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

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Project Proposal Report

Fernando W.G.P.N

B.Sc. (Hons) Degree in Information Technology

Department of information

Sri Lanka Institute of Information Technology

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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.

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The supervisor/s should certify the proposal report with the following declaration.

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

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

ABSTRACT

The restaurant industry is one of the most dynamic sectors in the food supply chain, where success depends on accurate demand forecasting, effective cost management, and reliable supplier chains. Small- and medium-sized restaurants in Sri Lanka are especially vulnerable to ingredient price variations due to seasonal effects, market volatility, and unreliable suppliers. Since the majority of restaurants have not adopted structured data collection methods, they have been compelled to use manual estimation processes, which result in wasteful pricing, poor supplier choice, and increased food loss.

Researches have shown that time series forecasting methods, like ARIMA and Prophet, are applicable to commodity and crop prices, and have been proven helpful with actual data. [1], [2]. Machine learning models such as LSTM have recently outperformed traditional methods in handling seasonality and non-linear data [3]. At the same time, supplier recommendation systems are becoming more and more popular within supply chain management, wherein Analytic Hierarchy Process (AHP) and ML-based ranking algorithms score suppliers according to cost, quality, and reliability [4], [6].

However, these solutions are largely for large supply chains and mature markets and have little applicability in small Sri Lankan eateries with poor availability of data.

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List Of Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
ARIMA	Autoregressive Integrated Moving Average
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Squared Error
MCDM	Multi-Criteria Decision Making
AHP	Analytic Hierarchy Process

1 INTRODUCTION

1.1 Background and Literature Survey

The restaurant industry is one of the most dynamic sectors in the global food supply chain, where operational success depends heavily on accurate demand forecasting, cost control, and efficient supplier management. A key challenge for restaurants, particularly in developing countries such as Sri Lanka, is the fluctuation of ingredient prices caused by seasonal variations, climatic conditions, and international market shifts. Small and medium-scale restaurants are particularly vulnerable because they often rely on manual practices for cost estimation, without structured demand records or digital systems to support procurement and waste management decisions.

Globally, research in this domain has focused on time-series forecasting techniques for predicting commodity and agricultural prices. Traditional models such as ARIMA and Exponential Smoothing have long been used for short-term forecasting [1]. More recently, machine learning and deep learning approaches, such as Random Forests**,** Gradient Boosting, and LSTM networks, have demonstrated superior performance in handling non-linear, seasonal, and volatile datasets [2], [3]. In parallel**,** supplier recommendation systems have gained attention in supply chain management, where multi-criteria decision-making (MCDM) methods like Analytic Hierarchy Process (AHP) and hybrid ML-based ranking algorithms have been applied to evaluate suppliers based on cost, reliability, and quality [4].

Despite these advancements, research in the context of restaurant operations in Sri Lanka is very limited. Most restaurants do not maintain systematic sales or wastage records, making it difficult to apply complex forecasting methods directly. This creates an opportunity for a tailored solution that combines demand forecasting, ingredient price prediction, supplier recommendation, and waste management into a lightweight, adaptive framework.

1.2 Relevant Studies and Techniques

To successfully implement the proposed system, mastery of several techniques is required:

- Time-series forecasting methods such as ARIMA, Prophet, and LSTM to model price fluctuations.
- Data preprocessing and feature engineering for handling incomplete or irregular restaurant datasets.
- Supplier ranking and recommendation using machine learning ranking algorithms and MCDM methods.

These techniques form the foundation of the project, with forecasting and recommendation as the two central components.

1.3 State of the art

Today, the forefront of price prediction is hybrid deep learning models, such as the application of LSTM with attention or reinforcement learning approaches for more robust predictions [5]. Similarly, supplier recommendation has evolved towards intelligent decision aid systems where ML models not only provide a ranking of the suppliers but also include the feature of anomaly detection to signal overpricing [6].

In waste management, existing systems utilize AI-driven demand forecasting combined with inventory monitoring to minimize loss, particularly in high-income economies with strong digital penetration [7]. The solutions, however, assume the availability of big, clean data, which makes direct application in Sri Lankan restaurants a far cry.

1.4 Research Problem

Most of the previous work has been for large supply chains or matured markets, resulting in a gap for solutions for Sri Lankan medium and small restaurants. Prior solutions are founded on end-of-day profit determination without system records of order quantities or wastage. Without systematic data gathering, restaurants cannot benefit from predictive analytics or automated supplier comparison.

Therefore, the research problem addressed in this project can be outlined as:

How is one integrated system to be created to forecast restaurant demand, anticipate price fluctuations in ingredients, and recommend reliable suppliers, and aid waste management in Sri Lankan restaurants where limited structured data is available?

2 OBJECTIVES

2.1 Main Objective

main objective is to design and implement a machine learning–based system that predicts the selling prices of restaurant food items (weekly/monthly) using both historical sales prices and historical ingredient cost data also current ingredient prices, while also recommending the most suitable suppliers for each ingredient based on cost and reliability.

2.2 Specific Objectives

Data Collection & Preprocessing

- Gather historical food sales prices and ingredient prices from restaurant records and market reports.
- Include current ingredient prices for short-term prediction adjustments.
- Preprocess data to handle missing values and align food–ingredient relationships.

Food Price Prediction

- Apply machine learning models (e.g., ARIMA, Prophet, Regression, LSTM) to predict weekly and monthly food selling prices.
- Compare model performance using accuracy metrics such as RMSE, MAPE, and R^2.

Supplier Recommendation

- Implement a supplier ranking mechanism considering cost, reliability, and freshness.
- Recommend the best-rated suppliers for each ingredient to restaurant owners.

System Integration

- Combine food price prediction outputs with supplier recommendation results in a single decision-support system.
- Provide actionable insights through notifications or report.

Evaluation

- Test the system using historical and simulated data.
- Measure its effectiveness in predicting selling prices and optimizing supplier selection.

3 METHODOLOGY

3.1 System Overview

The proposed system architecture is illustrated in *Figure 1*. It shows the flow from raw data sources (historical food prices, ingredient costs, and supplier information) through preprocessing and machine learning model training, to the final decision support user interface. The methodology describes how each stage contributes to achieving the main objective: predicting restaurant food selling prices and recommending cost-effective suppliers.

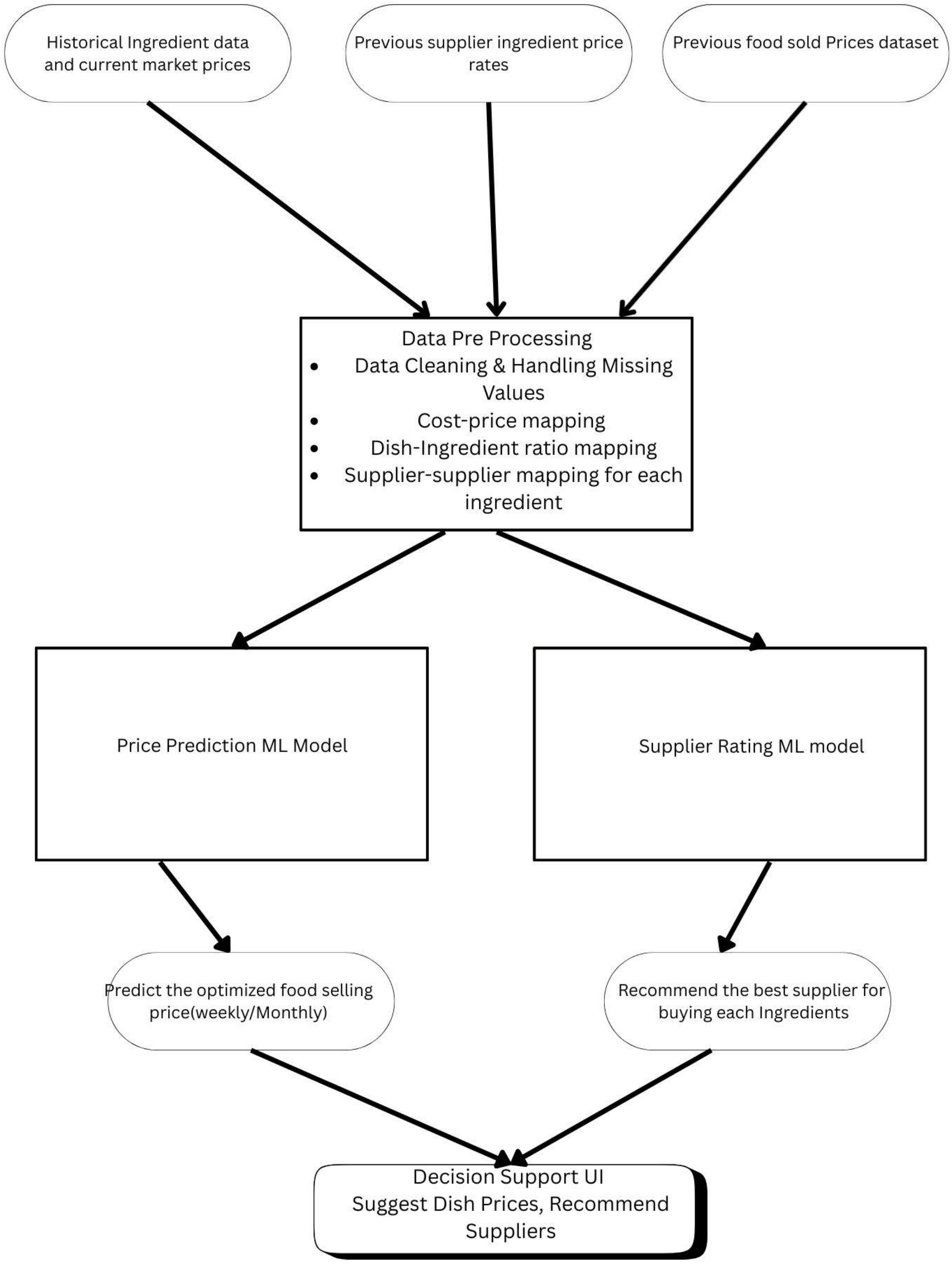

Figure 1: System architecture of the Food Price Prediction and Supplier Recommendation component

3.2 Data Collection

The data required for the project will be collected from three main sources:

- Historical food selling prices obtained from restaurants or simulated datasets.
- Ingredient prices (historical and current) obtained from wholesale/market price records.
- Supplier data including past price rates, delivery reliability, and freshness indicators.

If restaurants do not provide sufficient data, simulated datasets will be created using publicly available market prices combined with domain assumptions.

3.3 Data Preprocessing & Feature Engineering

Collected data will undergo several preprocessing steps to ensure consistency:

- Data cleaning: handling missing values, correcting anomalies, and smoothing outliers.
- Cost–price mapping: linking ingredient costs with dish selling prices.
- Dish–ingredient ratio mapping: defining ingredient proportions required per dish.
- Supplier–ingredient mapping: mapping each ingredient to available suppliers and comparing suppliers for cost, reliability, and freshness.

Additionally, feature engineering will be performed to improve model accuracy:

- Rolling averages of ingredient prices.
- Seasonal features (weekly/monthly indicators).
- Computed cost index for each dish.

3.4 Model Development

Two ML model pipelines will be implemented:

- **Food Price Prediction Model**
    - Models such as ARIMA, Prophet, Regression, and LSTM will be tested.
    - Weekly and monthly dish selling prices will be predicted using historical sales data combined with ingredient costs.
- **Supplier Recommendation Model**
    - A supplier ranking algorithm will compare multiple suppliers for each ingredient.
    - Criteria include cost, delivery reliability, and freshness ratings.

- Suppliers will be ranked, and the best supplier will be recommended per ingredient.

3.5 System Integration

The outputs from the two models will be combined in a **Decision Support Layer**:

- Suggested selling prices for dishes (weekly/monthly).
- Recommended suppliers for each ingredient.
- Reports and alerts delivered to restaurant owners for timely decision-making.

3.6 Evaluation

The system will be evaluated using both historical and simulated data.

- **Price Prediction**: Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 will be used as accuracy metrics.
- **Supplier Recommendation**: Supplier rankings will be validated against actual supplier performance and simulated test cases.

3.7 Task Scheduling

The Food Price Prediction and Supplier Recommendation component will be completed over an academic year (September–June). Since this component is fully handled by me, I will take responsibility for all tasks from data collection to evaluation. The schedule is as follows In the figure 2

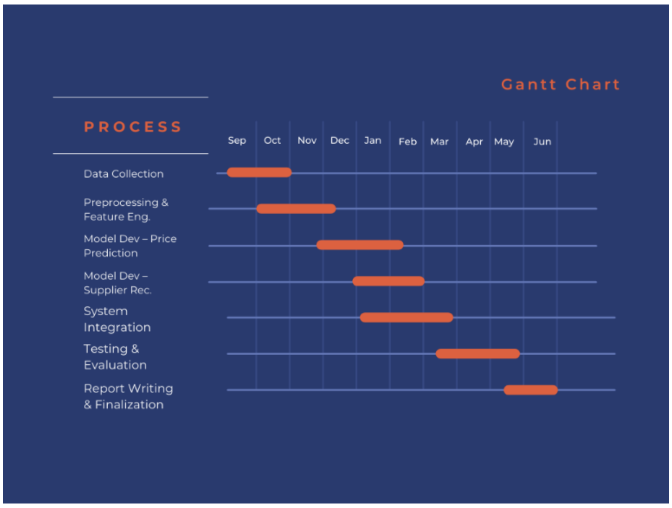

Figure 2: Gantt Chart for Food Price Prediction & Supplier Recommendation Component

3.8 Anticipated Outcome

By the end of the project, the system is expected to:

- Provide accurate weekly and monthly predictions of food selling prices.
- Recommend the most suitable suppliers per ingredient based on cost and reliability.
- Deliver actionable insights through reports and notifications to restaurant owners.
- Improve pricing decisions and supplier management in small and mid-sized Sri Lankan restaurants.

4 PROJECT REQUIREMENTS

4.1 Functional Requirements

• Predict weekly and monthly selling prices of restaurant dishes.

• Recommend the most suitable suppliers per ingredient based on cost, reliability, and freshness.

• Generate decision-support reports summarizing predicted prices and supplier rankings.

• Provide a user interface for restaurant owners to view predictions, supplier recommendations, and alerts.

• Send notifications when significant ingredient price fluctuations are detected.

• Allow exporting results (PDF/Excel) for business use.

4.2 Nonfunctional Requirements

• Performance**:** System generates predictions and recommendations within seconds.

• Scalability**:** Can handle data for 100+ dishes and multiple suppliers.

• Reliability**:** Supplier ranking applies consistent scoring rules.

• Usability**:** Intuitive UI suitable for non-technical restaurant owners.

• Maintainability**:** System can be extended to add demand forecasting or waste management modules later.

• Security: Owner data is accessible only to authorized users.

4.3 User Requirements

- Enter or upload current ingredient prices.
- View predicted dish selling prices (weekly/monthly).
- See ranked suppliers with reasons (cost, reliability, freshness).
- Receive alerts on cost changes.
- Export/download reports for business decisions.

4.4 System Requirements

4.4.1 Hardware Requirements

- Minimum**:** Intel Core i5 processor, 8 GB RAM, 256 GB SSD

- Recommended**:** Intel Core i7 processor (or AMD Ryzen 7), 16 GB RAM, 512 GB SSD, with optional GPU support

4.4.2 4.4.2 Software Requirements

• Programming Environment

- Python 3.10 or higher – chosen for stability and compatibility with ML libraries.

• Machine Learning Libraries

- Scikit-learn, Statsmodels, Prophet – for regression and time-series forecasting models.
- TensorFlow or PyTorch – for advanced sequence models such as LSTMs.

• Database

- SQLite – lightweight, file-based database suitable for local experiments.
- MongoDB – optional NoSQL database for flexible supplier and ingredient storage.

• Visualization

- Matplotlib, Seaborn – for generating data trend graphs, forecasts, and supplier comparison charts.

• User Interface **(**Optional**)**

- React – optional frontend framework if a web-based dashboard is required.

- Tools

  - GitHub – version control and collaborative code management.
  - Canva/Draw.io – creation of diagrams (system architecture, use cases).
  - MS Word – preparation and formatting of project documentation.

5 DESCRIPTION OF PERSONAL AND FACILITIES

5.1 Personal

This component of the project (Food Price Prediction and Supplier Recommendation) will be carried out individually by Fernando W.G.P.N, I am an undergraduate student in the B.Sc. (Hons) in Information Technology degree program at SLIIT. I have completed prior coursework in Data Science, Databases, and Web developments, which provides the necessary foundation to design and implement machine learning–based component for price forecasting and supplier recommendation.

5.2 Facilities

The research will utilize the following facilities:

- Computing Facilities: Personal laptop with (Ryzen 5, 24 GB RAM, 1 TB SSD memory) for development and testing of ML models.
- Software Tools: Python (Scikit-learn, TensorFlow, Prophet), MongoDB/SQLite, Jupyter Notebook, Flask/FastAPI for integration.
- University Facilities: Access to SLIIT labs, internet connectivity, and academic support resources.
- Collaboration & Documentation Tools: GitHub for version control, Canva/Draw.io for diagramming, MS Word for report preparation.

These facilities are sufficient to carry out the implementation, testing, and evaluation of the proposed system.

6 BUDGET AND BUDGET JUSTIFICATION

Total Project Budget: LKR 30,000 (USD 100 approximately)

Budget Breakdown by Category:

Table 1: Project Budget

Category	Item Description	Quantity	Unit Cost (LKR)	Total Cost (LKR)
Software & APIs	WhatsApp Business API	1 Year	5,000	5,000
Cloud Services	Cloud Compute Credit	-	10,000	10,000
Travel	Site Visits to Restaurant	10 visits	1,500	15,000
Total				**30,000**

Budget Justification:

Personnel: The majority of the costs (60%) goes to personnel, bearing in mind the labor-intensive process of software and data development and field work. PI's partial effort provides committed leadership and permits participation in other academic activities. Technical team pricing is critical for building a professional-looking prototype that will be ready for market.

Investment in Equipment and Technology: The 20% commitment for equipment and technology is essential to building and testing a sound system. Scalable test and deployment testing is afforded by cloud computing services; compatibility across a variety of hardware configurations that target users may use is supported by mobile devices.

Field research: 10% for travel and data collection the widely distributed nature of restaurants in Sri Lanka requires extensive face-to-face relationship building in order to gather trustworthy information and accurate operational data from small business owners.

7 REFERENCES

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