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

Project ID: 25_26J_393

Project Proposal Report

Thilakarathna W.P.N.S.

B.Sc. (Hons) Degree in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

August 2025

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

Project ID: 25_26J_393

Project Proposal Report

Thilakarathna W.P.N.S.

Supervisor: Mr. Ravi Supunya

Co-Supervisor: Mrs. Chathurya Kumarapperuma

B.Sc. (Hons) Degree in Information Technology

Department of Information Technology

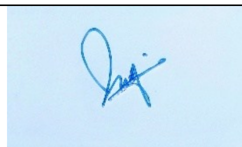
Sri Lanka Institute of Information Technology

Sri Lanka

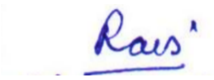
August 2025

Declaration

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
Thilakarathna W.P.N.S.	IT22073846	

The candidate mentioned above is conducting research for their undergraduate dissertation under my supervision.

		**19/09/2025**
…………………………………	…………………………………	………………
Signature of the Supervisor	Signature of the Co -Supervisor	Date
(Mr. Ravi Supunya)	(Mrs. Chathurya Kumarapperuma)	

Abstract

Demand forecasting in small to medium scale retail and restaurant environments in Sri Lanka is significantly hampered by the scarcity of historical sales data. Traditional forecasting models like ARIMA and LSTM require extensive datasets, making them unsuitable for these low-data settings. This leads to operational inefficiencies, including stockouts and excess inventory.

This research proposes a novel hybrid demand forecasting model that integrates machine learning with rule-based adjustments derived from contextual features such as cultural calendars, local weather patterns, and day-of-week effects. The methodology involves collecting minimal sales data, supplier invoice records, and rich contextual data to train a lightweight Gradient Boosting Machine. A rule-based engine will then be layered on top to adjust predictions for major cultural events and weather anomalies, knowledge which will be garnered from domain expert interviews. We anticipate that this hybrid approach will significantly outperform standalone statistical models and human intuition in accuracy.

The outcome of this research will be a practical, scalable forecasting framework designed specifically for data-scarce environments, empowering small businesses to optimize inventory and reduce waste.

Keywords: Demand Forecasting, Low-Data Environments, Hybrid Model, Machine Learning, Rule-Based Systems, Cultural Events, Small Business

Table of Contents

List Of Figures

List of Tables

List Of Abbreviations

Abbreviations	Description
SME	Small and Medium-sized Enterprise
ARIMA	Auto Regressive Integrated Moving Average
LSTM	Long Short-Term Memory
ML	Machine Learning
LKR	Sri Lankan Rupees
AWS	Amazon Web Services
SLIIT	Sri Lanka Institute of Information Technology
LGBM	Light Gradient Boosting Method

Table 1: List of Abbreviations

1. Introduction

1.1 Background

In today's highly competitive market landscape, small and medium-sized enterprises in Sri Lanka's retail and food service sectors face significant challenges in maintaining optimal inventory levels. These businesses, which form the backbone of the local economy, often struggle with frequent stockouts or excessive inventory due to unreliable demand forecasting methods. The core of this problem lies in their fundamental operational constraints: limited historical data availability and reliance on intuitive decision-making rather than data-driven approaches.

This research addresses these challenges by proposing an innovative hybrid forecasting model that combines machine learning with rule-based systems specifically designed for data-scarce environments. Unlike conventional approaches that require extensive historical data, our solution integrates easily accessible contextual factors such as cultural calendars, weather patterns, and temporal trends to generate accurate demand predictions. By bridging the gap between sophisticated forecasting techniques and the practical realities of small-scale operations, this project aims to provide Sri Lankan SMEs with an accessible, practical tool that enhances their operational efficiency and competitive advantage in the market.

1.2 Literature Survey

1.2.1 The challenge of data scarcity

Accurate demand forecasting is a cornerstone of efficient retail and restaurant management, directly impacting inventory control, supply chain logistics, and profitability. Traditional time-series forecasting methods, such as ARIMA, and modern deep learning approaches, like LSTMs, are prevalent in data-rich environments (Chaudhuri & Alkan, 2022). However, their performance is critically dependent on large volumes of high-quality historical data. Small businesses, particularly in developing nations like Sri Lanka, rarely maintain extensive digital sales records, often discarding them annually. This challenge is further exacerbated by a prevalent lack of digital literacy among owners, who may not perceive the long-term value of historical data or possess the skills to maintain it in a structured, digital format. This creates a significant barrier to adopting these advanced techniques, forcing owners to rely on error-prone intuition.

1.2.2 The role of external variables

Recent research has begun exploring the integration of external variables to improve forecasts. Studies have shown that weather data can significantly influence demand in sectors like hospitality (Leenatham & Khemavuk, 2020). Furthermore, cultural, and seasonal events are well-documented drivers of consumer behavior (Weber & Li, 2021). Despite this, the synthesis of these features into a cohesive model tailored for low-data scenarios and low-digital-literacy environments remains an under-explored niche.

1.3 Research Gap

Current forecasting research predominantly focuses on data-intensive models, neglecting the unique challenges faced by SMEs in developing economies. Key research gaps include:

- **Lack of low-data-specific models:**
  Absence of forecasting frameworks designed to operate with less than one year of historical data.
- **Neglect of proxy data sources:**
  Underutilization of alternative data sources, such as supplier invoices, restaurant owner's expertise on the field to compensate for missing sales data.
- **Overlooking digital literacy barriers:**
  Models are developed without considering low digital literacy of business owners and workers, hindering practical implementation

Others have attempted to solve the problem of forecasting in constrained environments by simplifying models or using qualitative methods. However, these approaches often fail to leverage available data effectively.

How others tried to solve it: Previous approaches typically fall into two categories:

- Applying complex models that fail due to insufficient data, leading to overfitting,

or

- Relying purely on owner intuition, which is subjective and error-prone.

Some studies have proposed using simple moving averages or linear regression, but these lack the nuance to capture important contextual events.

How we vary and build on previous work: This project builds upon the proven value of integrating external variables but varies fundamentally by designing for constraint from the outset.

Builds On: We leverage the proven effectiveness of lightweight ML and the established impact of contextual features like weather, holidays, and especially cultural events.

Varies From: Our approach moves away from a purely data-driven paradigm to a knowledge-driven hybrid one. We explicitly address the low-data, low-literacy context by:

- Using proxy data (e.g., supplier invoices) to compensate for missing sales records.
- Hard-coding human expertise through a transparent rule-based engine that handles rare but high-impact events that the ML model cannot learn from limited data.
- Prioritizing simplicity and interpretability using open-source technologies and logical rules to ensure the solution is accessible, trustworthy, and actionable for its intended users, Sri Lankan SME owners.

This hybrid model bridges a critical gap between theoretical forecasting power and practical applicability, offering a novel solution tailored to the real-world constraints of a data-scarce environment.

1.4 Research Problem

The core problem is the inability of small Sri Lankan restaurants and retail stores to generate accurate demand forecasts due to a combination of limited historical data and low digitization for handling sales data, leading to operational inefficiencies, lost sales from stockouts, and financial losses from wastage and an over-reliance on unreliable intuitive forecasting by owners.

2. Objectives

2.1 Key Objectives

To develop and validate a hybrid demand forecasting model that forecasts daily and weekly sales for small Sri Lankan retail and restaurant businesses that integrates lightweight machine learning with rule-based adjustments to achieve accurate predictions in a low-data environment.

2.2 Specific Objectives

- To identify and quantify the impact of key contextual features (cultural holidays, weather conditions, day-of-week) on demand patterns.
- To develop a rule-based adjustment framework that encodes domain expert knowledge from business owners to handle rare but impactful events.
- To collect and preprocess available historical sales data and proxy data (supplier invoices) for model training.
- To train and evaluate a suite of lightweight machine learning models (including Linear Regression, LightGBM, and Facebook Prophet) on the collected dataset.
- To integrate the best-performing ML model with the rule-based framework to create a final hybrid forecasting system.
- To validate the hybrid model's performance by comparing its accuracy against standalone ML models and human intuition (owner forecasts) using time-series cross-validation.

3. Methodology

3.1 Project Overview

This project aims to develop a hybrid forecasting system that combines a data-driven ML component with a knowledge-driven rule-based engine. The system will be designed to operate effectively with minimal historical data by leveraging rich contextual features and proxy data sources.

3.2 System Overview

The system architecture consists of two core modules:

1. **ML Forecasting Module:** A lightweight model (LightGBM/Prophet) trained on available sales and proxy data to generate a baseline forecast.

2. **Rule-Based Adjustment Engine:** A framework of if-then-else rules that adjusts the baseline forecast based on inputs from a cultural calendar, weather forecast, and expert-defined rules (e.g., IF is_vesak THEN multiply forecast by 2.0).

Final Forecast = ML Base Prediction × Rule-Based Adjustment Factor

System Overview Diagram

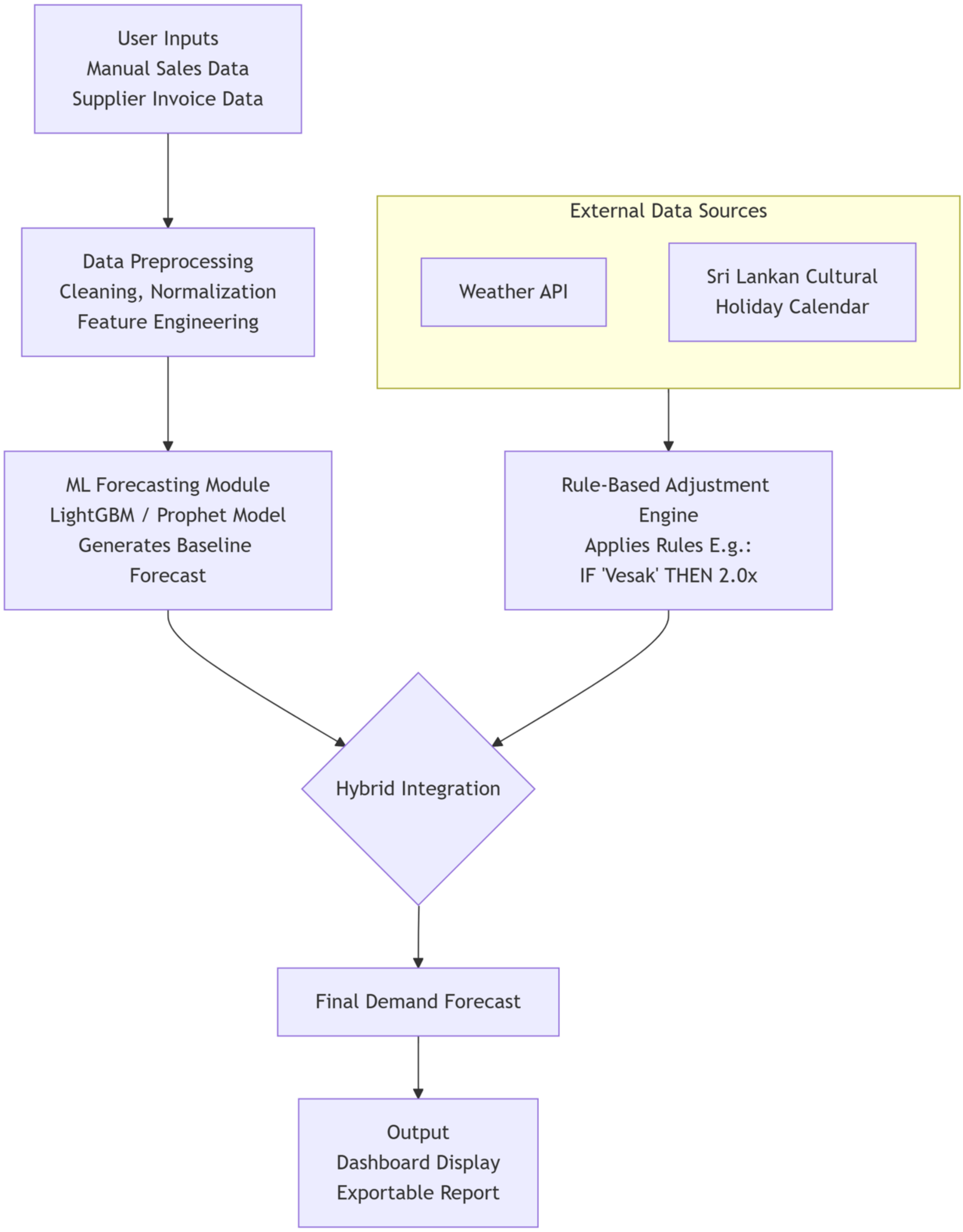


Figure 1: System Overview Diagram

3.3 Technology Selection

- Data Processing & ML Modeling: Python, Pandas, Scikit-learn, LightGBM, Facebook Prophet.
- Rule Engine Implementation: Python-based logic.

- Mobile/Web Interface (for output): React Native (Potential for future expansion).
- Data Storage (for model & rules): Firebase Firestore.
- Weather Data API: OpenWeatherMap.
- Cultural Calendar: Manually curated dataset for Sri Lankan holidays.

3.4 Software Development Process

The activities of the software development process are broken down into manageable segments using the software development lifecycle. Among the various models available, the Agile methodology is particularly well-suited for this project due to its iterative nature and ability to adapt to evolving requirements, such as refinements in machine learning models based on validation results and adjustments to the rule-based engine from user feedback.

The Agile software development process for this project consists of six primary phases:

1. **Requirements and Gathering:** This initial phase will focus on identifying the core needs of the end-users (small retail and restaurant owners) through structured interviews and surveys. Key activities include defining functional specifications for the forecasting system, such as the ability to input manual sales data, integrate weather APIs, and generate daily demand predictions. System constraints, including low-data environments, limited computational resources, and the need for a simple user interface, will also be thoroughly documented to guide the development process.

2. **Analysis:** In this phase, a comprehensive evaluation of the feasibility of various tools, technologies, and methodologies will be conducted. This includes assessing the suitability of lightweight machine learning algorithms (e.g., LightGBM, Prophet) for small datasets, selecting a cloud platform (Firebase) for data storage and model deployment, and choosing a backend framework (Python/Django) for system integration. The analysis will ensure the selected stack is robust, cost-effective, and aligns with the project's technical requirements and constraints.

3. **Design:** The design phase will involve developing the architectural blueprint and interface designs for the entire system. This includes creating:

- **Architectural Designs:** A system overview diagram detailing the data flow from data collection (sales logs, weather API, cultural calendar) through preprocessing, model inference, rule-based adjustment, and final forecast output.
- **Database Design:** Structuring the schema for Firebase Firestore to efficiently store historical data, user profiles, and model parameters.
- **Interface Designs:** Wireframes for a minimal, user-friendly dashboard where owners can view forecasts, preferably via a mobile-friendly web interface or simple notification system.

4. **Coding:** This phase involves the implementation of the system's core modules based on the designs finalized in the previous phase. Development will be segmented into key modules:

- **Data Preprocessing Module:** Coding scripts in Python using Pandas to clean, normalize, and engineer features from historical sales and contextual data.
- **Machine Learning Module:** Implementing, training, and validating the LightGBM and Prophet models using Scikit-learn and relevant libraries to generate baseline forecasts.
- **Rule-Based Engine Module:** Developing the logic in Python to apply dynamic adjustment factors based on real-time inputs from the cultural calendar and weather data.
- **Integration Module:** Combining the outputs of the ML model and the rule engine to produce the final forecast and making it accessible via a simple API or exportable report.

5. **Testing:** Rigorous testing will be conducted to validate the accuracy, reliability, and usability of the system. This includes:

- **Unit Testing:** Testing individual functions (e.g., a function that calculates a holiday multiplier) for correctness.
- **Integration Testing:** Ensuring the ML module and the rule engine communicate and function together seamlessly.
- **Validation Testing:** Employing Time-Series Cross-Validation to benchmark the forecasting accuracy (using MAE and MAPE metrics) of the hybrid model against standalone statistical models and human intuition.
- **Usability Testing:** Conducting tests with a small group of target users to ensure the interface and forecast output are intuitive and actionable.

6. **Maintenance:** Post-deployment, the system will enter a continuous maintenance phase. This involves monitoring the system's performance in a pilot study with partner businesses, logging errors, and tracking forecast accuracy over time. Updates will be incorporated periodically based on user feedback and technological advancements, such as retraining the ML models with new data or adding new rules for additional cultural events to ensure the system remains effective and relevant.

This structured, phase-gated approach ensures that the development process is systematic, transparent, and results in a high-quality, validated solution tailored to the specific challenges of demand forecasting in low-data environments.

Gantt Chart

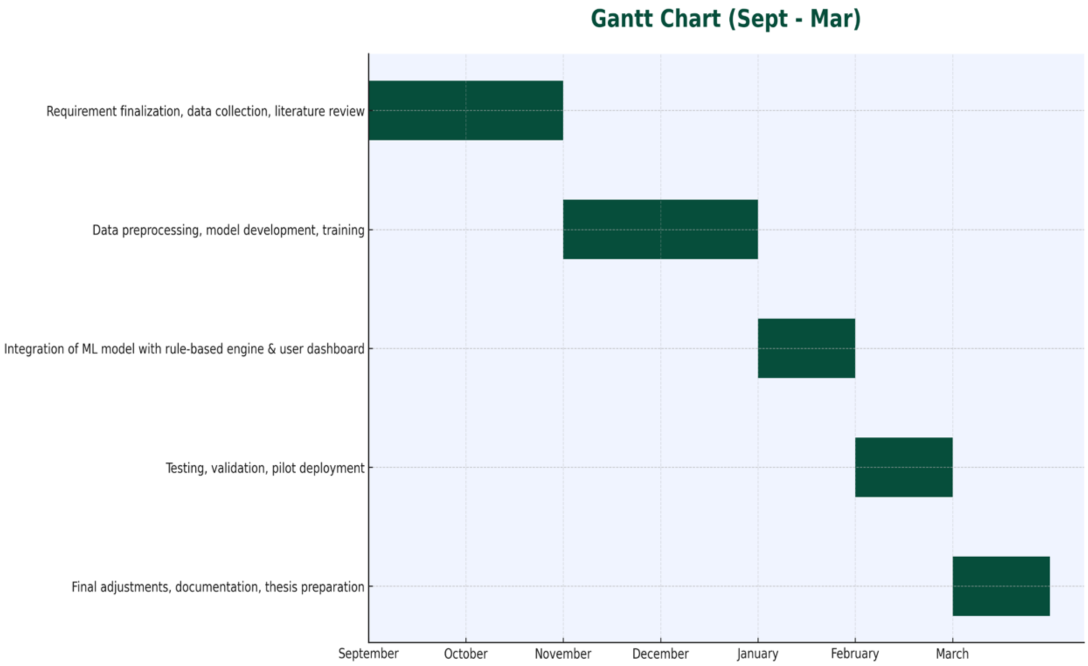


Figure 2: Gantt Chart

3.6 Feasibility Study

• Economic Feasibility

The proposed hybrid demand forecasting system is designed to be highly economically viable, offering a significant return on investment for small-scale retail and restaurant businesses in Sri Lanka by reducing losses from stockouts and excess inventory. The solution is a cost-effective software-based system with minimal hardware requirements. Key anticipated costs include:

1. **Planning and Design Costs:** Resources allocated for requirement gathering with business owners, system architecture design, and algorithm selection.
2. **Development Costs:** Expenses related to software development, including coding the data preprocessing pipelines, machine learning models, and the rule-based engine.
3. **Cloud Services and Data Storage Charges:** Minimal costs for using Firebase for data storage, model deployment, and hosting simple user dashboards. The use of open-source libraries keeps licensing costs at zero.
4. **Maintenance and Support Costs:** Ongoing expenses for updating the cultural calendar, retraining models with new data, and providing basic user support.

3.5.1 Dataset

The dataset for this project is essential for building and training the machine learning models and for defining the rules within the adjustment engine. It is designed to leverage existing, low-friction data sources relevant to the low-data environment. The components of the dataset are outlined as follows:

1. Historical Sales and Proxy Data

- **Features: Daily** sales figures, item-wise sales data, and supplier invoice records (as a proxy for sales volume).
- **Collection Method:** Manual entry or CSV upload of existing logbooks and supplier receipts from partner businesses. This data will be cleaned and normalized to form the primary training dataset for the baseline forecasting model

2. Contextual and Temporal Data

- **Features:** Public holidays, cultural events (e.g., Sinhala New Year, Vesak), day-of-the-week, and month.
- **Collection Method:** Compilation of a standardized Sri Lankan cultural calendar. This data will be hardcoded into the rule-based engine to trigger specific adjustment factors.

3. Meteorological Data

- **Features:** Daily temperature, precipitation (rainfall).

- **Collection Method:** Automated fetching via free-tier weather APIs (e.g., OpenWeatherMap) based on the business's location. This data will be used as an input feature for both the ML model and the rule engine

Data Privacy and Security

To ensure privacy and compliance, all business-specific sales data will be anonymized and stored securely using encryption. Businesses will retain full ownership of their data. Explicit consent will be obtained before using any business's data for model training or analysis**.**

This multi-source dataset provides a comprehensive foundation for developing a accurate and context-aware forecasting system tailored to the Sri Lankan retail environment.

The long-term value provided by optimized inventory management, reduced food waste, and increased sales far outweighs the minimal initial development costs, making the project economically sound and attractive for its target audience.

• Technical Feasibility

The technical feasibility of this project is high due to the deliberate selection of mature, well-documented, and lightweight technologies.

- The core machine learning models (LightGBM, Prophet) are specifically chosen for their efficiency and performance on small datasets.
- Python, along with libraries like Pandas and Scikit-learn, provides a robust and free environment for data processing and model development
- Firebase offers a scalable and low-cost backend solution for data storage and simple dashboard hosting, with easy integration into Python applications.
- The rule-based engine, built on logical statements, is technically straightforward to implement.
- The entire stack is composed of open-source or freemium tools, eliminating technical and financial barriers to development. Given the available technologies and academic resources, the project is technically achievable.

• Operational Feasibility

The proposed system is designed explicitly for the operational reality of small Sri Lankan businesses. Its success is highly feasible because:

- It does not require owners to have technical expertise; the interface and forecasts will be simple and actionable.
- It leverages data owners already possess (logbooks, invoices) or can access easily (weather), minimizing the burden of data entry.
- The solution is designed to be accessible via a simple web dashboard or even periodic report generation, matching the low-digital-literacy context.
- By directly addressing a critical pain point (inventory management), the system provides immediate, tangible value, which is a strong incentive for adoption and sustained use.

• Schedule Feasibility

The project is expected to be completed within a standard academic timeline of 6-7 months. The work breakdown is clear and well-scoped:

- Months 1-2: Requirement finalization, data collection from partner businesses, and literature review.
- Months 3-4: Data preprocessing, model development, and training.
- Month 5: Integration of the ML model with the rule-based engine and development of the user dashboard.
- Month 6: Testing, validation, and pilot deployment with partner businesses for feedback.
- Month 7: Final adjustments, documentation, and thesis preparation.

The adoption of the Agile methodology allows for iterative progress and accommodates changes, ensuring the project remains on schedule. This phased plan is realistic and achievable.

4. Description Of Personnel and Facilities

Research Team Structure:
Technical Team:
Research Associates:

The following facilities and resources will be utilized to ensure the successful completion of the project:

1. **Hardware Resources:**
    - Development Laptop: A high-performance laptop with sufficient processing power for training machine learning models and running development environments.
    - Mobile Testing Devices: Access to Android and iOS smartphones for testing the application interface and functionality in a real-world environment.
    - Cloud Computing Credits: Potential use of Google Colab Pro or AWS Educate credits for additional computational power required for training and validating ML models.

2. **Software Resources:**
    - Development Tools: The project will use open-source technologies, including:
        - Programming Language: Python 3.x
        - Libraries: Pandas, Scikit-learn, LightGBM, Facebook Prophet, Matplotlib/Seaborn.
        - Development Environment: Jupyter Notebook, VS Code.
        - Backend & Database: Firebase Firestore.
        - Version Control: Git and GitHub.
    - Productivity Software: Microsoft Word and LaTeX for documentation and report writing; PowerPoint for presentations.

3. **Academic and Institutional Resources:**
    - SLIIT Library: Access to online academic journals (IEEE Xplore, ACM Digital Library, SpringerLink) for literature survey and research.
    - High-Speed Internet: Reliable campus internet connectivity for research, software development, and cloud-based processing.
    - Supervisor Guidance: Regular meetings with supervisors for progress reviews, feedback, and strategic direction.

5. Budget And Budget Justification

Resource Type	Allocation (LKR)	Justification
Cloud Services (Firebase)	3000	For secure storage of models, rules, and historical data.
ML Model Development (Colab/AWS)	5000	For computational costs associated with model training and validation.
Data Collection & Curation	3000	Costs associated with gathering and digitizing manual records and contextual data.
Miscellaneous (Documentation, etc.)	1500	Contingency for internet, documentation, and other administrative tasks.
Total	**12500**	

Table 2 : Budget and Justification

6. Reference List

[1]. Chaudhuri, K.D., Alkan, B. A hybrid extreme learning machine model with harris hawks optimisation algorithm: an optimised model for product demand forecasting applications. Appl Intell 52, 11489–11505 (2022).

[2]. A.Leenatham and P. Khemavuk, "Demand Forecasting Using Artificial Neural Network Based on Quantitative and Qualitative Data," 2020 1st International Conference on Big Data Analytics and Practices (IBDAP), Bangkok, Thailand, 2020, pp. 1-6, doi: 10.1109/IBDAP50342.2020.9245614.

[3]. Chae, B., Sheu, C., & Park, E. O. (2024). The value of data, machine learning, and deep learning in restaurant demand forecasting: Insights and lessons learned from a large restaurant chain. Decision Support Systems, 184, 114291.

[4]. Weber, M., & Li, C. (2021). Cultural calendars and consumer demand: A predictive framework. Journal of Retailing and Consumer Services, 58, 102301.

[5]. N. K. Pandey, A. K. Mishra, V. Kumar, A. Kumar, M. Diwakar and N. Tripathi, "Machine Learning based Food Demand Estimation for Restaurants," 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 2023, pp. 1-5, doi: 10.1109/ISCON57294.2023.10112059.

[6]. S. K. Panda and S. N. Mohanty, "Time Series Forecasting and Modeling of Food Demand Supply Chain Based on Regressors Analysis," in IEEE Access, vol. 11, pp. 42679-42700, 2023, doi: 10.1109/ACCESS.2023.3266275.

7. Appendices

Appendix A: Survey Instruments

- Restaurant Owner Interview Guide
- Inventory Management Practices Survey
- User Experience Evaluation Questionnaire
- Supplier Feedback Form

Appendix B: Technical Specifications

- System Architecture Diagrams
- Database Schema Design
- API Documentation Framework
- Security Protocol Specifications

Appendix C: Risk Management Framework

- Technical Risk Assessment Matrix
- Mitigation Strategies for Each Risk Category
- Contingency Planning Procedures
- Quality Assurance Checkpoints

Appendix D: Ethical Considerations

- Informed Consent Forms
- Data Privacy Protection Protocols
- Participant Rights and Responsibilities
- Data Handling and Storage Procedures

This research application is a holistic study to overcome the out-of-stock problem for small-scale restaurants with the aid of novel AI based solutions that can use affordable communication technology and minimal data.