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AI-DRIVEN DEMAND FORECASTING AND WASTE MANAGEMENT SYSTEM FOR SRI LANKAN RESTAURANTS

Project ID: 25_26J_393

Project Proposal Report

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Dedication

We declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	Student ID	Signature
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The candidate mentioned above is conducting research for their undergraduate dissertation under my supervision.

……………………………… Signature of the Supervisor (Mr. Ravi Supunya)	……………………………… Signature of the Supervisor (Mrs. Chathurya Kumarapperuma)	30/08/2025 ……………… Date

Abstract

Sri Lanka's small-scale food and beverage suppliers - especially those serving restaurants and street vendors - have very little data that would allow them to accurately predict their demand and therefore plan their inventories. This results in overstocking, understocking and avoidable delivery trips. While larger enterprises use Enterprise Resource Planning (ERP) systems or sophisticated forecasting software, the expense, complexity, and data-sharing issues of these types of technologies make them prohibitive for smaller players.

The objective of this project is to develop a Supplier Demand Forecasting Dashboard to enable small suppliers to make more informed inventory decisions using low-data privacy preserving demand forecasts. The system will collect very minimal dish level sales data for the restaurants, convert this into ingredient level demand based on the predefined recipes, and finally use time series models such as ARIMA, Holt-Winters and Random Forest. These predictions will be combined across multiple restaurants so that raw sales data are not shared with each other using federated learning techniques.

The dashboard will provide total ingredient demand, trends over the weeks and reorder recommendations to enable suppliers to optimize stock levels and delivery to customers. The combination of lightweight machine learning, aggregation with no privacy leakage, and actionable inventory logic are well suited to the technical and economic realities of developing markets.

The proposed deliverable is a functional low cost prototype that would decrease inefficiencies in the supply chain and allow better procurement decisions to be made by small suppliers in Sri Lanka.

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List Of Abbreviations

Abbreviation	Description
• AI	Artificial Intelligence
• ML	Machine Learning
• ARIMA	Auto-Regressive Integrated Moving Average
• SMI	Supplier Managed Inventory
• WBS	Work Breakdown Structure
• UI	User Interface
• KPI	Key Performance Indicator

1. Introduction

1.1. Background

Small and medium-scale restaurants in developing countries such as Sri Lanka are constantly struggling to manage inventory and coordinate with suppliers. Unlike big businesses, these businesses do not have digital systems for sales recording, inventory tracking (of ingredients used in making their product) or demand forecasting. As a result, most restaurants depend on manual order accepting and forecasting of daily profit which often becomes inefficient in terms of shortages of ingredients, overstocking, or wastage of food. In addition, suppliers cannot optimize deliveries easily as they don't have any visibility regarding downstream demand. This lack of supply and demand diminishes profit and increases operational risk for both parties. The recent progress in Artificial Intelligence (AI) and Machine Learning (ML) has demonstrated potential in solving such problems, specifically using demand forecasting and inventory optimization. However, current solutions are tailored for data intensive, enterprise scale applications. The research showed a clear requirement for low-data, low-weight forecasting systems for small restaurants and for small suppliers in Sri Lanka.

1.2. Literature Survey

1.2.1. Demand Forecasting in Food Supply Chains

Demand forecast is an important part of food supply chain stability and efficiency. With well-informed predictions, businesses can closely align their procurement, production, and distribution activities with demand, minimizing shortages and waste. Moving average and exponential smoothing are quite well known forecasting methods that have been used for a long time in the food retail and hospitality industries. However, these methods do not account for complex demand in the seasonal pattern and rapidly changing demand of the consumer. To fill in these gaps, Machine Learning (ML) and Artificial Intelligence (AI) techniques such as Random Forest, Support Vector Machine and LSTM (Long Short Term Memory), and other deep learning models are gaining more attention. ML-based methods are reported to perform better than statistical methods in sales forecasting applications (studies) in large-scale food chains and supermarkets. For instance, AI-powered models can incorporate exogenous factors like the weather, holidays, and promotions to refine demand forecasts. However, most of the existing works are for enterprise level applications in which there are large amounts of historical data available. On the other hand, for small restaurants in developing countries, well-structured data sets are not available and thus these sophisticated models cannot be applied. This presents an opportunity to leverage low weight prediction methods to the low data environment while still achieving important accuracy and operation efficiency improvements.

1.2.2. Inventory Optimization Approaches

Inventory optimization is one of the significant research areas in the field of supply chain management and restaurant management as it has direct impact on profitability and customer satisfaction of the organization. The conventional methods are rule-based methods like Economic Order Quantity (EOQ) and Just in Time (JIT) that try to determine the optimal level of inventory with the least cost of holding stock. These approaches however, rely on assumptions of static demand and static supply, which are not commonly satisfied in dynamic foodservice settings. More recently, stochastic models and stochastic algorithms for optimization with uncertainty in the demand and the lead times have been proposed for the optimization of the order quantity. With the emergence of computational intelligence, Machine Learning (ML) and Artificial Intelligence (AI) techniques have been introduced with the aim to enhance the decision-making ability by projecting the consumption trend and dynamically determining threshold for reorder. Also, Supplier Managed Inventory (SMI) and Blockchain-based coordination mechanisms have been taken into consideration to add more transparency and trust into the supply chain. While the developments are promising, they are typically created for large organisations with high-functioning digital infrastructures and access to large amounts of data. Small restaurants in developing countries like Sri Lanka do not have the resources and technical know-how to set up such systems. Therefore, there is a need for low-data, parsimonious and low-cost models of inventory optimization based on forecasting and supplier coordination, that are especially relevant in low-data and resource-constrained environments.

1.2.3. Privacy-Preserving Forecasting

In recent years, the problems of supply chain management and demand forecasting have come to face a crucial challenge: Data privacy. Due to competitive, regulatory and trust issues, restaurant, retail and supplier owners are often reluctant to share raw transactional data. Traditional forecasting systems are typically based on a centralized aggregation of data that exposes them to data breaches, leaks, and information disclosure. To overcome these challenges, joint learning-based privacy-preserving forecasting methods, where the sensitive data are not revealed, are investigated by researchers. One of the most popular technologies is Federated Learning (FL) where the forecasting models are locally trained on each data source (e.g., restaurants) and only model updates are aggregated and sent to a central server. This allows suppliers to use cross-participant learning while ensuring protections are in place to guard store-level sales information. Another technique is called Differential Privacy, or adding statistical noise to the shared data or model outputs to ensure no single restaurant's data can be reverse engineered. In addition, secure multi-party computation and homomorphic encryption have been investigated to allow collective demand forecasting while input data are not decrypted in the process. Whilst these techniques are spreading into healthcare, finance, and large-scale retail, applications in small-scale food supply chains are still rare. In the majority of existing systems, the calculations are computationally intensive and demand robust digital infrastructure, which typically is not available to small restaurants in developing countries. Thus there is a clear research opportunity in modifying lightweight privacy preserving forecasting methods that offer a suitable balance between accuracy and tractability. By using aggregations of demand forecasts without sharing individual sales data, suppliers can increase inventory planning and distribution efficiency without violating the trust of the restaurant owners.

1.3. Research Gap

A comprehensive literature review identifies major recent contributions in the area of demand forecasting, inventory optimization, and privacy-preserving forecasting methods. However, several important gaps still remain, particularly in the case of small restaurants and suppliers in developing countries like Sri Lanka. These gaps can be split into the following groups:

1.3.1 Gap in Demand Forecasting

Most of the existing studies on food demand forecasting use time-series models (e.g., ARIMA, Holt-Winters) or state-of-the-art ML methods (e.g., LSTM, Random Forest) to predict customer demand. While these models show high accuracy, they use large structured datasets that are usually only available to supermarkets, chains, or digital platforms. Small restaurants in Sri Lanka are not very likely to keep systematic records thus making it a low data environment. As such, current forecasting techniques cannot be directly applied and there is a gap for lightweight, low-data forecasting methods that are appropriate for such applications.

1.3.2 Inventory Optimisation Gap

Traditional Inventory Management models like EOQ and JIT and new-age solutions like blockchain based Supplier Managed Inventory (SMI) are meant for large businesses with stable infrastructure and financial muscles. Small restaurants do not have access to such digital ecosystems and are therefore left to manual tracking. As a result, they are plagued by stockouts, over-ordering, and food waste. There is a gap of low cost, streamlined, AI-powered inventory optimization frameworks that can dynamically adapt to uncertain, small-scale environments.

1.3.3: Privacy-preserving Forecasting Gap

Recent efforts in federated learning, differential privacy and secure multi-party computation have made data sharing possible while preserving confidentiality. However, these methods are used primarily in fields including health care, finance, and large retail chains. Small restaurants do not want to provide suppliers with access to raw sales data for competitive and trust-related reasons, while suppliers need aggregated sales forecasts to make efficient planning decisions. This is caused by a lack of lightweight privacy-preserving forecasting mechanisms for small food supply chains.

1.3.4 Overall Gap

Although existing research can offer valuable tools, there is no integrated solution which combines:

- Low-data demand forecasting,
- Dynamic inventory optimization,
- Privacy preserving supplier dashboards.

This leaves small restaurants and suppliers in Sri Lanka without practical tools for digitalisation that can reduce inefficiencies, stockouts, and wastage. Filling this gap involves a contextually-appropriate aggregator system for forecasts, one that maintains privacy, and strengthens supplier decisions in developing-country settings.

1.9. Research Problem

The problems of small and medium scale restaurants in Sri Lanka are continuously associated with the issues of matching ingredient procurement with actual customer demand. Most restaurant owners do not keep records of sales or waste in a systematic manner but use them based on manual estimation and daily calculation of profit. This leads to stockouts which cause lost sales or over-purchasing which leads to food spoilage and lower bottom line. On the supplier side, a lack of precise demand visibility means suppliers are forced to rely entirely on ad hoc orders, which leads to inefficiencies in delivery scheduling and stock management.

While demand forecasting and inventory optimization has already proven its value in enterprise settings, existing solutions are seldom relevant to a developing-country context. Large datasets must be structured to feed advanced forecasting models (e.g. LSTM, Random Forest), but small restaurants don't have this kind of data. Likewise, blockchain-based Supplier Managed Inventory (SMI) systems and enterprise dashboards are too resource intensive for local adoption. Furthermore, the privacy issue prohibits restaurant owners from sharing transaction data to suppliers openly, which results in less scope for collaborative forecasting.

2. Objectives

2.1. Main Objectives

The Build a prototype dashboard that empowers suppliers to predict demand and optimize inventory with advanced analytics, including built-in data privacy.

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2.2. Specific Objectives

- Anonymized aggregation and pre-processing of historical demand and inventory data from suppliers (and optional exogenous factors such as promotions or seasonality).

- Develop and compare three forecasting models: ARIMA, Holt Winter (exponential smoothing) and Random Forest regression.

- Develop an aggregation strategy to merge model forecasts (e.g. weighted averaging or ensemble) to provide more robust forecasts.

- Implement privacy-preserving methods like federated learning so model training can use multiple sources of data without compromising raw data.

- Develop interactive supplier dashboard UI that displays forecasts, current inventories and alerts; drill-down analysis.

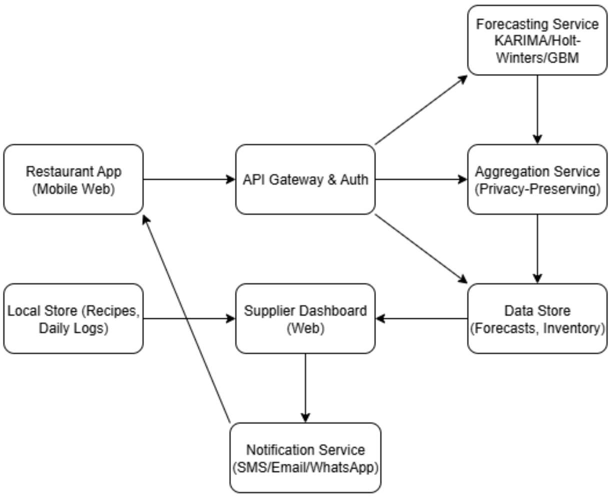
- Integrate inventory optimization logic (e.g., re-order point, Economic Order Quantity) to suggest order quantity based on forecasted demand

- Test the system based on standard measures (RMSE, MAPE) and perception of usability by users

Figure 2: Current Manual Inventory Process vs. Proposed AI-Assisted Process

3. Methodology

Figure 1: System Architecture Diagram



3.1 Data Collection And Preprocessing

- Historical demand and inventory data gathered from suppliers (CSV/API).
- Deal with missing values, outliers, and normalize data.
- Overview at appropriate times (daily/weekly)
- External factors can also be optional, such as seasonality, promotions.
- Federated preprocessing if there are multiple suppliers (data never leaves local systems)

3.2 Forecasting Models (Arima, Holt-Winters, Random Forest)

- ARIMA - most appropriate for stationary time-series, based on historical demand patterns.
- Holt-Winters - captures trend and seasonality in the demand.
- Random Forest Regression - captures nonlinear demand with other features
- Models calibrated using cross-validation, hyperparameter tuning.

3.3 Forecast Aggregation Strategy

- Ensemble strategy: weighted average of ARIMA, Holt-Winters, and Random Forest.
- Analyze weights according to their last performance (MAPE, RMSE).
- In federated learning, raw data is not shared between suppliers, but aggregate model parameters.

3.4 Privacy-Preserving Techniques

- Federated Learning (FL): local models can be trained by the supplier, only gradients/parameters are transmitted.

- Differential Privacy (optional): add controlled noise to updates.
- Eliminate the leakage of raw transactional data while making collaborative forecasting possible.

3.5 Dashboard Ui Design

- Responsive dashboard (React/Dash), web based
- Features:
    - Time series demand forecast graphs
    - Inventory heatmaps
    - Alerts (stockouts/overstock)
    - drill-down per product/category/time
    - Export options (Excel/PDF)

3.6 Inventory Optimization Logic .

- Implement EOQ (Economic Ordering Quantity) and Reorder Point based on forecast
- Accounting for forecast error: safety stock.
- Dashboard - Suggested replenishment levels with cost optimization goals

Evaluation Metrics:

Primary Metrics:

Prediction Accuracy:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

Inventory Level Considerations:

- Decrease in the number of stockouts
- Reduction of the percentage of spoilage
- Increased inventory turnover

Operating Efficiency:

- Time saved performing inventory procedures
- Higher speed of order processing (basis: Bersohn, 2007 SW 83 operating efficiency measures)

Secondary Metrics:

- User adoption and satisfaction of the dashboard
- Cost savings per store per month as a result of optimized order
- Supplier satisfaction with communication aspects (communication channels, dashboard usability, WhatsApp API alerts)
- System reliability: frequency of downtime vs. uptime

Data Analysis Methods:

- Descriptive Statistics: To establish baseline performance of inventory and demand forecasting
- Regression Analysis: To understand efficiencies (e.g., accuracy of forecasts vs. order delays).
- Model Comparison: Evaluating MAE, RMSE, MAPE for forecasting models (ARIMA, Holt-Winters, Random Forest)
- Qualitative Analysis: Supplier/analyst interviews, and focus group discussions coded thematically for usability and trust.

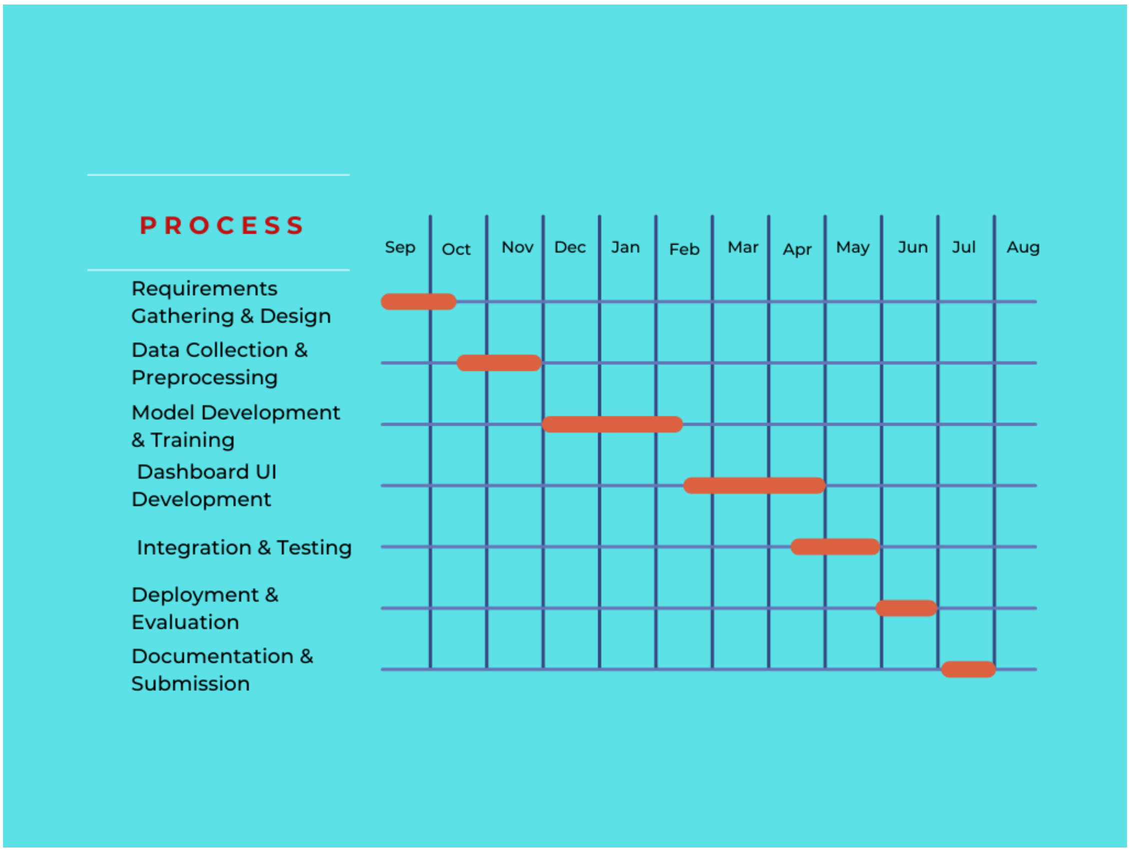


Figure 1: Work Breakdown Structure and Timeline

4. Description Of Personnel and Facilities

- **Personnel**:

This component of the project (Supplier Demand Forecasting Dashboard) will be carried out individually by Alawaththa A.K.A.A , I am an undergraduate student in the B.Sc. (Hons) in Information Technology degree program at SLIIT..

- **Facilities**:

Development PCs, cloud server (AWS/Azure), lab access at SLIIT.

- **Software**:

Python (statsmodels, scikit-learn, pandas), Dash/React, SQL/MongoDB.

5. Budget And Budget Justification

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7. Appendices

Appendix A: Questionnaires

- Supplier Interview Guide (forecasting practices, challenges, inventory decision making)
- Inventory Management Practices Survey (questions asked of suppliers)
- User Experience Evaluation questionnaire (to collect the feedback about usability of the dashboard).
- Supplier Feedback Form (after you deploy, ask them how useful and accurate they think it is).

Appendix B: Technical Requirements

- System Architecture Diagrams (Figure 3: System Architecture and Figure 4: Data Flow).
- Database Schema Design (entity relationship diagram to model demand, inventory, forecasts)
- API Documentation Framework (export/data entry points)
- Security Protocol Specifications (privacy controls for authentication, federated learning)

Appendix C: Risk Management Model

- Technical Risk Assessment Matrix (e.g. data quality issues, model drift, system downtime).
- Mitigation plans for each class of risk (e.g. backup data, periodic retraining)
- Contingency Planning Procedures (reversion to baseline forecast on ML model failure).

- Quality Assurance Check Points (model validation, dashboard performance indicators).

Appendix D: Ethics.

- Informed Consent Statements (for suppliers who are surveyed).
- Data Privacy Protection (federated learning, anonymization of supplier data)
- Patient Rights and Duties (people who are involved in trials)
- Data Processing and Storage Practices (Secure Storage, Restricted Access, Compliance with SLIIT).