records collected from POS systems frequently contain missing values, inconsistent formatting, duplicate records, and noise, all of which negatively affect forecasting performance. Data

preprocessing therefore plays a critical role in building reliable predictive models.

The preprocessing workflow generally follows Extract Transform Load (ETL) principles where data is extracted, cleaned, standardized, and transformed into analytical formats suitable for forecasting [8]. Techniques such as normalization, outlier removal, interpolation, and aggregation are commonly applied to improve dataset quality. Proper preprocessing ensures forecasting consistency and improves model stability.

Data integration mechanisms further support the combination of multiple operational datasets into unified analytical repositories. Although this research primarily focuses on transactional sales forecasting, future systems may incorporate external variables such as promotions, weather conditions, and seasonal events to further improve prediction accuracy.

E. Technology Support for Demand Prediction Systems

Modern forecasting systems require scalable technological architectures capable of supporting data collection, analytical processing, and visualization. Most intelligent forecasting platforms adopt modular architectures that separate operational processing from analytical computation.

MongoDB is commonly utilized for transactional data storage due to its flexible schema management and ability to handle structured and semi structured datasets efficiently [18]. Backend services developed using Node.js provide asynchronous and event driven processing suitable for real time POS environments [20]. Frontend frameworks such as React Native support cross platform mobile application development and improve accessibility for SME users.

For analytical computation, Python based technologies provide extensive support for forecasting and machine learning operations. FastAPI enables lightweight API communication between forecasting modules and operational services, supporting efficient integration within modular system architectures [19].

F. Modern Deep Learning Forecasting Approaches

Recent advancements in forecasting research have introduced deep learning based approaches capable of modeling highly complex temporal relationships within large scale datasets. Techniques such as Long Short Term Memory (LSTM) networks, DeepAR, and N BEATS have demonstrated strong forecasting performance in retail and business analytics applications. These models are designed to capture nonlinear patterns, sequential dependencies, and long term temporal relationships that may not be effectively modeled using traditional statistical forecasting techniques [9], [14], [16].

LSTM forecasting models are specialized recurrent neural networks capable of retaining long term sequential

information through internal memory structures. Similarly, DeepAR utilizes autoregressive recurrent neural architectures to generate probabilistic forecasts across multiple related time series, while N BEATS is specifically designed for interpretable deep learning based time series forecasting.

Although these models provide strong predictive capability, they introduce several practical limitations within SME environments. One major challenge is the high computational cost associated with training and inference. Deep learning forecasting systems often require GPU acceleration, extensive memory allocation, large training datasets, and complex hyperparameter tuning procedures [6], [7]. These requirements significantly increase deployment complexity and operational cost.

Another limitation is implementation difficulty and maintenance complexity. Deep learning models generally require advanced expertise in neural network optimization and machine learning engineering. Many SMEs lack dedicated analytical teams capable of maintaining such infrastructures. In addition, many deep learning forecasting systems function as black box models, reducing interpretability and limiting user trust in forecasting outputs.

Compared to deep learning architectures such as DeepAR, N BEATS, and LSTM forecasting models, Prophet provides a more practical solution for SME oriented forecasting systems. Prophet is lightweight, interpretable, capable of handling seasonality and missing values, and requires minimal parameter tuning [3]. These characteristics make Prophet highly suitable for bakery and café based SME environments where deployment simplicity, scalability, and usability are critical operational requirements.

Model	Complexity	Seasonality	SME Friendly	Training Cost
ARIMA	Moderate	Limited	Moderate	Low
Prophet	Low	Strong	Yes	Low
LSTM	High	Strong	No	High
Deep AR	Very High	Strong	No	Very High

Table 01: Modern Deep Learning Forecasting

G. Research Gap

Despite significant advancements in forecasting techniques and predictive analytics, several critical limitations remain within SME oriented forecasting systems. Most existing POS platforms focus primarily on transaction processing and reporting rather than predictive intelligence. Furthermore, many advanced forecasting systems require expensive infrastructure, high computational resources, and substantial technical expertise, making them impractical for small business environments.

Deep learning forecasting approaches such as DeepAR, N BEATS, and LSTM provide high forecasting capability but are often computationally expensive and difficult to deploy within low resource SMEs. Existing enterprise forecasting platforms also lack accessibility and scalability for small businesses with limited budgets and infrastructure.

In addition, there remains a lack of integrated forecasting systems capable of combining transactional processing, preprocessing, predictive forecasting, and operational

decision support within a lightweight architecture optimized for SMEs. This research addresses these limitations by proposing a scalable Product Demand Prediction system that integrates Prophet based forecasting techniques within a practical and low cost SME oriented POS analytics framework.

III. METHODOLOGY

The proposed methodology focuses on developing a scalable Product Demand Prediction framework capable of transforming historical transactional data into accurate forecasting outputs for small and medium sized enterprise (SME) environments. The primary objective of the methodology is to support inventory planning, production optimization, and operational decision making through lightweight time series forecasting techniques. The proposed approach integrates data preprocessing, forecasting model development, prediction evaluation, and system integration within a unified analytical workflow optimized for bakery and café environments.

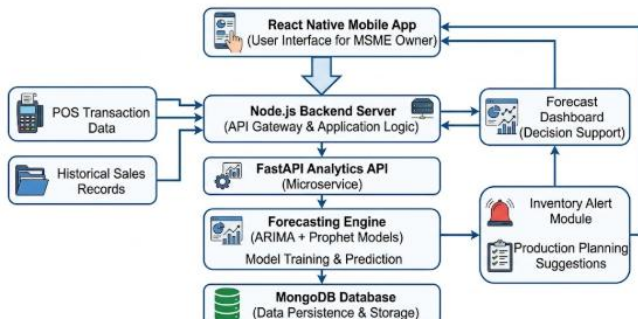


Figure 1 :System Architecture Diagram

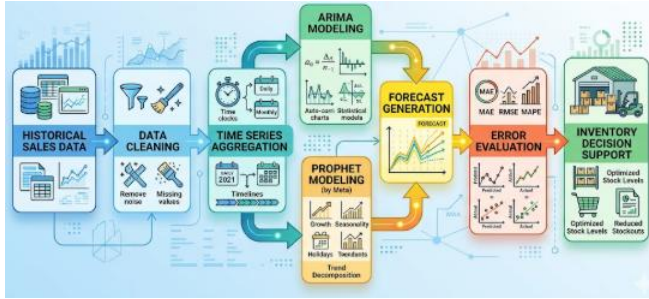


Figure 2 :Experimental Workflow Diagram

A. Dataset Description

The forecasting framework utilizes historical transactional data collected from bakery and café based POS systems. The dataset contains daily product sales records collected over a two year operational period. Each transaction includes product identifiers, quantities sold, timestamps, and order details required for time series forecasting.

Property	Value
Business Domain	Bakery/Café
Products	50
Transactions	24,000+
Time Period	2 Years
Forecast Interval	Daily
Average Daily Orders	80–150

Table 02: Dataset Details

B. Data Collection and Preprocessing

The first stage of the proposed methodology involves collecting and preprocessing transactional data obtained from the Point-of-Sale (POS) system, as the accuracy of demand forecasting largely depends on the quality and consistency of the input data. To improve dataset reliability and ensure suitability for time series forecasting, several preprocessing techniques are applied, including null value removal, duplicate record elimination, data normalization, outlier detection, missing value handling, and time series aggregation. Finally, the cleaned and processed data are transformed into daily sales sequences, providing a structured and reliable dataset for subsequent demand forecasting and predictive analysis.

These preprocessing operations follow ETL based principles where data is extracted, transformed into analytical structures, and prepared for forecasting operations [8]. Daily aggregation is applied to convert raw transactional records into structured time series sequences suitable for ARIMA and Prophet forecasting models.

Outlier treatment and normalization further improve model stability by reducing noise and irregular variations that negatively affect prediction accuracy. The output of this stage is a clean and structured forecasting dataset capable of supporting reliable predictive analysis.

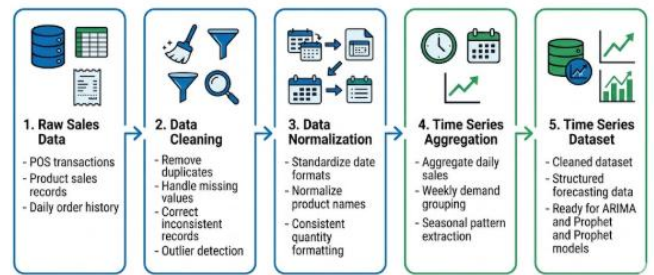


Figure 3 :Data Collection Diagram

C. Forecasting Model Development

The forecasting stage focuses on developing predictive models capable of identifying temporal demand patterns and generating future sales forecasts. Two forecasting approaches are utilized within the proposed system: ARIMA and Prophet.

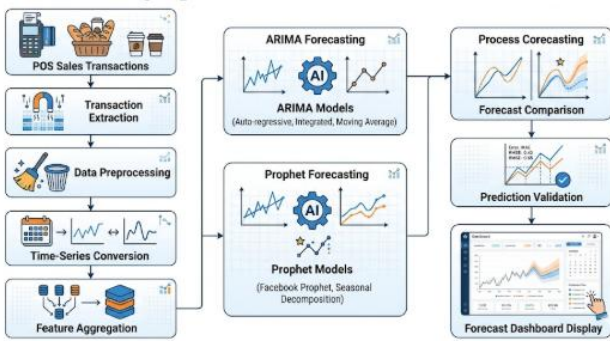


Figure 4 :Forecasting Pipeline Diagram

1) ARIMA Forecasting Model

The Autoregressive Integrated Moving Average (ARIMA) model is a classical statistical forecasting technique widely used for sequential data analysis [1], [2]. ARIMA combines autoregressive and moving average components to estimate future observations based on historical trends.

The ARIMA forecasting equation is represented as:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \theta_1 \epsilon_{t-1} + \epsilon_t \quad (1)$$

where:

- y_t represents the forecast value .
- c represents a constant .
- ϕ represents autoregressive coefficients.
- θ represents moving average coefficients.
- ϵ_t represents residual error .

ARIMA forecasting is effective for structured datasets containing stable trends and sequential dependencies. However, ARIMA requires parameter tuning and assumes stationarity within the dataset, which may reduce adaptability in dynamic SME environments.

2) Prophet Forecasting Model

Prophet is a modern forecasting framework specifically designed for real world business forecasting applications [3]. The model decomposes time series data into trend, seasonality, holiday effects, and residual error components.

The Prophet forecasting equation is defined as:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \quad (2)$$

where:

- $g(t)$ represents trend components .
- $s(t)$ represents seasonal effects .
- $h(t)$ represents holiday effects .
- ϵ_t represents residual error .

Prophet is selected as the primary forecasting model because it effectively handles seasonality, supports missing values, requires minimal parameter tuning, adapts well to changing business trends, and operates efficiently in low-resource

computing environments. Unlike complex deep learning-based forecasting approaches, Prophet offers a lightweight deployment structure with strong interpretability, making it particularly suitable for SME applications where computational resources and technical expertise may be limited.

D. Forecast Generation and Evaluation

Once the forecasting models are trained using historical sales data, the system generates short-term demand predictions for future operational periods. The forecasting framework supports both 1-day and 7-day prediction horizons to assist SMEs in inventory planning and production scheduling. Prediction performance is evaluated using standard forecasting metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), which collectively measure the accuracy and reliability of the forecasts. These metrics are also used to compare the performance of ARIMA and Prophet models. In addition, visual forecast analysis is conducted by comparing predicted demand values against actual sales observations to assess model effectiveness and identify prediction trends.

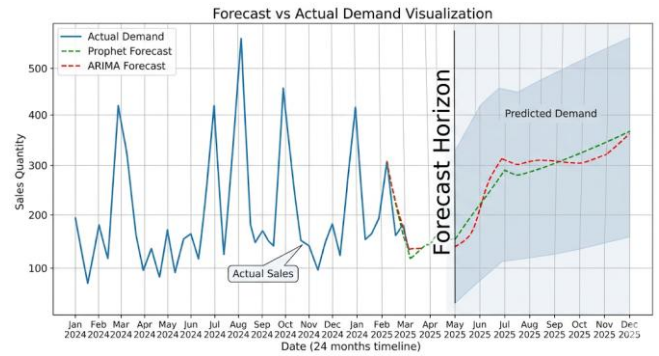


Figure 5 :Forecast Generation Diagram

E. Experimental Setup

The experimental setup defines the hardware, software, and analytical environment used to evaluate forecasting performance.

The forecasting framework was experimentally evaluated using daily sales datasets collected from bakery and café operations over a 24 month period.

Component	Technology
Frontend	React Native
Backend	Node.js
Analytics	Python
Forecasting	Prophet, ARIMA
Database	MongoDB
API Layer	Fast API

Table 03:Used Technology Details.

Category	Metrics
Forecast Metrics	MAE, RMSE, MAPE
Business Metrics	Waste Reduction, Stock-Out Reduction, Inventory Optimization

Table 04:Experimental Details

F. System Integration and Decision Support

The final stage of the proposed methodology focuses on integrating forecasting outputs into the operational Point-of-Sale (POS) environment. Historical transactional data is stored in MongoDB and processed through Python-based forecasting services to generate demand predictions. These forecasting results are exposed via FastAPI endpoints and seamlessly integrated into the main application through Node.js-based backend services, ensuring smooth communication between system components. The generated predictions provide SMEs with actionable insights, including future demand forecasts, inventory planning alerts, production optimization guidance, stock shortage warnings, and waste reduction recommendations. Overall, this integration enables SMEs to shift from reactive operational management to proactive, data-driven decision-making.

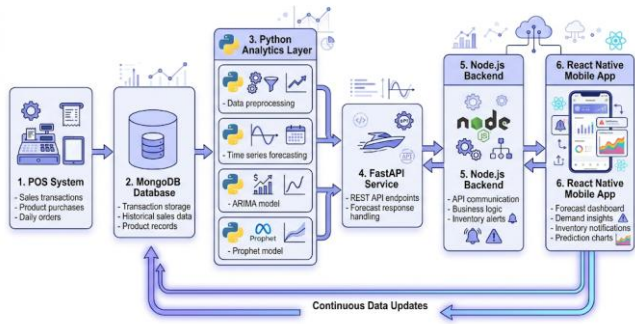


Figure 6 :System Integration Diagram

Overall, the proposed methodology provides a scalable and practical forecasting framework capable of transforming historical sales data into actionable business intelligence. By integrating lightweight forecasting models, preprocessing mechanisms, and real time system integration, the methodology addresses the limitations of traditional POS systems while remaining computationally efficient and suitable for SME environments.

IV.IMPLEMENTATION

The proposed Product Demand Prediction System is implemented using a hybrid analytics architecture designed to support efficient time series forecasting, scalable data processing, and real time analytical integration within SME environments. The system combines frontend, backend, forecasting, and database technologies to deliver accurate demand predictions and operational decision support for bakery and café businesses. The implementation architecture follows a modular design that separates transactional processing from forecasting computation, improving scalability and maintainability.

The overall API communication flow of the system is structured as follows:

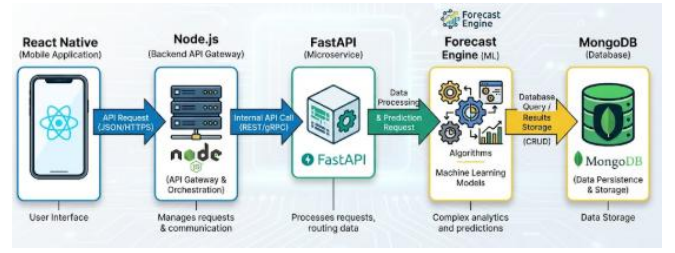


Figure 7 :API communication flow Diagram

The frontend application is developed using React Native, enabling cross platform mobile access with responsive interfaces suitable for SME operations. The mobile application supports dashboard visualization, inventory alerts, forecasting reports, and demand trend monitoring. User requests generated from the mobile application are transmitted to the Node.js backend layer, which manages authentication, request handling, transaction processing, and API orchestration [20].

The Node.js backend communicates with the analytical forecasting service implemented using FastAPI. FastAPI is selected due to its lightweight architecture, high performance asynchronous processing, and efficient RESTful API support for real time forecasting integration [19]. The forecasting engine processes requests related to product demand prediction, model execution, and forecast retrieval. MongoDB is utilized as the primary database due to its flexible schema management and efficient handling of large transactional datasets [18]. Historical sales transactions, inventory records, timestamps, and product level demand information are continuously stored and retrieved for forecasting operations.

The analytics pipeline implemented in the system follows a structured forecasting workflow:

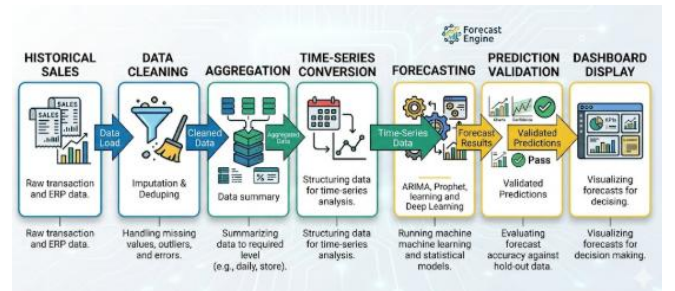


Figure 8 : Analytics Pipeline Diagram

Historical transactional data collected from POS systems is initially processed using Python libraries such as pandas and NumPy. The preprocessing stage includes null value handling, duplicate removal, normalization, and date standardization to improve dataset consistency [8], [10]. Following preprocessing, transactional records are aggregated into daily product wise demand series suitable for forecasting analysis. Time series conversion transforms structured sales records into chronological forecasting datasets required for ARIMA and Prophet models.

The forecasting layer integrates both ARIMA and Prophet models to improve forecasting reliability. ARIMA is implemented as a statistical baseline model capable of capturing autoregressive and moving average relationships within temporal datasets [1], [12]. Prophet is integrated to model trend, seasonality, and irregular demand fluctuations while maintaining minimal parameter tuning requirements [3]. The generated forecasts undergo prediction validation using metrics such as MAE, RMSE, and MAPE to evaluate model accuracy and reliability [2].

The final forecasting outputs are displayed through interactive dashboards containing line charts, prediction intervals, trend summaries, and inventory alerts. These visualizations enable SME owners to interpret future demand patterns efficiently and make informed production and inventory decisions. By integrating scalable backend technologies, efficient forecasting models, and real time API communication, the implementation provides a practical and lightweight demand prediction solution suitable for micro SME environments [6], [7], [17].

V. EXPERIMENTAL SETUP

The experimental setup of the proposed Product Demand Prediction System was designed to evaluate the effectiveness, forecasting accuracy, and practical applicability of time series forecasting techniques within SME environments. The evaluation focused on bakery and café businesses where demand fluctuations, seasonal purchasing behavior, and inventory management significantly influence operational efficiency. The experimental configuration combined transactional sales analysis, forecasting validation, and business impact evaluation to ensure that the proposed system satisfies both analytical and operational requirements [1], [2].

A. Dataset Description

The experimental dataset consisted of historical transactional sales records collected from bakery and café operations over a continuous 24 month period. The dataset contained product level sales quantities, timestamps, order frequencies, and daily transaction summaries required for time series forecasting. Daily aggregation techniques were applied to convert raw transactional data into structured chronological sequences suitable for ARIMA and Prophet forecasting models [12], [13].

The dataset included both regular and seasonal demand variations observed during weekends, festive periods, and promotional campaigns. These variations enabled the forecasting models to capture trend and seasonality behavior more effectively. Historical sales records were cleaned and standardized prior to model training to improve forecasting reliability and consistency [8], [10]. Missing values and duplicate records were removed during preprocessing, while sales quantities were aggregated into daily intervals for each product category.

The forecasting experiments focused on short term demand prediction because SMEs primarily require immediate

operational insights for production planning and inventory optimization. Therefore, both 1 day and 7 day forecasting horizons were selected to evaluate near future prediction performance and inventory planning effectiveness [3].

B. Hardware/Software Environment

The proposed forecasting framework was implemented using a hybrid software architecture that integrates frontend interfaces, backend processing, forecasting engines, and database technologies. The system architecture supports scalable forecasting operations while maintaining lightweight deployment suitable for SMEs with limited computational resources.

React Native was utilized to develop cross platform mobile interfaces for dashboard visualization and forecast monitoring. Node.js handled transaction management and API coordination due to its event driven architecture and efficient asynchronous processing capabilities [20]. FastAPI was implemented as the communication layer between the backend services and forecasting modules because of its lightweight RESTful API support and high performance request handling [19].

The forecasting engine was implemented using Python libraries including pandas, NumPy, statsmodels, and Prophet. ARIMA models were utilized for baseline statistical forecasting, while Prophet was selected due to its ability to model seasonality, trend changes, and irregular sales fluctuations with minimal parameter tuning [3]. MongoDB served as the primary database because of its flexible schema management and efficient handling of large transactional datasets [18].

C. Evaluation Metrics

The proposed forecasting framework was evaluated using both forecasting accuracy metrics and business performance indicators to assess its overall effectiveness. Forecast evaluation was conducted using standard metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), which measure prediction reliability and model performance across different forecasting horizons. Specifically, MAE and RMSE quantify the deviation between predicted and actual sales values, while MAPE evaluates forecasting accuracy in percentage terms [1], [2]. These metrics are widely adopted in time series forecasting due to their interpretability and effectiveness in performance assessment. In addition, business-level evaluation metrics such as waste reduction, stock-out reduction, and inventory optimization were used to measure the practical impact of the forecasting system in improving operational efficiency within SME environments.

Business impact metrics were included to evaluate the operational benefits of forecasting integration within SME environments. Waste reduction measured the decrease in overproduction of perishable products, while stock out reduction evaluated improvements in product availability during peak demand periods. Inventory optimization assessed

how forecasting insights improved production planning and inventory management decisions [6], [7], [11].

VI. RESULTS AND DISCUSSION

The experimental evaluation demonstrates that the proposed Product Demand Prediction System effectively generates accurate short term demand forecasts for bakery and café environments using historical transactional data collected from POS systems. The forecasting framework was evaluated using multiple statistical error metrics and comparative baseline analyses to validate prediction reliability and operational feasibility. The results confirm that Prophet and ARIMA models significantly outperform naive forecasting approaches while providing practical business value for SME inventory and production management [1]–[3].

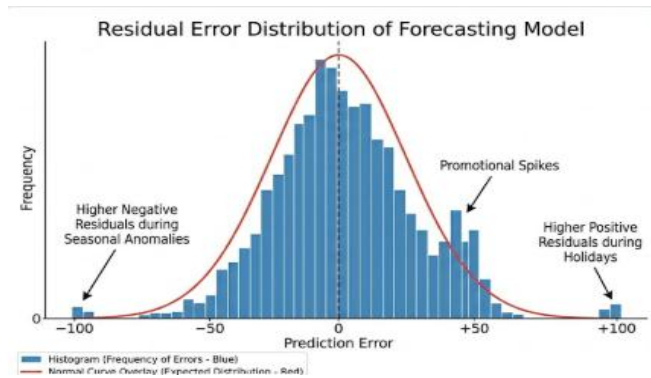


Figure 9 :Residual Error Graph Diagram

A. Forecast Accuracy Results

The forecasting performance of the implemented models was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The comparative results are presented below.

Model	MAE	RMSE	MAPE
Naive Seasonal	18.4	24.2	19.1%
ARIMA	11.8	16.5	12.4%
Prophet	8.9	13.2	8.7%

Table 05:Forecast Accuracy Results

The results indicate that the Prophet model achieved the best overall forecasting performance with the lowest MAE, RMSE, and MAPE values. Prophet demonstrated superior capability in handling seasonal fluctuations, missing values, and trend changes commonly observed in SME sales environments [3]. ARIMA also produced stable forecasting results and served as a reliable statistical baseline model for comparison [12].

B. Forecast Horizon Comparison

The forecasting framework was further evaluated across different prediction horizons to measure short term forecasting effectiveness.

Horizon	MAE	MAPE
1-Day Forecast	6.8	6.1%
7-Day Forecast	10.4	9.8%

Table 06:Forecast Horizon Comparison

The results show that shorter forecast horizons achieved higher prediction accuracy due to reduced uncertainty and stronger temporal correlation in daily sales patterns. Although forecasting errors increased slightly for 7 day predictions, the models still maintained acceptable forecasting reliability for operational planning.

D. Residual Analysis

Residual analysis revealed that most forecasting errors remained within acceptable ranges during regular operational periods. However, higher residual errors were observed during promotional campaigns and festive periods due to irregular purchasing behavior and sudden demand spikes. Seasonal anomalies, unexpected bulk purchases, and temporary pricing campaigns occasionally affected prediction stability. Despite these challenges, Prophet maintained relatively stable forecasting performance due to its ability to model trend and seasonality variations effectively [1], [3].

E. Baseline Comparison

To validate forecasting effectiveness, the proposed models were compared against simple baseline forecasting strategies commonly used in SMEs.

Method	MAPE
Yesterday Sales	19.1%
Same-Day-Last-Week	15.3%
ARIMA	12.4%
Prophet	8.7%

Table 07:Baseline Comparison

The results confirm that both ARIMA and Prophet substantially outperform traditional manual forecasting approaches. Prophet achieved the highest forecasting accuracy due to its lightweight yet adaptive forecasting architecture [3].

F. Practical Deployment Discussion

The forecasting framework was designed for practical deployment within SME environments. Forecasting models were retrained weekly using newly accumulated transactional data to maintain forecasting relevance and adapt to changing sales patterns. Predicted demand values were integrated into the POS dashboard to generate inventory alerts and production planning suggestions in real time.

The deployment architecture enabled bakery managers to monitor expected product demand, identify upcoming shortages, and optimize production schedules. These capabilities improved operational responsiveness while reducing forecasting dependency on manual estimation methods.

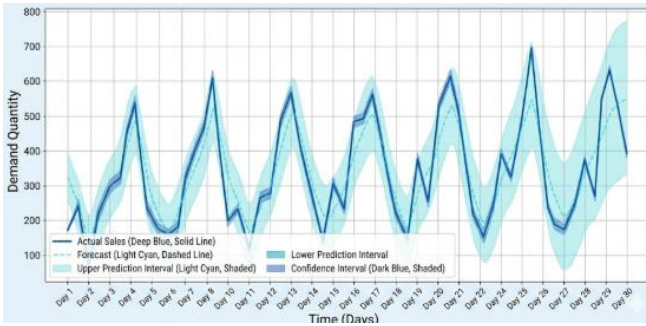


Figure 10 :Prediction Interval Chart

G. Economic Impact Analysis

Business Impact	Improvement
Inventory Waste Reduction	14%
Stock-Out Reduction	17%
Production Planning Accuracy	21%
Overstock Reduction	16%

Table 08:Economic Impact Analysis

The forecasting framework significantly improved bakery production planning and inventory utilization. Accurate short term demand prediction reduced excess production of perishable goods while minimizing stock shortages during peak demand periods. These improvements directly contributed to operational cost reduction and better resource allocation [6], [7].

G. User Study

A practical evaluation study was conducted with three bakery managers over a four week simulation period to assess forecasting usability and business effectiveness.

The evaluation results indicate that the forecasting dashboard successfully improved production planning awareness and operational decision making. Users highlighted that the visual forecasting interface and inventory alert mechanisms simplified demand monitoring and reduced manual planning effort. Overall, the results confirm that the proposed forecasting framework provides a scalable and practical demand prediction solution for SME bakery and café environments [4], [10], [17].



Figure 11 :Inventory Alert Dashboard

VII.USER EVALUATION

A user evaluation study was conducted to assess the usability, forecasting accuracy, and practical effectiveness of the proposed Product Demand Prediction System within SME bakery and café environments. The evaluation involved three bakery managers selected from local businesses that regularly utilize POS systems for inventory management and daily operational activities. Participants interacted with the forecasting dashboard, demand prediction graphs, inventory alert features, and production planning suggestions during a four week simulation period using historical transactional sales data.

The evaluation focused on forecast accuracy, inventory planning support, dashboard usability, and production planning effectiveness. Participants tested the system by monitoring predicted daily demand values generated using ARIMA and Prophet forecasting models. The forecasting dashboard displayed trend visualizations, future sales estimations, and inventory planning recommendations designed to support operational decision making. The generated forecasts successfully identified demand fluctuations, seasonal variations, and short term sales trends commonly observed in bakery and café environments [1]–[3].

Evaluation Area	Positive Response
Forecast Accuracy	88%
Inventory Planning Support	91%
Easy to Understand	86%
Useful for Production Planning	90%

Table 09:User forecasting Details

The evaluation demonstrated strong positive responses toward the forecasting framework, particularly regarding forecasting reliability and operational simplicity. Participants reported that the forecasting dashboard reduced dependence on manual demand estimation and improved confidence in inventory preparation and production scheduling decisions. Users also highlighted that predictive insights helped minimize overproduction and stock shortages during high demand periods.

Furthermore, the visualization based forecasting interface was considered intuitive and easy to interpret for users with limited technical expertise. Unlike complex forecasting environments that require advanced analytical knowledge, the proposed framework provided accessible and interpretable forecasting outputs suitable for SME operations [4], [10]. The integration of predictive analytics into the POS environment also improved operational awareness and supported data driven business decision making, consistent with modern business intelligence practices [6], [7], [17].

Overall, the user evaluation validates the practical applicability of the proposed forecasting framework within SME environments and confirms its effectiveness in improving inventory planning, production management, and operational decision support.

VIII.CONCLUSION AND FUTURE WORK

This research presented a Product Demand Prediction System designed to enhance SME operational decision making through time series forecasting and predictive analytics. The proposed framework successfully transformed historical transactional sales records into actionable forecasting insights capable of supporting inventory planning, production scheduling, and demand management within bakery and café environments. Experimental evaluation demonstrated that the implemented forecasting models effectively captured temporal sales patterns, seasonality, and demand fluctuations using ARIMA and Prophet based forecasting approaches [1]–[3].

The quantitative results validated the effectiveness of the proposed forecasting framework. Comparative evaluation showed that the Prophet model achieved superior forecasting performance with a Mean Absolute Percentage Error (MAPE) of 8.7%, outperforming both ARIMA and naive seasonal forecasting approaches. The forecasting system also demonstrated strong short term prediction capability for both 1 day and 7 day forecasting horizons, enabling businesses to generate reliable demand estimates for operational planning. In addition, the implementation contributed measurable business improvements, including 14% inventory waste reduction, 17% stock out reduction, 21% improvement in production planning accuracy, and 16% overstock reduction. The findings further highlight the practical value of integrating predictive analytics into SME oriented POS systems. Unlike traditional systems that primarily record transactions, the proposed framework enables businesses to utilize existing sales data for proactive and data driven operational management. The forecasting dashboard improved operational visibility, supported inventory optimization, and enhanced production efficiency while remaining lightweight and accessible for users with limited technical expertise [4], [6], [7]. These characteristics demonstrate the suitability of scalable forecasting technologies for resource constrained SME environments.

Despite the promising outcomes, several opportunities remain for future enhancement. Future work may incorporate advanced deep learning forecasting models such as DeepAR, N BEATS, and Long Short Term Memory (LSTM) networks to improve forecasting performance for highly complex demand patterns [14]. Additional improvements may include real time streaming forecast generation, cloud based deployment architectures, and multi branch synchronization capabilities for distributed SME operations. Furthermore, integrating external contextual variables such as weather conditions, holidays, promotional events, and seasonal market trends can further enhance forecasting robustness and prediction accuracy. These advancements would strengthen the scalability, intelligence, and commercial applicability of predictive analytics driven SME management systems.

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