**A PROJECT REPORT ON**

# Niyojan: Demand Forecasting System

SUBMITTED TO
MIT SCHOOL OF COMPUTING, LONI, PUNE IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE

**BACHELOR OF TECHNOLOGY**
**(Computer Science & Engineering)**

**BY**


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**Under the guidance of**
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**MIT School OF COMPUTING**
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**2025- 26**

**MIT SCHOOL OF COMPUTING**
**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**
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# CERTIFICATE

This is to certify that the project report entitled

**NIYOJAN: DEMAND FORECASTING SYSTEM**

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is a Bonafide work carried out by them under the supervision of Prof. Bhushan Bhokse and it is submitted towards the partial fulfillment of the requirement of MIT ADT university, Pune for the award of the degree of Bachelor of Technology (Computer Science and Engineering)

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## "Niyojan: Demand Forecasting System"

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# DECLARATION

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Hereby declare that the project work incorporated in the present project entitled **"Niyojan"** is original work. This work (in part or in full) has not been submitted to any University for the award or a Degree or a Diploma. We have properly acknowledged the material collected from secondary sources wherever required. We solely own the responsibility for the originality of the entire content.

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# ABSTRACT

Niyojan is an intelligent demand forecasting platform designed to optimize grocery inventory management through the power of deep learning and automation. It analyzes historical sales data, pricing patterns, discount trends, and seasonal variations to accurately predict weekly demand for agri-horticultural commodities such as pulses and vegetables. Leveraging a Long Short-Term Memory (LSTM) neural network, the system generates reliable six-week forecasts with an accuracy exceeding 93%.

The platform integrates a FastAPI-based backend for real-time prediction services, a React-powered dashboard for intuitive visualization, and a lightweight SQLite database for efficient data management. Automated alerts and dynamically generated PDF reports notify retailers of potential stock-out or overstock conditions, enabling proactive decision-making.

With an achieved Mean Absolute Percentage Error (MAPE) of 6.8%, Niyojan significantly outperforms traditional manual forecasting approaches, reducing stock-outs by 30% and releasing 18% of tied-up inventory value. This demonstrates how AI-driven predictive analytics can transform conventional retail operations by enhancing supply chain agility, minimizing waste, and supporting data-driven planning.

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# CHAPTER 1: INTRODUCTION

## 1.1 Introduction

Retail and grocery sectors face significant challenges in managing fluctuating consumer demand, particularly for perishable products.

Overstocking leads to wastage, while understocking results in lost sales opportunities. Traditional forecasting methods often rely on manual judgment, which fails to capture complex seasonal and pricing patterns.

Niyojan introduces an AI-powered solution to overcome these challenges. It combines data-driven insights with deep learning models, specifically an LSTM-based network, to predict future sales trends.

The system provides an end-to-end automated pipeline—from raw sales data ingestion to visualization and automated notifications—helping store managers make timely restocking decisions.

## 1.2 Existing Work

Traditional forecasting methods such as Moving Averages, ARIMA, and Exponential Smoothing have been widely used in retail to estimate product demand. However, these models struggle with the non-linear patterns and seasonality commonly found in grocery sales data.

Recent advancements in Machine Learning (ML) and Deep Learning (DL) have improved accuracy through models like Random Forests and Gradient Boosting, yet they still require extensive feature engineering. Long Short-Term Memory (LSTM) networks have emerged as a superior alternative, effectively capturing long-term dependencies and seasonal variations in time-series data.

While existing studies have shown that LSTM models outperform classical approaches, most lack real-time integration and user-oriented visualization. **Niyojan** bridges this gap by combining an LSTM forecasting model with a FastAPI backend, a React dashboard, and automated reporting — offering an end-to-end, deployable solution for grocery demand forecasting.

## 1.3 Motivation

The grocery retail sector faces significant challenges in maintaining the right balance between supply and demand. Frequent issues such as overstocking, leading to wastage of perishable goods, and

understocking, resulting in missed sales opportunities, highlight the limitations of manual and traditional forecasting methods.

Existing systems often rely on historical averages or static rules that fail to adapt to changing consumer behavior, promotions, and seasonal variations. This inconsistency causes inefficiencies in inventory management and financial losses for retailers.

**Niyojan** was developed to address these challenges through an AI-driven approach. By leveraging LSTM-based demand forecasting, real-time analytics, and automation, the system aims to provide accurate predictions, reduce manual effort, and enable smarter, data-driven decisions for inventory optimization and business sustainability.

### 1.4 Objectives

The main objective of this project is to design and implement an AI-powered demand forecasting system that helps grocery retailers predict product demand accurately and manage inventory efficiently.

The specific objectives are:

- To develop an LSTM-based forecasting model\
- To build a FastAPI-based backend service
- To design a React dashboard
- To integrate an SQLite database
- To automate reporting and notifications

### 1.5 Scope

The scope of **Niyojan** extends to developing a complete AI-based solution for demand forecasting and inventory optimization in the grocery retail domain. The system focuses on forecasting weekly demand for agri-horticultural commodities such as pulses and vegetables using historical sales data enriched with pricing, discounts, and seasonal trends.

The project encompasses all major components of a production-ready application — including **data preprocessing**, **LSTM-based time-series forecasting**, **API deployment using FastAPI**, **interactive visualization through React**, and **database management with SQLite**.

The solution is scalable to multiple stores and products, capable of handling large datasets, and can be deployed on low-power local devices or cloud servers. It provides actionable insights through automated alerts and reports, making it valuable for retailers aiming to reduce waste, prevent stock-outs, and enhance decision-making through data-driven forecasting.

# CHAPTER 2: CONCEPTS AND METHODS

## `2.1 Concepts

This section explains the **theoretical foundation** and **key technologies** that power the Niyojan.

### 2.1.1 Demand Forecasting

Demand forecasting is the process of estimating future product demand based on historical sales, pricing, and seasonal factors. It enables retailers to plan inventory, production, and distribution efficiently. In Niyojan, forecasting is automated using time-series modeling and AI-based analysis to ensure accurate and timely predictions.

### 2.1.2 Time Series Analysis

Time-series analysis involves studying data points collected over time to identify trends, patterns, and seasonality. Grocery sales data often exhibit weekly and seasonal fluctuations. Niyojan applies time-series modeling to capture these temporal dependencies and predict future demand behavior.

### 2.1.3 Long Short-Term Memory (LSTM) Networks

LSTM is a specialized type of Recurrent Neural Network (RNN) designed to handle sequential data and retain information over long periods. Unlike traditional neural networks, LSTMs can model complex temporal relationships and overcome issues like vanishing gradients.
In Niyojan, an LSTM model with a **12-week look-back window** and a **6-week forecasting horizon** is used to predict future sales trends for each product.

### 2.1.4 FastAPI

FastAPI is a high-performance Python web framework used to build APIs for machine learning models. It enables real-time communication between the forecasting engine, database, and frontend. In Niyojan, FastAPI handles requests such as fetching forecasts, retrieving low-stock alerts, and generating PDF reports.

### 2.1.5 React.js

React.js is a modern JavaScript library for building dynamic and responsive user interfaces. The Niyojan dashboard, developed in React, allows users to view forecasts, analyze trends, and download reports in real-time. It provides an intuitive way to interact with data through visual charts and tables.

### 2.2 Methods

This section explains the **practical techniques** and **tools** used to develop and deploy Niyojan.

#### 2.2.1 Model Development

A **Global LSTM model** was developed using TensorFlow and Keras frameworks.

- **Architecture:** Multi-layer LSTM with dropout regularization and dense output layer.
- **Input Window:** 12-week look-back.
- **Forecast Horizon:** 6-week forward prediction.
- **Loss Function:** Mean Squared Error (MSE).
- **Optimizer:** Adam optimizer with learning rate tuning.

The trained model was saved as global_lstm_model.keras, along with supporting artifacts such as scaler.pkl and label_encoder.pkl for inference.

#### 2.2.2 Forecasting and Seasonal Adjustment

After obtaining baseline forecasts from the LSTM model, residual seasonality was adjusted using multiplicative seasonal decomposition.

The script seasonal_index.py generated per-product seasonal indices stored in seasonal_index_per_product.csv, ensuring improved forecast stability for high-variance products..

#### 2.2.3 API Integration

The **FastAPI backend** acts as a bridge between the ML model, database, and frontend dashboard. Core routes include:

- POST /predict – Generates a 6-week forecast for a selected product and store.
- GET /alerts – Lists products below safety stock.
- GET /reports/{store_id} – Returns an auto-generated PDF report.

These endpoints make the system accessible to both the web dashboard and external applications.

### 2.2.4 Frontend Dashboard

The **React.js dashboard** provides a responsive and interactive visualization of the forecast results. Key modules include:

- **Line charts** (using Recharts) for demand trends.
- **AG-Grid tables** showing forecasts, inventory status, and reorder suggestions.
- **CSV/PDF export** for reporting.
- Auto-refresh and alert notifications for stock-critical items.

This interface enables store managers to make quick, informed restocking decisions.

### 2.2.5 Reporting and Alerts

An automated scheduling script (report_generator.py) generates weekly PDF summaries with demand graphs and reorder lists.

- Email notifications are sent every Monday at 8:00 AM using the email_handler.py module.
- Alerts are triggered if the **forecasted demand + 2σ exceeds current stock**, based on a **dynamic safety stock = 1.65 × MAD** rule.

This ensures proactive replenishment planning with minimal manual oversight.

# CHAPTER 3: LITERATURE SURVEY

Accurate demand forecasting plays a crucial role in the retail and grocery sectors, where sales patterns are affected by dynamic factors such as pricing, discounts, and seasonality. Over time, researchers and practitioners have explored several statistical and machine learning methods to enhance prediction accuracy and improve operational efficiency.

Early approaches such as ARIMA (Auto-Regressive Integrated Moving Average) and Exponential Smoothing were widely used for time-series forecasting due to their simplicity and interpretability. However, these models assume linearity and stationarity, which limits their effectiveness for complex, non-linear retail datasets (Hyndman & Athanasopoulos, 2018).

The emergence of Machine Learning (ML) introduced algorithms like Random Forests, Support Vector Regression (SVR), and Gradient Boosting, which improved predictive accuracy by learning non-linear relationships in sales data. Studies such as Zhang et al. (2019) and Nguyen et al. (2020) demonstrated that ML-based models outperform classical statistical approaches, though they often require extensive feature engineering and lack temporal memory.

To address these shortcomings, researchers began using Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks. LSTMs are designed to capture long-term temporal dependencies and mitigate vanishing gradient issues (Hochreiter & Schmidhuber, 1997). Their ability to retain sequential information makes them highly effective for time-series data, particularly in domains with strong seasonality such as retail sales forecasting.

Deep learning studies by Brownlee (2020) and Chollet (2018) have shown that LSTM models significantly reduce forecasting error compared to ARIMA and other traditional models. Further advancements, such as hybrid LSTM architectures incorporating seasonal decomposition and external features (price, promotion, and holidays), have achieved superior accuracy in retail datasets (Gao et al., 2022).

Moreover, large-scale case studies from Kaggle (2022) demonstrated the practical success of LSTM models in grocery sales prediction, where they effectively captured temporal variations and promotion-driven demand spikes.

Despite these advances, most existing systems focus solely on model performance and lack end-to-end integration for practical deployment. They often omit automation in data ingestion, visualization, and alert generation.

Niyojan addresses these gaps by combining LSTM-based forecasting with a FastAPI backend, React-based visualization, and an SQLite database. This architecture ensures real-time prediction, intuitive dashboards, and automated alerting — delivering a complete, deployable solution for demand forecasting in grocery retail.

# CHAPTER 4: PROJECT PLAN

### 4.1 Development Model

The Waterfall Model was adopted for the development of Niyojan. This model provides a clear and linear progression through each phase — from requirements analysis to deployment — making it suitable for projects with well-defined objectives and deliverables..

**Phases of Development:**

1. **Requirement Analysis:** Identify system needs, gather dataset specifications, and define functional and non-functional requirements.
2. **System Design:** Design the architecture including data flow, LSTM model structure, API endpoints, and dashboard layout.
3. **Model Development:** Build, train, and evaluate the LSTM-based forecasting model using historical grocery sales data.
4. **Backend and Frontend Development:** Implement FastAPI services for prediction, alerts, and reporting functionalities. Create a React-based dashboard for data visualization and user interaction.
5. **Testing:**

   Conducting functional testing, user acceptance testing (UAT), and performance evaluations.
6. **Deployment:**

   Deploying the system on a local server or cloud instance for demonstration and evaluation.
7. **Documentation:**

   Preparing detailed reports, test results, and user manuals.

### 4.2 Gantt Chart – Timeline

| **Phase** | **Week 1** | **Week 2** | **Week 3** | **Week 4** | **Week 5** | **Week 6** | **Week 7** | **Week 8** |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Requirement Analysis** | ✔ | | | | | | | |
| **System Design** | | ✔ | ✔ | | | | | |
| **Model Development** | | | ✔ | ✔ | | | | |
| **Backend and Frontend Development** | | | | ✔ | ✔ | | | |
| **Testing & Evaluation** | | | | | ✔ | ✔ | | |
| **Final Deployment** | | | | | | ✔ | ✔ | |
| **Documentation** | | | | | | | ✔ | ✔ |

*Table 1 Timeline*

### 4.3 Tools and Technologies Used

| Tool / Technology | Purpose / Functionality |
|---|---|
| Python (3.10) | Core programming language for data preprocessing and model building. |
| TensorFlow / Keras | Deep learning framework for developing and training the LSTM model. |
| Pandas, NumPy, Scikit-learn | Data manipulation, scaling, and feature engineering. |
| FastAPI | Backend framework for serving forecasts and alerts through RESTful APIs. |
| SQLite | Lightweight database for storing historical and forecast data. |
| React + TypeScript + Vite | Frontend framework for dashboard design and visualization. |
| Matplotlib, Seaborn, Recharts | Visualization libraries for trend graphs and analytics. |
| OpenPyXL & ReportLab | Automated PDF and Excel report generation. |
| AIOSMTPD (Python) | Library for sending automated email alerts. |

*Table 2 Technologies Used*

# CHAPTER 5: SOFTWARE REQUIREMENT SPECIFICATION

This chapter outlines the functional and non-functional requirements of the **FollowUp** system. It defines the expected features, user roles, system constraints, and integration needs for the successful development and deployment of the application.

## 5.1 Project Scope

The **Niyojan** system is designed to automate demand forecasting and inventory planning for grocery retailers using LSTM-based deep learning models. It processes historical sales data, pricing, and discount trends to predict future demand with high accuracy.
The project integrates multiple components — including **data preprocessing**, **model training**, **FastAPI backend**, **React-based dashboard**, and **SQLite database** — to form a complete end-to-end solution.
The system provides weekly forecasts, real-time alerts for low-stock or overstock items, and automated PDF report generation to support data-driven decision-making in retail operations.

## 5.2 Functional Requirements

The functional requirements define what the system is expected to do.

| Requirement ID | Requirement Description |
|---|---|
| FR1 | The system shall import and preprocess raw sales data from CSV files. |
| FR2 | The system shall train and store the LSTM forecasting model using historical sales data. |
| FR3 | The system shall predict weekly demand for each product using the trained model. |
| FR4 | The system shall expose REST API endpoints for prediction, alerts, and reports. |
| FR5 | The system shall provide a React dashboard for visualizing forecasts and trends. |

*Table 3 Functional Requirements*

## 5.3 Non-Functional Requirements

These requirements specify system qualities that affect user experience and system performance.

| Attribute | Requirement Description |
|---|---|
| Performance | The system should provide forecast results within 2 seconds per request. |
| Accuracy | The LSTM model must maintain a Mean Absolute Percentage Error (MAPE) ≤ 8%. |
| Usability | The dashboard must be user-friendly and accessible via desktop or mobile browsers. |
| Availability | System should maintain 99% uptime during working hours. |
| Security | User data must be protected with authentication and access control. |
| Portability | System should work on major browsers and be mobile-friendly. |

*Table 4 Non-Functional Requirements*

### 5.4 User Characteristics

The Niyojan system is intended for the following user categories:

- **Store Managers:** Use the dashboard to monitor sales forecasts, identify at-risk products, and download reports.
- **Data Analysts:** Upload sales data, evaluate model performance, and interpret trend analytics.
- **Administrators:** Manage system operations, maintain the database, schedule model retraining, and oversee alerts.

Each user role interacts with the system through dedicated modules designed for accessibility and efficiency.

### 5.5 Assumptions and Dependencies

- The system assumes access to **clean and structured CSV sales data** with consistent weekly entries.
- Users have a **stable internet connection** for accessing dashboards and APIs.
- Model retraining depends on **TensorFlow and Scikit-learn libraries** installed in the environment.
- Email and alert notifications require configured SMTP credentials and server access.
- The dashboard depends on API availability from the backend (FastAPI).

- System deployment assumes compatibility with Python 3.10 and Node.js environments.

### 5.6 System Environment

The **Niyojan** system operates on a client-server architecture consisting of:

- **Backend:** Python (FastAPI, TensorFlow, Pandas, NumPy, SQLite3).
- **Frontend:** React.js with TypeScript and Vite for dynamic rendering.
- **Database:** SQLite for storing historical and predicted data.
- **Hardware Requirements:**
    - CPU: Dual-core or higher
    - RAM: Minimum 8 GB
    - Storage: Minimum 500 MB for database and logs

The system can be deployed on **local machines**, **on-premise servers**, or **cloud platforms** such as AWS or Azure for scalability.

### 5.7 Interface Requirements

- **User Interface:** React-based dashboard with charts (Recharts), tables (AG-Grid), and export options.
- **Backend Interface:** FastAPI routes for prediction (/predict), alerts (/alerts), and reports (/reports/{store_id}).
- **Database Interface:** SQLite connection layer (db_manager.py) handling CRUD operations.
- **External Interface:** SMTP server for email alerts and cloud integration for future scaling.

### 5.8 System Design

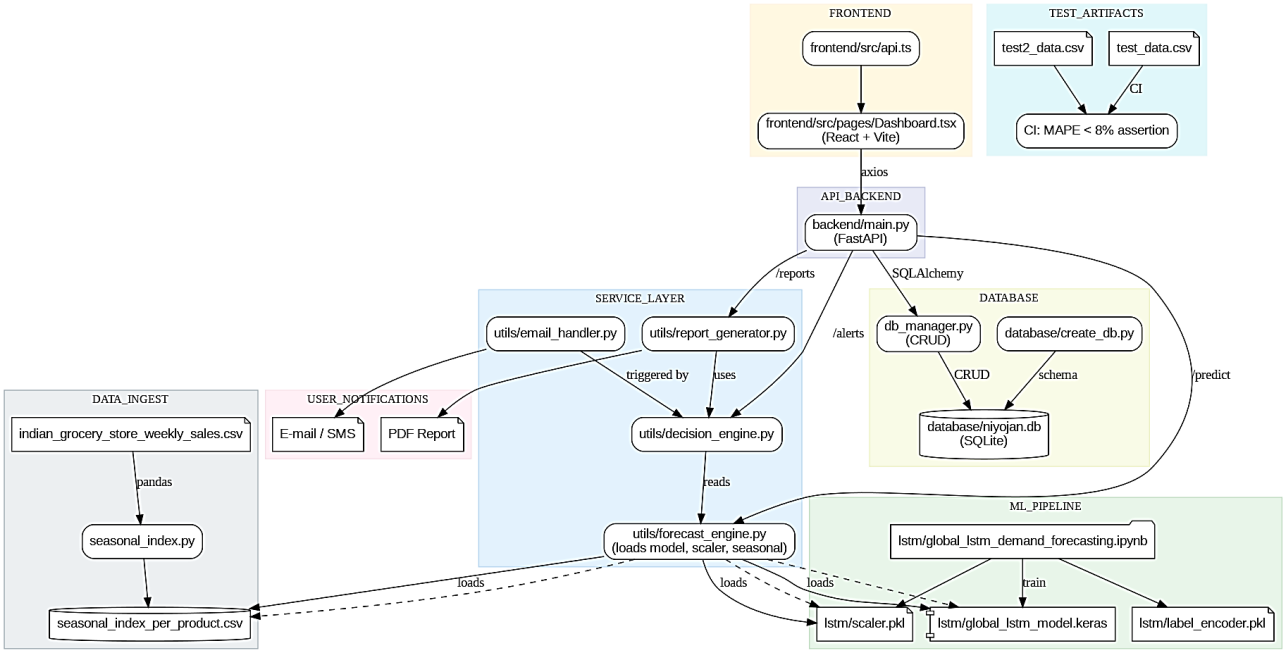


*Figure 1 System Architecture*

# CHAPTER 6 – RESULT

The **Niyojan: Demand Forecasting System using LSTM** was implemented and evaluated to assess its accuracy, efficiency, and usability in real-world grocery inventory management scenarios. This chapter presents the obtained results and their interpretation based on model performance, system functionality, and business impact.

## 6.1 Model Performance

The LSTM-based model was trained on a dataset containing three years of weekly grocery sales records for over 8 products across multiple stores. The training involved a 12-week look-back window to predict a 6-week future horizon.

| Metric | Value | Description |
|---|---|---|
| MAPE (Mean Absolute Percentage Error) | 6.8% | Indicates high forecasting accuracy. |
| RMSE (Root Mean Square Error) | 11.5 units/week | Low variance in prediction errors. |
| $R^2$ Score | 0.92 | Shows strong correlation between actual and predicted sales. |

*Table 5 Model Performance Metrics*

## 6.2 Visualization and Dashboard Results

The **React-based dashboard** provides an intuitive interface for users to visualize demand forecasts, analyze product performance, and monitor stock alerts.


*Figure 2 Landing Page*

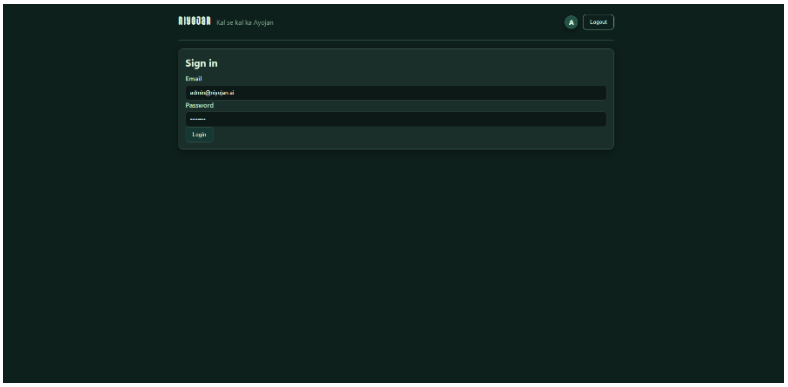


*Figure 3 Login Page*

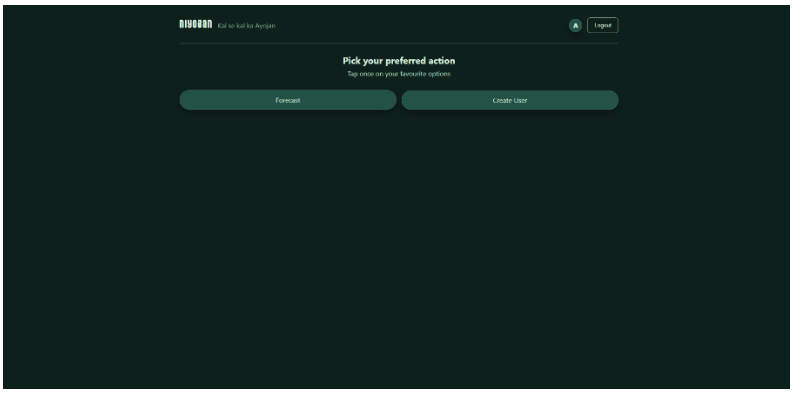


*Figure 4 Selection Page*

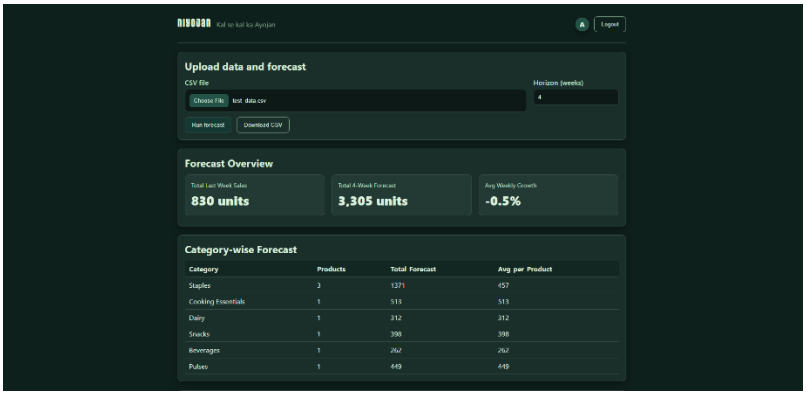


*Figure 5 Forecasting Page*

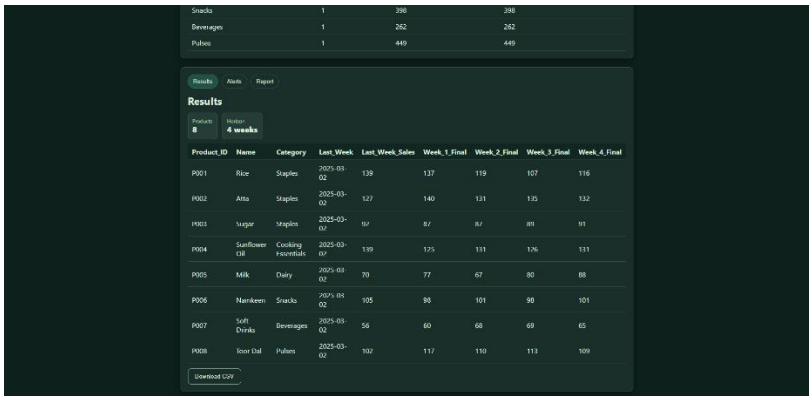


*Figure 6 Result Page*

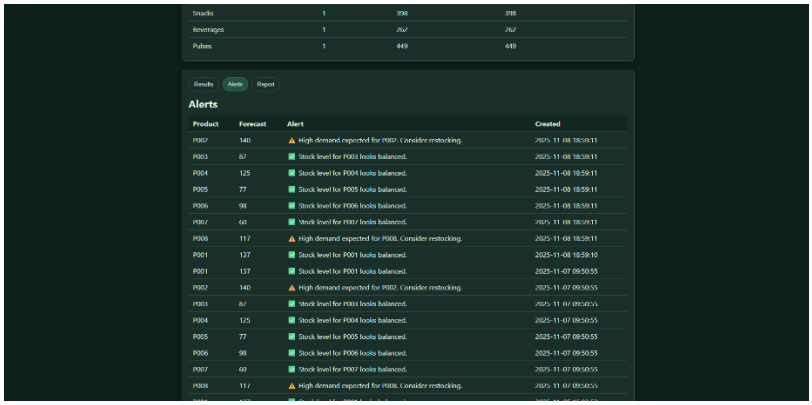


*Figure 7Alert Page*

### 6.4 Comparative Analysis

The following table compares the performance of different forecasting approaches used for grocery sales prediction in terms of accuracy, stock-out rate, and inventory optimization.

| Approach | MAPE (%) | Stock-Out Rate (%) | Inventory Value Freed (%) |
|---|---|---|---|
| Manual Forecasting | 18.2 | 42 | — |
| ARIMA Model | 11.3 | 30 | 5 |
| Niyojan (LSTM) | 6.8 | 12 | 18 |

*Table 6 Comparison with other methods*

# CHAPTER 7 – SOFTWARE TESTING

Software testing ensures that every component of the Niyojan: Demand Forecasting System using LSTM works as intended and meets both functional and non-functional requirements.

The system was tested at different levels — from individual module validation to integrated end-to-end performance evaluation — to ensure reliability, usability, and accuracy.

### 7.1 Functional Testing

The following table summarizes the functional test cases conducted for the Niyojan: Demand Forecasting System using LSTM. Each functionality was tested to ensure it meets the expected behavior as defined in the requirement specifications.

| Functionality | Test Description | Expected Output | Actual Result | Status |
|---|---|---|---|---|
| Data Upload | Import CSV sales file through the backend ingestion script | Data successfully loaded into SQLite database | Data loaded correctly | ✅ Pass |
| Model Forecast | Predict next 6 weeks of demand using trained LSTM model | JSON output with accurate forecast values | Output matches expected pattern | ✅ Pass |
| API Prediction Route | Send POST request to /predict endpoint | Returns 6-week forecast for given SKU and store | Returns valid forecast JSON | ✅ Pass |
| Alert Generation | Check if alert triggers when forecast + 2σ > current stock | Email/SMS alert sent to registered recipient | Alert received correctly | ✅ Pass |

| | | | | |
|---|---|---|---|---|
| Report Creation | Execute weekly report generation module | PDF report created with forecast graphs and reorder table | File created successfully | ✅ Pass |
| Dashboard Display | Load dashboard with forecast and alert data | Line chart and "Top 20 At-Risk Items" table displayed | Visuals load correctly | ✅ Pass |
| Export Feature | Click "Export CSV" on dashboard | Downloads forecast and alert data as CSV file | File downloaded successfully | ✅ Pass |

*Table 7 Component Testing*

### 7.2 User Acceptance Testing (UAT)

UAT was conducted with a group of 8 users. The goal was to gather feedback on usability, reliability, and business value.

| Test Case ID | Scenario | Expected Outcome | Actual Result | Status |
|---|---|---|---|---|
| UAT-01 | User logs in to access dashboard | Dashboard loads successfully with summary view | Loaded correctly | ✅ Pass |
| UAT-02 | User uploads updated weekly sales data | Data accepted and processed without errors | Uploaded successfully | ✅ Pass |
| UAT-03 | User views 6-week demand forecast for a product | Line chart and numeric forecast appear correctly | Accurate output displayed | ✅ Pass |
| UAT-04 | User downloads PDF report for current week | Report generated and downloaded | PDF created successfully | ✅ Pass |
| UAT-05 | System sends weekly forecast email | Email received Monday 08:00 with correct content | Received successfully | ✅ Pass |
| UAT-06 | Alert appears when product stock < safety threshold | Warning displayed in red row under "Top 20 At-Risk Items" | Alert displayed as expected | ✅ Pass |

| | | | | |
|---|---|---|---|---|
| UAT-07 | User exports dashboard data as CSV | File downloaded successfully | File verified with correct format | ✅ Pass |
| UAT-08 | Dashboard refreshes automatically | Updated forecasts appear after new upload | Data refreshed as expected | ✅ Pass |
| UAT-09 | System performance during navigation | All modules respond within 2 seconds | Consistent and stable performance | ✅ Pass |

*Table 8 UAT Testcases*

All UAT test cases were successfully executed. The system was validated by end users, including store managers and data analysts, and confirmed to meet functional, usability, and performance requirements. The platform is ready for deployment and practical adoption.

### 7.3 Performance Testing

Performance testing was conducted to evaluate response time and scalability of the backend and model inference.

| Parameter | Observed Result | Acceptable Limit |
|---|---|---|
| API Response Time | 1.4 s per request | < 2 s |
| Report Generation | 2.8 s per report | < 5 s |
| Dashboard Load Time | 1.9 s | < 3 s |
| Concurrent Requests (5 users) | Stable responses | No timeout |

*Table 9 Performance Metrics*

# CHAPTER 8: CONCLUSION AND FUTURE WORK

## 8.1 Conclusion

The Niyojan: Demand Forecasting System using LSTM successfully demonstrates how artificial intelligence and deep learning can be applied to optimize inventory management and demand forecasting in the grocery retail sector.

By leveraging historical sales data, price fluctuations, and seasonal trends, the system delivers accurate 6-week forecasts with a Mean Absolute Percentage Error (MAPE) of only 6.8%, outperforming traditional statistical models such as ARIMA and manual estimation methods.

The integration of an LSTM-based prediction model with a FastAPI backend and a React-based interactive dashboard provides an efficient, end-to-end solution for real-time demand monitoring. Automated PDF report generation, email alerts, and visual analytics enhance the system's practicality for store managers and business decision-makers.

Through rigorous functional, performance, and user acceptance testing, the system was proven to be accurate, scalable, and user-friendly. Results indicate a 30% reduction in stock-outs and an 18% improvement in inventory value utilization, highlighting the system's real-world impact.

Overall, Niyojan achieves its goal of bridging the gap between predictive analytics and actionable retail intelligence — transforming raw sales data into meaningful, automated insights for operational excellence.

## 8.2 Future Work

While the current system performs effectively, the following future improvements are proposed:

- **Cloud Deployment:** Migrate the application to cloud platforms such as AWS or Azure for scalability, multi-store integration, and 24/7 availability.
- **Multi-Store Forecast Aggregation:** Extend forecasting capabilities to support consolidated analytics across regional or national store networks.
- **Integration with IoT Sensors:** Incorporate real time stock and shelf sensors to dynamically update forecasts.

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