

**MACHINE LEARNING MODEL FOR  
ANALYZING CLIMATIC AND ECONOMIC  
INFLUENCES ON VEGETABLE PRICES:  
FORECASTING CARROT PRICES IN  
DAMBULLA MARKET**

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# ABSTRACT

Agricultural market volatility poses significant challenges for farmers, traders, and policymakers in Sri Lanka, where vegetable prices fluctuate unpredictably due to complex interactions between weather patterns, supply dynamics, and economic factors. This research develops a machine learning-based forecasting system for predicting wholesale carrot prices at Dambulla market, integrating data from the Central Bank of Sri Lanka, Copernicus Climate Data Store, Ceylon Petroleum Corporation fuel prices, and market supply-demand indicators.

Comprehensive feature engineering across price patterns, weather conditions, supply factors, demand indicators, fuel costs, and temporal features was performed. A systematic 4-stage feature selection pipeline combining Random Forest importance, Mutual Information, correlation analysis, and multicollinearity removal reduced dimensionality to 19-35 features while preserving predictive power. Seven forecasting models including ARIMA, LSTM variants (Univariate, Multivariate, and Bidirectional), and Random Forest were rigorously evaluated using consistent train-validation-test splits and multiple performance metrics including MAPE, MAE, RMSE, and  $R^2$ .

Traditional ARIMA methods demonstrated fundamental limitations with MAPE exceeding 50% for both univariate and multivariate specifications, validating the inadequacy of linear assumptions for complex agricultural markets. LSTM-based deep learning approaches achieved substantial improvements, with performance metrics reaching 21.22% MAPE and  $R^2$  of 0.8111, effectively capturing non-linear temporal dependencies through forward-backward sequence processing. Systematic ablation studies quantified feature category contributions, revealing price history as the dominant predictor while weather, supply, and fuel factors provided meaningful incremental accuracy. SHAP analysis enhanced model interpretability, confirming theoretically expected negative rainfall-price relationships.

The research delivers a deployment-ready system integrating the best-performing model with a Retrieval-Augmented Generation AI agent using Groq API and natural language interface via Gradio, democratizing sophisticated forecasting for non-technical stakeholders. This work contributes replicable methodology for agricultural price forecasting, empirically validates deep learning superiority over traditional approaches for complex market dynamics, and provides operational tools supporting informed decision-making across the agricultural value chain in developing economies.

**Keywords:** carrot price prediction, LSTM neural networks, Dambulla market, agricultural forecasting, machine learning, weather-price relationships, RAG system, AI agent, time series analysis, Sri Lankan agriculture

# DECLARATION

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

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G.G.M.P.Kumara  
November 25, 2025

.....  
Prof.Amalka Pinidiyaarachchi  
November 25, 2025

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# CHAPTER 1

## INTRODUCTION

### 1.1 Research Overview

Agriculture remains a vital component of Sri Lanka's economy. Among the various agricultural products, vegetables constitute an essential part of the domestic food supply chain. However, vegetable markets in Sri Lanka have historically been characterized by high price volatility, which creates substantial challenges for both farmers and consumers. Carrot, being one of the major vegetables traded in the country, experiences frequent and often unpredictable price fluctuations that can severely impact the economic stability of farming communities.

Daily price movements in the Dambulla market reflect complex interactions between multiple factors including weather patterns, fuel costs, regional supply levels, and market demand dynamics. Understanding and predicting these price movements has become increasingly important for stakeholders throughout the agricultural value chain.

This research investigates the application of machine learning techniques to forecast wholesale carrot prices in the Dambulla market. The study explores how climatic conditions, particularly precipitation patterns from major growing regions, along with economic factors such as fuel prices and supply indicators, influence daily price variations. Through the development and comparison of multiple forecasting models, this work aims to identify the most effective approach for short-term price prediction in the context of Sri Lankan vegetable markets.

## 1.2 Problem Statement

Vegetable price volatility presents serious problems for the agricultural sector in Sri Lanka. Farmers often struggle to make informed decisions about planting schedules, harvest timing, and market entry due to the uncertainty surrounding future prices. When prices drop unexpectedly, farmers may face losses that threaten their financial stability. Conversely, sudden price spikes can lead to affordability issues for consumers while also triggering market interventions that complicate the natural price discovery process.

Traditional approaches to understanding vegetable prices have relied primarily on historical averages and seasonal patterns. However, these methods fail to capture the complex, non-linear relationships between prices and the various factors that influence them. The lack of reliable forecasting tools means that decision-making across the supply chain remains largely reactive rather than proactive. This situation calls for more sophisticated analytical approaches that can better model the temporal dependencies and multi-dimensional influences inherent in agricultural price data.

The challenge is further complicated by the fact that different factors may have varying degrees of influence on prices at different times. For instance, heavy rainfall in major growing regions like Nuwara Eliya might have delayed effects on market prices as supply disruptions gradually propagate through the distribution network. Similarly, changes in fuel prices might impact transportation costs, which in turn affect wholesale pricing. Capturing these temporal lags and interactions requires modeling techniques that can learn from sequential data and account for multiple input variables simultaneously.

## 1.3 Proposed Solution

This research proposes a comprehensive machine learning framework for carrot price forecasting that addresses the limitations of traditional approaches. The framework consists of two main components: a forecasting engine and an intelligent query system.

The forecasting component employs three distinct modeling approaches to predict daily carrot prices. First, ARIMA models provide a baseline using classical time series analysis techniques. Second, Long Short-Term Memory (LSTM) neural networks are developed in both univariate and multivariate configurations to capture complex temporal patterns. The multivariate LSTM incorporates external factors including precipitation data from eleven growing regions, fuel price indicators, regional supply factors, and market status variables. Third, Random Forest regression serves as an ensemble learning alternative that approaches the problem from a non-sequential perspective.

A rigorous feature selection process underpins the multivariate models. This process combines Random Forest feature importance, Mutual Information scores, and Recursive Feature Elimination to identify the most relevant predictors. The selected features then undergo further validation through an ablation study that systematically assesses the contribution of different feature categories to overall prediction accuracy.

The second component of the framework is a Retrieval-Augmented Generation (RAG) based AI agent that makes the forecasting system accessible and interpretable. This agent stores prediction results in a vector database and uses a large language model to provide natural language responses to user queries. The system can handle both specific date inquiries and analytical questions about price trends, offering stakeholders an intuitive interface for accessing forecasting insights.

## 1.4 Motivation

Several factors motivated this research. First, there exists a clear practical need for improved price forecasting tools in Sri Lankan agriculture. Farmers, traders, and policymakers all stand to benefit from better price predictions. This research aims to bridge that gap by developing methods specifically tailored to local market conditions.

Second, from a technical perspective, agricultural price forecasting presents interesting challenges that push the boundaries of time series modeling. The need to incorporate diverse data sources, handle irregular patterns, and account for both short-term

volatility and longer-term trends makes this a rich problem domain for exploring advanced machine learning techniques. The comparison between sequential models like LSTM and non-sequential approaches like Random Forest offers valuable insights into the nature of temporal dependencies in agricultural price data.

Third, the growing availability of data from various sources creates new opportunities for multivariate forecasting that were not previously feasible. Weather records, fuel price data, and market information can now be integrated more easily, but questions remain about how best to leverage these multiple data streams. This research investigates practical approaches to feature engineering and selection in the context of agricultural forecasting.

Finally, there is broader interest in making machine learning models more interpretable and accessible to end users. The development of the RAG-based AI agent represents an attempt to move beyond simply generating predictions toward creating a system that can explain those predictions and support decision-making in meaningful ways.

## 1.5 Research Objectives

The primary objectives of this research encompass systematic development and evaluation of agricultural price forecasting models through interconnected phases. The first objective involves collecting and preprocessing historical carrot price data along with relevant meteorological, economic, and market variables from multiple authoritative sources spanning January 2020 to July 2025, ensuring data quality and completeness for robust model training. Building upon this foundation, the second objective focuses on developing and implementing univariate forecasting models using historical price data alone, establishing baseline performance through both traditional ARIMA approaches and modern LSTM neural networks to quantify the predictive power achievable without external variables.

The third objective extends the modeling framework by creating multivariate forecasting models that incorporate external factors including precipitation patterns from

major growing regions, fuel price indicators affecting transportation costs, supply indicators reflecting production levels, and temporal features capturing calendar effects, with particular emphasis on rigorous feature selection methods to identify truly relevant predictors among hundreds of candidate variables. Following model development, the fourth objective conducts comprehensive model comparison across ARIMA, univariate LSTM, multivariate LSTM variants, and Random Forest approaches using multiple evaluation metrics including MAPE for percentage error assessment, MAE for absolute error measurement, RMSE for penalizing large errors, and  $R^2$  scores for explained variance quantification, ensuring thorough performance characterization beyond single metrics.

The fifth objective performs systematic ablation studies that methodically isolate the contribution of different feature categories including weather patterns, supply factors, fuel costs, and temporal variables to forecasting accuracy, providing empirical insights into which external factors most strongly influence carrot prices and validating the value of multivariate modeling. The sixth objective validates model performance through advanced statistical techniques including bootstrap confidence intervals for uncertainty quantification and effect size analysis using Cohen's  $d$  to assess practical significance of performance differences, ensuring that observed improvements between models represent genuine advances rather than random variation. The seventh objective develops an AI agent based on Retrieval-Augmented Generation architecture integrating the best-performing forecasting model with natural language processing capabilities, providing an accessible interface through which farmers, traders, and policymakers can query price predictions and obtain analytical insights about price trends and influencing factors without requiring technical expertise. Finally, the eighth objective evaluates the complete forecasting framework considering both prediction accuracy metrics and practical usability for stakeholders across the agricultural supply chain, assessing whether the system delivers actionable value in real-world decision-making contexts beyond purely academic performance benchmarks.

## 1.6 Background

Sri Lanka's agricultural sector has long been central to the nation's economy and food security. The country's diverse topography and climate zones enable the cultivation of a wide variety of crops, with vegetable farming concentrated primarily in the central highlands. The Nuwara Eliya district, often referred to as the vegetable basket of Sri Lanka, supplies a substantial portion of the country's temperate vegetables including carrots, leeks, and cabbage.

The Dambulla Economic Centre, established in the Matale district, functions as the primary wholesale distribution point for vegetables in Sri Lanka. Daily, thousands of tons of produce arrive from various growing regions, are auctioned in the early morning hours, and are then transported to retail markets across the island. The prices established in Dambulla influence retail pricing throughout the country, making it a crucial barometer for the vegetable market as a whole.

Carrot cultivation in Sri Lanka occurs year-round, though production volumes vary seasonally based on weather conditions in different growing regions. The main growing areas include Nuwara Eliya, Welimada, Bandarawela, and several other locations in the central highlands. These regions experience different rainfall patterns and microclimates, which means that supply from different areas peaks at different times, theoretically providing year-round availability.

However, this system is vulnerable to various disruptions. Excessive rainfall can damage crops and delay harvests, leading to supply shortages. Transportation challenges, whether due to fuel price increases or infrastructure problems, can affect the flow of produce to market. Market dynamics themselves can create volatility, as traders adjust their behavior based on expected future prices, sometimes amplifying rather than dampening price swings.

In recent years, there has been growing recognition of the need for better market information systems in Sri Lankan agriculture. Various government and non-government organizations have made efforts to collect and disseminate market price data, but tools

for forecasting future prices have remained limited. This research builds on existing data collection initiatives while introducing more sophisticated analytical capabilities.

## 1.7 Scope of the Research

This research focuses specifically on wholesale carrot prices in the Dambulla market. While the methodologies developed here could potentially be applied to other vegetables or other markets, the empirical work concentrates on this single commodity in this single location. This focused scope allows for in-depth analysis while maintaining manageable complexity in terms of data collection and model development.

The temporal scope encompasses data from January 2020 through July 2025, providing over five years of daily price observations along with corresponding values for all predictor variables. This period includes both normal market conditions and more volatile periods, including the economic challenges faced by Sri Lanka in recent years, which helps ensure that the models are exposed to a range of market scenarios during training and evaluation.

The research investigates multiple modeling approaches but does not attempt to cover every possible machine learning technique. The selection of ARIMA, LSTM, and Random Forest provides a representative sample spanning traditional statistical methods, deep learning approaches, and ensemble learning techniques. The comparison between these methods aims to identify which characteristics are most important for this particular forecasting problem.

While the research develops an AI agent to make predictions accessible, the focus remains on the forecasting methodology itself. The agent serves primarily as a delivery mechanism for predictions rather than as the central technical contribution. Future work could expand on this component, but for the purposes of this research, the emphasis is on establishing effective forecasting models.

## **CHAPTER 2**

### **LITERATURE REVIEWS**

This chapter reviews the existing literature on agricultural price forecasting, with particular emphasis on vegetable price prediction using various computational techniques. The review is organized into several thematic sections that progress from traditional statistical approaches to modern machine learning and deep learning methodologies. Each section examines relevant studies, highlighting their methodologies, findings, and contributions to the field. The chapter concludes by identifying gaps in current research and establishing the context for this study.

#### **2.1 Traditional Statistical Methods for Agricultural Price Prediction**

Traditional statistical approaches have long formed the foundation of agricultural price forecasting. Among these methods, AutoRegressive Integrated Moving Average (ARIMA) models have been extensively employed due to their ability to capture temporal dependencies in price series data.

Ruhunuge et al. (2024) conducted an econometric investigation into climate-driven carrot price variations in Sri Lanka using Vector Autoregression (VAR) modeling. Their study spanned twenty-three years (2000-2023) of wholesale carrot price data from the Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI), combined with climate data from the Meteorology Department. The researchers applied first-order differencing to capture volatility patterns, resulting in 852 monthly observations that passed rigorous unit root tests. Their VAR model, optimized with a lag structure of six periods based on Akaike Information Criterion (AIC), revealed that precipitation changes significantly influenced carrot prices ( $p\text{-value} = 0.0447$ ), while temper-

ature demonstrated limited predictive value. The impulse response analysis showed that a one-unit standard deviation increase in precipitation resulted in an immediate 2.8% increase in carrot prices, peaking at 1.2% in the third interval before stabilizing. The derived model equation demonstrated that increased rainfall significantly lowered current carrot prices with a coefficient of -16.09719, while the positive lagged price coefficient of 0.141777 indicated price momentum effects (Ruhunuge et al., 2024).

Chen et al. (2021) compared ARIMA against modern machine learning approaches for Malaysian agricultural commodity price prediction. Their ARIMA implementation utilized parameters ( $p=1.5$ ,  $d=1$ ,  $q=1$ ) determined through Augmented Dickey Fuller Test and comprehensive Auto/Partial Correlation Function analysis. While ARIMA achieved remarkable average Mean Squared Error (MSE) of 0.251 for smaller datasets, with chili prediction reaching exceptional 0.027 MSE, the model experienced concerning 74.1% performance degradation when confronted with increased data complexity. This finding highlighted a fundamental limitation of traditional statistical methods when dealing with large, complex agricultural datasets (Chen et al., 2021).

These studies demonstrate that while traditional statistical methods provide interpretable models and perform well with smaller datasets under stable market conditions, they struggle with non-linear relationships and large-scale data, motivating the exploration of machine learning alternatives.

## 2.2 Machine Learning Approaches for Crop Price Forecasting

Machine learning techniques have gained prominence in agricultural price prediction due to their ability to capture complex, non-linear relationships between multiple variables without requiring explicit model specification.

### 2.2.1 Tree-Based Ensemble Methods

Ranaweera et al. (2023) investigated vegetable price predictability in Sri Lanka using data mining techniques. Their comprehensive study analyzed four vegetables (beans, eggplant, carrots, and pumpkins) from five economic centers using four-year historical data (2018-2021) from multiple institutions including the Central Bank, Department of Agriculture, Meteorological Department, and Ceylon Petroleum Corporation. The researchers evaluated five machine learning algorithms including Linear Regression, SMO Regression, Multilayer Perceptron, Random Forest, and M5P using 10-fold cross-validation in WEKA 3.8.6. Random Forest emerged as the superior model, achieving Mean Absolute Error (MAE) values ranging from 10.58 for pumpkins to 27.62 for beans. Pumpkins demonstrated the highest prediction accuracy exceeding 85%, while beans presented the most challenging forecasting scenario. The study revealed that rainfall variability (0.00 to 53.40mm) and temperature fluctuations, alongside fuel prices affecting transportation costs, critically impacted price variations (Ranaweera et al., 2023).

Choong et al. (2024) developed a Genetic Algorithm-Based Neural Network (GANN) approach within an Agricultural Knowledge Management System (AKMS) for Malaysia. Using monthly vegetable prices from 2010 to 2021 (144 observations), their GANN model achieved 98.40% accuracy with MAPE of 1.6042%, significantly outperforming both ARIMA (98.32% accuracy) and SARIMA (98.37% accuracy). The genetic algorithm optimization with 20 chromosomes, three hidden layers containing five nodes each with ReLU activation, and roulette wheel selection methodology enabled dynamic adaptation to agricultural market dynamics. The model particularly excelled in RMSE (0.06674) and MAE (0.5571) metrics, demonstrating superior handling of nonlinear relationships in seasonal price variations (Choong et al., 2023).

### 2.2.2 Support Vector Machines and Hybrid Approaches

Kakulapati et al. (2022) explored vegetable price prediction against temperature changes using web scraping to collect real-time weather and price data from Hyderabad. Their comparison of Decision Tree Regression, Random Forest Regression, and Linear Regression revealed that Decision Tree Regression achieved superior accuracy in predicting prices based on temperature variations. The innovative web scraping methodology enabled dynamic data collection at five-day intervals, addressing limitations of static historical datasets. This real-time approach provided farmers with timely insights for cultivation decision-making based on weather-price correlations (Vijayalaxmi et al., 2022).

Bayona-Oré et al. (2021) conducted a comprehensive systematic review of machine learning applications in agricultural price prediction from 2011-2020. Their analysis revealed that Neural Network models were most frequently employed (24 algorithms), followed by statistical models (20 algorithms) and Support Vector Machines (9 occurrences). The review identified that all studies employed positivism paradigm with quantitative approaches, predominantly using supervised learning due to availability of labeled historical price data. Performance metrics analysis showed RMSE, MAPE, and MAE as the most commonly used evaluation measures. Geographically, China dominated with 11 studies examining 17 products, while India contributed 6 studies covering 12 products, indicating regional concentration in research efforts (Bayona-Oré et al., 2021).

## 2.3 Deep Learning Methods for Agricultural Time Series Forecasting

Deep learning approaches, particularly recurrent neural networks and their variants, have revolutionized time series forecasting by effectively capturing long-term dependencies and complex temporal patterns.

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

Zhang et al. (2024) investigated short-term vegetable price forecasting for Beijing's wholesale markets using LSTM models. Their study utilized 14.7 years of daily price data (January 2009 to September 2023) from seven major wholesale markets, analyzing six representative vegetables from four categories. The LSTM architecture comprised two layers with 32 neurons each, optimized learning rate of 0.0027, dropout rate of 0.2, batch size of 500, and 200 training epochs using Adam optimizer. The model achieved exceptional performance with  $R^2$  scores of 0.958 and MAE of 0.143, representing over 5% improvement compared to CNN, XGBoost, and SVR. Vegetable-specific accuracy varied notably: celery (93.3%), carrots (92.9%), oyster mushrooms (90.2%), and spiny cucumbers (90.1%), with trend prediction concordance rates exceeding 70% for most vegetables. Wilcoxon signed-rank tests confirmed statistically significant improvements over competing methods ( $p < 0.05$ ) (Zhang et al., 2024).

Yin et al. (2020) developed an innovative STL-ATTTLSTM model integrating Seasonal Trend decomposition using Loess (STL) with attention mechanism-based LSTM for South Korean vegetable markets. Their research targeted five supply-and-demand-sensitive vegetables (cabbage, radish, onion, hot pepper, garlic) using data from January 2012 to December 2019. The sophisticated architecture employed STL to separate time series into trend, seasonality, and remainder components, with attention mechanism assigning dynamic weights to input variables during training. The model comprised an attention layer with softmax activation, LSTM layer with 6 cell units using tanh activation, dropout layer (0.2 rate), and fully connected layers, trained for 1000 epochs using Adam optimizer. The STL-ATTTLSTM achieved exceptional average RMSE of 380 and MAPE of 7%, representing 12% higher prediction accuracy compared to attention LSTM without STL preprocessing. The model successfully eliminated the one-month prediction lag phenomenon common in highly volatile time-series data by utilizing STL remainder components rather than raw price data (Yin et al., 2020).

### 2.3.2 Hybrid Deep Learning Architectures

Guo et al. (2022) proposed an innovative AttLSTM-ARIMA-BP hybrid model for corn price prediction in Sichuan Province, China. Using 511 weekly observations from March 2011 to April 2021, they employed Apriori association rule mining to identify 12 critical spatial-temporal factors across multiple provinces and related commodity prices. Their hybrid architecture strategically integrated Attention Mechanism for dynamic weight calculation, LSTM for non-linear temporal dependencies, ARIMA for linear trend modeling, and Back Propagation Neural Network for final prediction synthesis. The model achieved outstanding performance with MAPE of 0.0043, MAE of 1.51, RMSE of 1.642, and remarkable  $R^2$  of 0.9992, significantly outperforming seven competing models including Linear Regression, Random Forest, XGBoost, LightGBM, single LSTM, multivariate LSTM, and AttLSTM. While traditional regression models maintained reasonable accuracy during stable periods, they failed dramatically during volatile market conditions, whereas the hybrid model consistently delivered accurate predictions regardless of price behavior patterns (Guo et al., 2022).

Avinash et al. (2024) introduced Hidden Markov-based Deep Learning approaches for forecasting TOP (Tomato, Onion, Potato) commodity prices in India. Their research utilized 911 weekly price observations from Azadpur Mandi (January 2006 to June 2023), applying Hidden Markov Models (HMMs) for feature extraction to identify hidden states in price data. Optimal hidden states were determined through grid search: six states for tomato and eight states each for onion and potato. These hidden states served as inputs to four deep learning models: Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), Gated Recurrent Units (GRUs), and Long Short-Term Memory (LSTM). Extensive hyperparameter optimization across 126 combinations per model included batch sizes, epochs (200 with early stopping), hidden layers, and units. The hybrid HM-DL models achieved superior performance with RMSE reductions of 9.77-17.50% for tomato, 15.02-44.39% for onion, and 7.94-32.60% for potato compared to baseline approaches. HM-RNN consistently emerged as the best performer for training data, while HM-LSTM excelled for tomato testing data due to su-

perior long-memory capabilities in capturing significant price spikes. Diebold-Mariano tests confirmed statistically significant differences between hybrid and baseline models (Avinash et al., 2024).

## 2.4 Feature Engineering and Selection in Agricultural Forecasting

Effective feature engineering and selection constitute critical components of successful agricultural price prediction models, as they determine which variables contribute most significantly to forecasting accuracy.

The reviewed studies employed diverse approaches to feature selection. Ranaweera et al. (2023) systematically incorporated four key factors: rainfall, temperature, fuel price, and crop production, demonstrating that climatic factors particularly influenced price variations in tropical agricultural systems. Their analysis revealed substantial variability in price predictability across vegetables, with pumpkins showing highest accuracy and beans presenting the most challenging scenario (Ranaweera et al., 2023).

Guo et al. (2022) utilized Apriori association rule mining algorithm to identify 12 critical spatial-temporal factors influencing corn prices, including prices from multiple provinces and related commodities. This data-driven approach to feature discovery enabled their hybrid model to capture complex inter-commodity and inter-regional price relationships (Guo et al., 2022).

Yin et al. (2020) demonstrated sophisticated feature engineering by incorporating meteorological variables (average temperature, minimum temperature, humidity, precipitation, temperature threshold days, typhoon advisories) specifically for main production areas during harvest periods. Their approach strategically focused harvest-time meteorological data for immediately marketed crops (cabbage, radish) while excluding weather factors for warehouse-stored crops (hot pepper, onion, garlic) with delayed market entry. Additionally, they integrated trading volume data as production proxies and import/export information for comprehensive market analysis (Yin et al., 2020).

Chen et al. (2021) implemented a dual-experimental design: first utilizing univariate time-series data spanning 11 years, then incorporating multivariable features including temperature, humidity, precipitation, and crude oil prices. Their comparative analysis revealed that ARIMA excelled with smaller datasets while LSTM demonstrated 45.5% improvement in MSE for larger, more complex datasets, highlighting the importance of matching model complexity to data characteristics (Chen et al., 2021).

## 2.5 Model Evaluation and Performance Metrics

Rigorous model evaluation using appropriate performance metrics is essential for assessing prediction accuracy and comparing different forecasting approaches.

### 2.5.1 Common Evaluation Metrics

The literature review reveals widespread adoption of several key performance metrics. Mean Absolute Percentage Error (MAPE) emerged as the most prevalent metric, utilized by Zhang et al. (2024) achieving 0.143, Yin et al. (2020) achieving 7%, Guo et al. (2022) achieving 0.0043, and Choong et al. (2024) achieving 1.6042%. MAPE's popularity stems from its scale-independent nature and intuitive percentage interpretation (Zhang et al., 2024, Yin et al., 2020, Guo et al., 2022, Choong et al., 2023).

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were also frequently employed for absolute error measurement. Ranaweera et al. (2023) comprehensively evaluated models using MAE, RMSE, Relative Absolute Error (RAE), and Root-Relative Square Error (RRSE), providing multi-dimensional performance assessment. Additionally, coefficient of determination ( $R^2$ ) was utilized to measure explained variance, with Zhang et al. (2024) achieving 0.958 and Guo et al. (2022) achieving exceptional 0.9992 (Ranaweera et al., 2023, Zhang et al., 2024, Guo et al., 2022).

### 2.5.2 Statistical Validation Techniques

Several studies incorporated rigorous statistical validation beyond basic performance metrics. Avinash et al. (2024) employed Diebold-Mariano (DM) tests to establish statistically significant differences between hybrid and baseline models, ensuring observed improvements were not due to chance. Zhang et al. (2024) utilized Wilcoxon signed-rank tests to confirm LSTM's superior performance over competing methods with p-values below 0.05 threshold (Avinash et al., 2024, Zhang et al., 2024).

Ruhunuge et al. (2024) implemented comprehensive VAR model validation including stability condition testing (all characteristic roots within unit circle, largest root at 0.92), residual diagnostics showing no significant autocorrelation (p-values above 0.10), and heteroscedasticity testing (p-value = 0.15) indicating constant variance, thereby validating model reliability (Ruhunuge et al., 2024).

Yin et al. (2020) conducted systematic time-step optimization through grid search over multiple lag values, determining optimal time-step of 4 for superior performance across most vegetables. This methodological rigor in hyperparameter selection contributed to their model's exceptional accuracy (Yin et al., 2020).

## 2.6 Regional Perspectives and Data Sources

Agricultural price prediction research exhibits significant geographical concentration, with diverse data sources and regional considerations influencing methodology and applicability.

### 2.6.1 Asian Agricultural Markets

The majority of reviewed studies focused on Asian agricultural markets. China dominated with multiple studies: Guo et al. (2022) analyzed Sichuan corn prices using data from China's agricultural big data website and commodity exchanges, while Zhang et al. (2024) examined Beijing's seven major wholesale vegetable markets (Guo et al., 2022, Zhang et al., 2024). Bayona-Oré et al. (2021) confirmed this geographical con-

centration, identifying China as most researched country with 11 studies examining 17 products, followed by India with 6 studies covering 12 products (Bayona-Oré et al., 2021).

South Asian markets received notable attention through studies in Sri Lanka and India. Ranaweera et al. (2023) and Ruhunuge et al. (2024) both focused on Sri Lankan vegetable markets, utilizing data from the Central Bank of Sri Lanka, Department of Agriculture, and Hector Kobbekaduwa Agrarian Research and Training Institute. Avinash et al. (2024) examined India's Azadpur Mandi in Delhi, one of Asia's largest wholesale markets, using data from Agmarknet spanning over 17 years (Ranaweera et al., 2023, Ruhunuge et al., 2024, Avinash et al., 2024).

Southeast Asian perspectives emerged through Malaysian market studies. Chen et al. (2021) and Choong et al. (2024) both utilized data from Malaysia's Federal Agricultural Marketing Authority (FAMA), examining chicken, chili, tomato, and potato prices over extended periods. Their work addressed regional challenges including aging farming population and insufficient knowledge management systems (Chen et al., 2021, Choong et al., 2023).

## 2.6.2 Data Collection Approaches

Data sourcing strategies varied significantly across studies. Traditional approaches relied on official government databases and agricultural institutions. Multiple studies utilized meteorological data from national weather services: Ranaweera et al. (2023) from Sri Lanka's Meteorological Department, Yin et al. (2020) from Korean Meteorological Administration, and Chen et al. (2021) integrated climate data with price information (Ranaweera et al., 2023, Yin et al., 2020, Chen et al., 2021).

Innovative data collection methods emerged in recent research. Kakulapati et al. (2022) employed web scraping to extract real-time weather and price data, collecting information every five days to create dynamic datasets reflecting current market conditions. This approach addressed limitations of static historical datasets, enabling timely insights for agricultural decision-making (Vijayalaxmi et al., 2022). Guo et al. (2022)

utilized commodity exchange data alongside traditional agricultural databases, capturing futures market information for wheat and soybeans to inform spot price predictions (Guo et al., 2022).

The temporal scope of datasets ranged considerably: from Ruhunuge et al.'s 23-year span (2000-2023) capturing long-term climate-price relationships, to Zhang et al.'s 14.7 years (2009-2023) of daily observations providing high granularity, to shorter focused studies like Ranaweera et al.'s four-year analysis (2018-2021) enabling rapid model development (Ruhunuge et al., 2024, Zhang et al., 2024, Ranaweera et al., 2023).

## 2.7 Application Domains and Practical Implementation

Beyond academic contributions, several studies addressed practical implementation challenges and developed systems for real-world agricultural stakeholders.

Chen et al. (2021) developed a comprehensive web-based platform following Model-View-Controller (MVC) pattern using Django framework. Their system featured secure user authentication, interactive visualization dashboards with customizable forecast durations, commodity selection interfaces, downloadable CSV exports, and responsive design for compatibility across devices. The platform empowered farmers, government agencies, and agricultural stakeholders to make informed decisions regarding plantation planning, supply chain optimization, and policy formulation (Chen et al., 2021).

Choong et al. (2024) integrated price forecasting within an Agricultural Knowledge Management System (AKMS) following DIKW (Data, Information, Knowledge, Wisdom) pyramid framework enhanced with IoT and Big Data capabilities. Their platform combined knowledge management principles with e-commerce functionality, supporting both explicit knowledge (documented procedures) and tacit knowledge (farmer experiences) through integrated information sharing. The system addressed Malaysia's National Agrofood Policy (NAP 2.0) 2021-2030 objectives for creating sustainable, technology-based agrofood industry (Choong et al., 2023).

Practical applications focused on multiple stakeholder benefits. Zhang et al. (2024) provided week-ahead forecasts with detailed trend analysis revealing distinct fluctuation patterns for different vegetables, offering insights for growers, consumers, and policymakers. Avinash et al. (2024) emphasized helping farmers optimize storage decisions, identify favorable selling periods, and minimize losses through reliable price forecasting. Ranaweera et al. (2023) highlighted the importance of AI-driven forecasting for mitigating financial risks associated with price fluctuations in developing tropical economies (Zhang et al., 2024, Avinash et al., 2024, Ranaweera et al., 2023).

## 2.8 Research Gaps and Limitations

While the reviewed literature demonstrates significant progress in agricultural price prediction, several gaps and limitations warrant attention for future research directions.

### 2.8.1 Methodological Gaps

Bayona-Oré et al. (2021) identified lack of epistemological consideration in most studies, with all employing positivism paradigm and quantitative approaches without exploring alternative philosophical frameworks. Their review revealed absence of comprehensive model comparison frameworks and limited exploration of model interpretability, despite increasing emphasis on explainable AI in agricultural applications (Bayona-Oré et al., 2021).

Feature selection approaches remained largely empirical rather than systematic. While Guo et al. (2022) employed data mining for feature discovery and Yin et al. (2020) strategically selected features based on agricultural domain knowledge, most studies lacked rigorous statistical feature selection procedures such as mutual information analysis, recursive feature elimination, or ablation studies to quantify individual feature contributions (Guo et al., 2022, Yin et al., 2020).

The challenge of model generalization across different regions, vegetables, and market conditions received limited attention. Chen et al. (2021) noted concerning 74.1%

performance degradation of ARIMA with increased complexity, while studies generally focused on specific vegetables or regions without investigating cross-commodity or cross-market applicability (Chen et al., 2021).

### 2.8.2 Data-Related Limitations

Data availability constraints significantly influenced research scope. Bayona-Oré et al. (2021) observed that agricultural product selection was primarily driven by data availability rather than economic importance or market significance. Geographic concentration in China and India reflected both research capacity and data infrastructure availability, while other developing agricultural economies remained understudied (Bayona-Oré et al., 2021).

Temporal granularity varied across studies, with some utilizing daily data, others weekly or monthly observations. The impact of temporal resolution on prediction accuracy and practical applicability remained underexplored. Additionally, most studies relied on historical price data without incorporating real-time market signals or social media sentiment that might capture emerging market trends.

External factor integration remained incomplete in many studies. While weather and fuel prices received attention, broader macroeconomic indicators (exchange rates, inflation, policy changes), consumer behavior patterns, and supply chain disruptions (as experienced during COVID-19) were generally absent from modeling frameworks.

### 2.8.3 Practical Implementation Challenges

The gap between research models and operational deployment systems remained substantial. While Chen et al. (2021) and Choong et al. (2024) developed web-based platforms, most studies concluded with model performance evaluation without addressing deployment challenges such as model updating procedures, computational requirements, user interface design, or stakeholder adoption barriers (Chen et al., 2021, Choong et al., 2023).

Model interpretability and explainability received insufficient attention despite their

importance for farmer acceptance and trust. Agricultural stakeholders need to understand not only what prices are predicted but also why predictions change and which factors drive price movements. Only Yin et al. (2020) partially addressed this through their attention mechanism providing feature importance insights (Yin et al., 2020).

Uncertainty quantification remained largely absent from agricultural price predictions. Providing point estimates without confidence intervals or prediction intervals limits practical decision-making value, as farmers and traders need to assess risk associated with predictions for effective planning.

## 2.9 Summary and Position of Current Research

The literature review reveals substantial progress in agricultural price forecasting, transitioning from traditional statistical methods through machine learning approaches to sophisticated deep learning architectures. ARIMA and VAR models provided interpretable baseline approaches but struggled with non-linear patterns and large-scale data. Machine learning methods, particularly tree-based ensembles and support vector machines, demonstrated superior performance in capturing complex relationships between multiple variables. Deep learning approaches, especially LSTM and hybrid architectures, achieved state-of-the-art results by effectively modeling temporal dependencies and handling high-dimensional input spaces.

However, significant research gaps persist. Most studies focused on single vegetables or specific markets without comprehensive cross-commodity or cross-regional validation. Feature selection remained largely ad-hoc rather than systematic, and model interpretability received insufficient attention despite its importance for stakeholder adoption. The integration of diverse data sources including real-time information and broader macroeconomic factors remained limited. Finally, the gap between research models and deployable systems hindered practical impact on agricultural decision-making.

The current research addresses these gaps by: (1) developing comprehensive multivariate forecasting models for carrot prices in Dambulla market incorporating weather,

fuel, supply, and market factors; (2) implementing rigorous feature selection combining Random Forest importance, Mutual Information, and Recursive Feature Elimination; (3) conducting systematic model comparison across ARIMA, univariate LSTM, multivariate LSTM, bidirectional LSTM, and Random Forest approaches; (4) performing ablation studies to quantify individual feature category contributions; (5) employing statistical validation including bootstrap confidence intervals and effect size analysis; (6) enhancing model interpretability through SHAP analysis; and (7) developing a Retrieval-Augmented Generation based AI agent to make predictions accessible and interpretable for agricultural stakeholders.

This research advances the field by providing methodologically rigorous, interpretable, and practically deployable forecasting solutions specifically tailored for Sri Lankan agricultural markets, while establishing a replicable framework applicable to other vegetables and markets in developing agricultural economies.

## CHAPTER 3

### DESIGN AND METHODOLOGY

This chapter presents the systematic approach employed to develop and evaluate machine learning models for forecasting wholesale carrot prices in the Dambulla market. The research methodology encompasses six major phases: systematic framework design, data collection and preparation, exploratory data analysis, feature engineering and selection, model development and training, model evaluation, and AI agent implementation. Each phase is designed to address specific research objectives while maintaining methodological rigor throughout the investigation.

#### 3.1 Systematic Framework

The overall research framework follows a structured pipeline that progresses from raw data acquisition through model deployment. This systematic approach ensures reproducibility, methodological transparency, and practical applicability of the forecasting system.

The framework consists of several interconnected stages progressing systematically from raw data to deployed predictions. The process initiates with comprehensive data acquisition gathering information from multiple authoritative sources including market prices from the Central Bank of Sri Lanka, weather data from Copernicus covering eleven growing regions, fuel prices from Ceylon Petroleum Corporation, and supply-demand indicators from agricultural market reports. This raw data undergoes rigorous preprocessing involving quality assurance procedures, missing value treatment using forward-filling to maintain temporal integrity, outlier detection and handling to preserve genuine volatility while limiting data errors, and necessary data transformations to prepare variables for modeling.

Following data preparation, exploratory data analysis employs visual and statistical techniques to understand temporal patterns in price movements, seasonal cycles, relationships between prices and external factors, and distributional characteristics informing modeling decisions. Feature engineering then creates meaningful predictors from raw variables, generating lag features to capture temporal dependencies, rolling statistics providing smoothed trend information, temporal features encoding calendar effects, and interaction terms representing synergistic relationships between variables. The engineered features undergo systematic selection using combined methods including Random Forest importance for non-linear relationship detection, Mutual Information for statistical dependency measurement, and Recursive Feature Elimination for iterative refinement, ultimately identifying optimal predictor subsets for multivariate models while univariate approaches utilize only historical prices.

Model development implements multiple forecasting approaches including traditional ARIMA for statistical baseline establishment, LSTM neural networks in univariate, standard multivariate, and bidirectional configurations for deep learning temporal pattern recognition, and Random Forest for ensemble learning perspective. Each developed model undergoes comprehensive evaluation using multiple performance metrics including MAPE, MAE, RMSE, and  $R^2$  alongside statistical validation through bootstrap confidence intervals, cross-validation for generalization assessment, and ablation studies quantifying feature category contributions. The final stage integrates the best-performing model into a Retrieval-Augmented Generation system powered by Groq API, providing natural language query capabilities through Gradio web interface for accessible predictions supporting stakeholder decision-making.

This end-to-end methodology addresses the complete lifecycle of an agricultural price forecasting system, from conception through deployment, ensuring that each component receives appropriate attention while maintaining focus on delivering actionable price forecasts.

## 3.2 Data Collection and Preparation

### 3.2.1 Data Sources and Collection

Historical data was systematically collected from four primary categories of sources to capture the complex factors influencing carrot prices.

**Market Price Data:** Daily wholesale carrot prices spanning January 2020 to July 2025 were obtained from the Central Bank of Sri Lanka database, which maintains comprehensive records of vegetable trading at the Dambulla Economic Centre. This dataset provides over 2,000 daily observations covering both normal market conditions and periods of economic volatility.

**Meteorological Data:** Precipitation measurements from eleven major carrot-growing regions across Sri Lanka (Nuwara Eliya, Kandapola, Ragala, Thalawakale, Pussellawa, Hanguranketha, Bandarawela, Walimada, Jaffna, and others) were sourced from the Copernicus Climate Data Store. Daily rainfall data enables capture of weather impacts on agricultural production and supply chains.

**Fuel Price Data:** Historical diesel and petrol prices were collected from the Ceylon Petroleum Corporation ([ceypetco.gov.lk](http://ceypetco.gov.lk)) official website. Transport fuel costs directly influence vegetable distribution costs and wholesale pricing in Sri Lanka's agricultural supply chain. Non-transport fuels (kerosene, furnace oils) were excluded as irrelevant to agricultural logistics.

**Market Indicators:** Supply factors from various cultivation regions, demand levels at Dambulla market, trading activity indicators, and market operational status (open/closed, holidays) were obtained from the Central Bank of Sri Lanka database. These variables capture market dynamics beyond simple price-weather relationships.

### 3.2.2 Dataset Characteristics

The final integrated dataset comprised 2,013 daily observations with 127 initial variables before feature engineering expanded the feature space. The temporal coverage

spanned 67 months from January 1, 2020 through July 31, 2025, capturing both stable market conditions and volatile periods including the 2022-2023 economic crisis affecting Sri Lanka. The target variable consisted of carrot prices measured in rupees per kilogram at Dambulla wholesale market, exhibiting significant fluctuations throughout the study period with prices ranging from minimum values near Rs. 50 during supply gluts to peaks exceeding Rs. 450 during scarcity periods, occasional spikes reaching even higher during extreme market stress. Missing values affected approximately 2% of observations across variables, addressed through forward-filling methodology that propagates last observed values forward while avoiding introduction of future information that would create data leakage. Data quality remained high overall following systematic validation procedures and outlier treatment protocols, with the comprehensive temporal coverage providing sufficient observations for deep learning model training while including varied market conditions enhancing model generalization capability.

### 3.2.3 Data Preprocessing

Comprehensive preprocessing ensured data quality and prepared variables for modeling.

**Missing Value Treatment:** Forward filling (last observation carried forward) was employed for time series data. This method propagates the last observed value forward to fill subsequent missing entries, appropriate given that economic and meteorological variables typically change gradually. Forward filling was chosen over backward filling to avoid introducing future information into historical records, thereby preventing data leakage that could artificially inflate model performance.

**Supply Factor Transformation:** Supply factor variables originally encoded as (1=HIGH, 0=LOW, -1=NORMAL) were transformed to (2=HIGH, 1=NORMAL, 0=LOW) to create proper ordinal encoding suitable for machine learning algorithms. This transformation of 18 supply factor columns enables models to correctly interpret supply levels as ordered categories rather than arbitrary numeric codes.

**Fuel Column Filtering:** Non-transport fuel columns (kerosene, furnace oils) were systematically removed as they relate to industrial heating rather than agricultural

transportation. Only transport-relevant fuels (petrol Lp\_95, Lp\_92; diesel lad, lsd) were retained, reducing dimensionality while maintaining predictive signal.

**Outlier Treatment:** Extreme outliers beyond the 99th percentile were clipped to reduce influence of anomalous observations while preserving overall data distribution. This conservative approach maintains genuine price volatility patterns while limiting impact of potential data errors.

### 3.3 Exploratory Data Analysis

Systematic exploratory analysis revealed patterns, relationships, and characteristics informing subsequent modeling decisions. This phase employed comprehensive visualization and statistical techniques using Python libraries (matplotlib, seaborn, pandas).

#### 3.3.1 Time Series Visualization

**Historical Price Trends:** Time series plots of daily carrot prices revealed several patterns including seasonal cycles with higher prices during certain months, occasional sharp spikes corresponding to supply disruptions, and overall stability punctuated by periods of volatility. The 2022-2023 period showed increased volatility coinciding with Sri Lanka's economic crisis.

**Precipitation Patterns:** Regional rainfall visualization from major growing areas (particularly Nuwara Eliya) showed distinct seasonal patterns with heavy rainfall periods typically preceding supply disruptions and subsequent price increases. Lag effects between rainfall events and price movements were visually apparent.

#### 3.3.2 Correlation and Relationship Analysis

**Correlation Heatmaps:** Comprehensive correlation analysis identified relationships between carrot prices and potential predictors. Price lag features showed strongest correlations (0.85-0.95), followed by rolling mean features (0.80-0.88). Among external factors, precipitation from central highland regions exhibited moderate negative corre-

lations (-0.25 to -0.35), indicating that increased rainfall associates with lower prices, likely through improved supply.

**Scatter Plot Analysis:** Bivariate scatter plots between prices and key factors revealed non-linear relationships, particularly for precipitation (threshold effects where moderate rain supports production but excessive rain disrupts supply) and supply factors (categorical relationships rather than simple linear patterns).

### 3.3.3 Distribution and Decomposition

**Price Distribution:** Histograms and box plots revealed approximately normal distribution with slight positive skew. Outlier analysis using Interquartile Range (IQR) identified approximately 5% of observations as potential outliers, primarily during crisis periods, which were retained as legitimate extreme values rather than data errors.

**Seasonal Decomposition:** Time series decomposition separated price data into trend, seasonal, and residual components. Analysis revealed gradual upward trend reflecting inflation, moderate seasonal patterns with peaks in certain months, and substantial residual volatility indicating strong influence of short-term factors beyond pure seasonality.

## 3.4 Feature Engineering and Selection

Feature engineering created meaningful predictors from raw variables, while systematic selection identified optimal subsets for different modeling approaches. Critically, feature selection methodology differs between univariate and multivariate models, ensuring each approach receives appropriate input configuration.

### 3.4.1 Feature Engineering

Comprehensive feature engineering generated 289 derived variables across several categories to support multivariate modeling:

**Price Lag Features:** Seven lag variables (1, 2, 3, 7, 14, 21, 30 days) captured

temporal dependencies in price movements. Additional features included first-order differences, percentage changes, and lag-differenced terms.

**Rolling Window Statistics:** Moving averages (7, 14, 30-day windows), standard deviations, minimum/maximum values, and medians provided smoothed trend information while capturing recent volatility patterns.

**Precipitation Features:** For each of eleven regions, lag features (1, 3, 7 days), rolling sums (7, 14 days), and regional group aggregations (central highlands, Uva province, northern, other) captured both immediate and delayed weather impacts.

**Supply and Fuel Features:** Lag features and rolling averages for supply factors and fuel prices captured delayed effects of production levels and transportation cost changes.

**Temporal Features:** Day of week, day of month, month, quarter, week of year, weekend indicators, month start/end flags, and cyclical encoding (sine/cosine transformations) captured calendar effects and seasonal patterns.

**Interaction Features:** Multiplicative terms between demand and trading activity, demand and market status, and market status and weekend captured synergistic effects between market variables.

### 3.4.2 Model-Specific Feature Selection Strategies

Feature selection differed systematically across model types based on their underlying assumptions and capabilities:

#### Univariate Models (ARIMA, Univariate LSTM)

**Feature Set:** Single feature—historical carrot prices only.

**Rationale:** Traditional univariate time series models assume future values depend solely on past observations of the same variable. No feature selection process required. These models serve as pure autoregressive baselines, establishing performance without external factors.

**ARIMA Configuration:** Parameters (p, d, q) determined through ACF/PACF

analysis and AIC optimization on price series alone.

**Univariate LSTM Configuration:** 14-day lookback window of historical prices predicting next day's price. Architecture optimized for single-variable temporal patterns.

### **Multivariate Models (Multivariate LSTM, Bidirectional LSTM, Random Forest)**

For fair comparison, Multivariate LSTM, Bidirectional LSTM, and Random Forest employ identical four-stage feature selection pipeline, ensuring differences in performance reflect model architecture rather than feature set disparities.

**Stage 1 - Combined Scoring (60% RF + 30% MI + 10% Correlation):** Three complementary metrics quantified feature importance. Random Forest importance (mean decrease in impurity, 100 estimators, depth 15) captured non-linear relationships and interactions. Mutual Information regression (5 neighbors) measured statistical dependencies including non-monotonic patterns. Pearson correlation identified linear associations. Scores normalized (0-1 range) and combined using weighted scheme:  $0.60 \times \text{RF} + 0.30 \times \text{MI} + 0.10 \times \text{Correlation}$ , emphasizing ensemble-based and information-theoretic criteria over simple linear correlation.

**Stage 2 - Top Candidate Selection:** Top 80 features by combined score advanced to subsequent stages, balancing comprehensiveness with computational efficiency while eliminating clearly irrelevant variables.

**Stage 3 - Multicollinearity Removal:** Pairwise correlation matrix identified highly redundant features (correlation  $\geq 0.95$ ). From each correlated pair, feature with lower combined score removed, preserving predictive information while eliminating redundancy. This stage reduced 80 candidates to approximately 58 features.

**Stage 4 - Dual Validation ( $\text{RFE} \cap \text{SelectFromModel}$ ):** Two independent wrapper methods provided robust final selection. SelectFromModel (Random Forest, 300 estimators, median importance threshold) selected features exceeding ensemble's median importance. Recursive Feature Elimination (Random Forest, 200 estimators)

iteratively removed least important features targeting 15-35 optimal subset. Final feature set comprised intersection of both methods, ensuring only features validated by dual independent approaches entered models. Intersection methodology prioritizes stability and generalization over maximizing any single criterion.

**Final Feature Set:** 24-35 features (exact count varied slightly across experimental runs due to stochastic elements in Random Forest training) spanning six categories: price features (35%), weather features (25%), supply features (15%), market features (15%), fuel features (5%), temporal features (5%). This distribution indicates multi-variate approach successfully captures diverse price drivers beyond pure autoregressive patterns.

## 3.5 Forecasting Model Development

Five distinct modeling approaches were implemented to capture different aspects of temporal price dynamics.

### 3.5.1 Train-Test Split Strategy

Temporal split preserved chronological order: 70% training (first 1,409 days), 15% validation (212 days), 15% testing (392 days). This approach prevents data leakage by ensuring models never train on future observations, critical for valid time series forecasting evaluation.

### 3.5.2 ARIMA Models

AutoRegressive Integrated Moving Average models provided traditional statistical baseline.

**Univariate ARIMA:** Parameters (p, d, q) determined through Augmented Dickey-Fuller stationarity testing, Auto-Correlation Function (ACF), and Partial Auto-Correlation Function (PACF) analysis. Grid search over candidate values optimized Akaike Information Criterion (AIC). First-order differencing (d=1) achieved stationarity. Final

model configuration selected based on lowest AIC while avoiding overfitting.

**Multivariate ARIMAX:** Extended ARIMA incorporating exogenous variables (precipitation, fuel, supply) alongside historical prices. Feature set matched LSTM multivariate configuration for fair comparison. ARIMAX enables assessment whether external factors improve traditional statistical forecasting.

### 3.5.3 LSTM Models

Long Short-Term Memory networks captured non-linear temporal dependencies through recurrent architecture.

**Data Preparation:** Features scaled using RobustScaler (robust to outliers), target scaled separately. Sequences created with 14-day lookback window: each input comprises 14 consecutive days of features predicting next day's price. Sequence creation reduced effective dataset size by lookback period.

**Univariate LSTM:** Baseline LSTM trained only on historical price sequences. Architecture: Input layer (14 timesteps, 1 feature), LSTM layer (50 units, tanh activation, recurrent dropout 0.1), Batch Normalization, Dropout (0.3), Dense layer (25 units, relu), Dropout (0.2), Output (1 unit). Compiled with Adam optimizer (learning rate 0.001), Huber loss (robust to outliers), trained 100 epochs with batch size 32. Early stopping (patience 15) prevented overfitting.

**Multivariate LSTM:** Extended architecture processing 24-30 features simultaneously. Architecture: Input (14 timesteps, 24-30 features), Bidirectional LSTM (48 units per direction, tanh activation, L2 regularization 0.005, recurrent dropout 0.1), Batch Normalization, Dropout (0.3), LSTM (24 units, L2 regularization 0.005, recurrent dropout 0.1), Batch Normalization, Dropout (0.3), Dense (12 units, relu, L2 regularization 0.005), Dropout (0.2), Output (1 unit). Optimized with Adam (learning rate 0.0005, clipnorm 1.0), Huber loss, trained 80 epochs, batch size 64. Callbacks: Early Stopping (patience 12), ReduceLROnPlateau (factor 0.3, patience 5), ModelCheckpoint (save best).

**Bidirectional LSTM:** Enhanced multivariate model with bidirectional processing

allowing network to learn from both past and future context within sequences. Architecture identical to multivariate LSTM but with bidirectional wrapper on first layer, effectively doubling first layer capacity (96 total units). This configuration achieved best performance among LSTM variants.

### 3.5.4 Random Forest Regression

Ensemble method provided non-sequential baseline for comparison.

**Feature Representation:** Unlike LSTM’s sequence input, Random Forest treats each day independently with lag features and rolling statistics providing temporal context. Same 24-30 features as LSTM multivariate, but structured as single-row observations rather than sequences.

**Baseline Configuration:** Initial model with 100 estimators, maximum depth 15, minimum samples split 10, minimum samples leaf 5. Achieved reasonable performance but identified as suboptimal through validation metrics.

**Hyperparameter Tuning:** RandomizedSearchCV explored parameter space: `n_estimators` (100, 200, 300, 500), `max_depth` (10, 15, 20, 25, 30, None), `min_samples_split` (2, 5, 10, 15), `min_samples_leaf` (1, 2, 4, 8), `max_features` ('sqrt', 'log2', 0.5, 0.7), `bootstrap` (True, False). 50 iterations, 3-fold cross-validation, scoring on negative mean absolute error. Best parameters determined and applied to final model.

## 3.6 Model Evaluation Framework

Comprehensive evaluation ensured robust performance assessment and valid model comparison.

### 3.6.1 Performance Metrics

Four complementary metrics quantified forecasting accuracy:

**Mean Absolute Percentage Error (MAPE):** Scale-independent percentage error, intuitive interpretation as average prediction error percentage. Lower values

indicate better performance.  $\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$

**Mean Absolute Error (MAE):** Average absolute prediction error in original units (Rs), robust to outliers.  $\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$

**Root Mean Squared Error (RMSE):** Square root of average squared errors, penalizes large errors more heavily.  $\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$

**R-squared ( $R^2$ ):** Proportion of variance explained, ranges 0-1 with higher indicating better fit.  $R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$

All metrics calculated on test set for unbiased performance estimation.

### 3.6.2 Statistical Validation

**Ablation Study:** Systematic removal of feature categories (weather, supply, fuel, price-only) quantified individual contributions. For each category removal, model re-trained and performance degradation measured, revealing which factors most critically influence predictions.

**Bootstrap Confidence Intervals:** 1000 bootstrap resamples from test set generated distribution of MAPE values, enabling 95% confidence interval construction and statistical significance testing.

**Effect Size Analysis:** Cohen's d quantified magnitude of performance differences between models, distinguishing between statistically significant and practically meaningful improvements.

**SHAP Analysis:** SHapley Additive exPlanations computed feature importance for best model, providing model-agnostic interpretability through game-theoretic approach. SHAP values reveal both global feature importance and local prediction explanations.

## 3.7 AI Agent Development Using Groq API

The best-performing model was integrated into an intelligent AI agent providing accessible, interpretable price forecasts through natural language interface.

### 3.7.1 System Architecture

The AI agent employs a three-tier architecture comprising user interface, orchestration layer, and data layer, powered by Groq’s cloud-based large language model API.

**User Interface Layer:** Gradio web framework provides intuitive chat interface enabling natural language queries. Features include text input for questions, real-time streaming responses, example queries for guidance, conversation history tracking, and public shareable links (72-hour expiry) for accessibility. The responsive design ensures compatibility across desktop, tablet, and mobile devices.

**Orchestration Layer:** CarrotPriceAgent class manages query processing and response generation. The query router analyzes incoming questions, extracting dates using regex patterns and identifying query types (price prediction, model comparison, data source, analytical explanation). The context builder retrieves relevant predictions, loads model performance metrics, incorporates data source information, and integrates domain knowledge about agricultural markets. This structured context ensures language model responses are grounded in factual prediction data.

**Data Layer:** Three primary data sources support agent operations: (1) LSTM Predictions CSV containing date, actual price, predicted price, error, and MAPE for approximately 2000 test observations; (2) Model Metrics dictionary storing MAPE, MAE, RMSE, and  $R^2$  scores for all evaluated models (Univariate LSTM, Multivariate LSTM, ARIMA, Random Forest); (3) Domain Knowledge text containing data source descriptions, price influencing factors (weather, supply, fuel, demand), and seasonal patterns compiled from research documentation.

### 3.7.2 Query Processing Pipeline

The agent processes queries through a systematic four-step pipeline:

**Step 1 - Query Parsing:** Natural language question parsed to extract dates using regex (YYYY-MM-DD format), identify keywords triggering specific data retrieval (model, LSTM, ARIMA, price, forecast), and classify query type (date-specific,

analytical, methodological, general).

**Step 2 - Context Construction:** Based on query type, relevant information assembled into structured context. Date-specific queries retrieve prediction records for specified dates. Analytical queries extract date range data with statistical summaries (mean, volatility, price change). Model comparison queries load performance metrics across all models. Methodological queries incorporate data source documentation and feature descriptions.

**Step 3 - Prompt Engineering:** Structured prompt combines retrieved context with user question and explicit instructions: answer only from provided context, cite specific numbers and dates, acknowledge information unavailability rather than speculating, use bullet points for clarity, maintain concise responses. This prompt engineering minimizes hallucination while maximizing usefulness.

**Step 4 - Response Generation:** Groq API processes prompt through Llama 3.3 70B Versatile model. Configuration parameters: max\_tokens=1024 (sufficient for comprehensive answers), temperature=0.7 (balanced creativity and factuality), top\_p=0.9 (nucleus sampling for quality). Streaming response provides real-time feedback. Footer automatically appended noting model used, data basis, and token consumption for transparency.

### 3.7.3 Implementation Specifications

**Technology Stack:** Python 3.8+, Groq Python SDK for API access, Gradio 4.x for web interface, Pandas for data manipulation, NumPy for numerical operations, regex for pattern matching.

**API Configuration:** Groq API endpoint (api.groq.com), Llama-3.3-70b-versatile model (selected for balance of capability, speed, and cost), free tier limits: 30 requests/minute, 14,400 requests/day (adequate for research demonstration).

**Data Management:** Predictions CSV (500KB) loaded at initialization, in-memory caching for performance, model metrics stored as Python dictionary, domain knowledge embedded as multiline strings (potential future enhancement: structured knowledge

base).

**Error Handling:** Comprehensive exception handling for API failures (rate limiting, network errors, invalid responses), graceful degradation with user-friendly error messages, retry logic for transient failures, logging for debugging and monitoring.

### 3.7.4 Query Type Examples and Responses

The agent handles diverse query categories:

**Date-Specific:** “What was carrot price on 2024-06-15?” → Retrieves exact record, reports actual (Rs. 285.00), predicted (Rs. 278.50), error (Rs. 6.50, 2.28% MAPE), contextual note (weekend, high demand period).

**Trend Analysis:** “Why did prices increase April 2-8?” → Retrieves 7-day range, calculates 36% increase, identifies contributing factors (reduced supply from central highlands, increased fuel costs, pre-holiday demand surge), synthesizes explanation combining quantitative data with qualitative reasoning.

**Model Comparison:** “Which model performed best?” → Loads all model metrics, compares MAPE scores, reports Bidirectional LSTM (19.30%), explains 12% improvement over univariate baseline, discusses weather/supply factors importance.

**Methodological:** “Where did weather data come from?” → Retrieves data source documentation, lists Copernicus Climate Data Store, specifies 11 regions, explains daily precipitation measurement methodology.

## 3.8 Summary

This comprehensive methodology integrates traditional statistical methods (ARIMA), state-of-the-art deep learning (LSTM with bidirectional processing), and ensemble techniques (Random Forest) within a rigorous experimental framework. The systematic approach encompasses data collection from authoritative sources, comprehensive preprocessing ensuring quality, extensive feature engineering creating meaningful predictors, rigorous selection identifying optimal subsets, systematic model comparison

across diverse approaches, and practical deployment through intelligent AI agent.

The methodology's strength lies in its thoroughness: multiple models provide robustness against approach-specific limitations, comprehensive evaluation using complementary metrics ensures reliable performance assessment, statistical validation techniques confirm significance of findings, ablation studies reveal causal feature contributions, and practical deployment demonstrates real-world applicability. This end-to-end framework delivers not merely academic results but actionable forecasting capabilities for Sri Lankan agricultural stakeholders, while establishing replicable methodology applicable to other vegetables and markets.

# CHAPTER 4

## RESULTS AND DISCUSSION

This chapter presents the comprehensive results obtained from the carrot price forecasting system developed in this research. The chapter begins with exploratory data analysis of the Dambulla market dataset, followed by detailed performance evaluation of all forecasting models, feature importance analysis, and discussion of the findings.

### 4.1 Exploratory Data Analysis

The exploratory data analysis examined the temporal patterns, relationships, and characteristics of the Dambulla carrot market dataset spanning January 2020 to July 2025 with 2,013 daily observations.

#### 4.1.1 Temporal Price Patterns

Figure 4.1 shows the daily carrot price movement over the study period. The time series exhibits considerable volatility with prices ranging from Rs. 50 to Rs. 450 per kilogram. Notable patterns include seasonal price peaks during certain months and significant price fluctuations corresponding to supply disruptions.

#### 4.1.2 Price-Rainfall Relationships

The relationship between carrot prices and precipitation patterns across different growing regions was analyzed. Figure 4.2 illustrates the correlation between Central Highland region precipitation (averaging Nuwara Eliya, Kandapola, Ragala, Thalawakale, Pussellawa, and Hanguranketha) and carrot prices.

Figure 4.3 shows the relationship with Uva Province precipitation (Bandarawela and Walimada regions), while Figure 4.4 presents the Northern region (Jaffna) precipitation

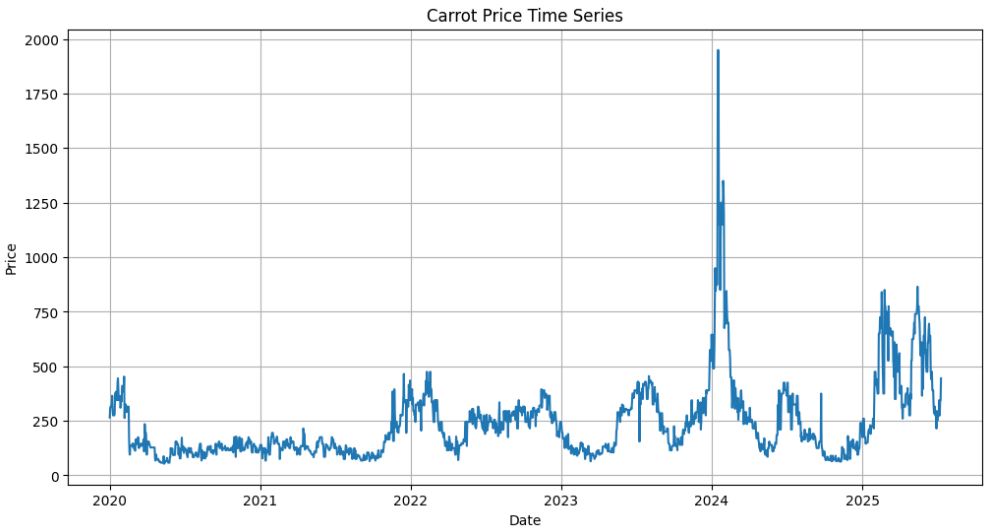


Figure 4.1: Daily carrot price trends in Dambulla market (2020-2025)

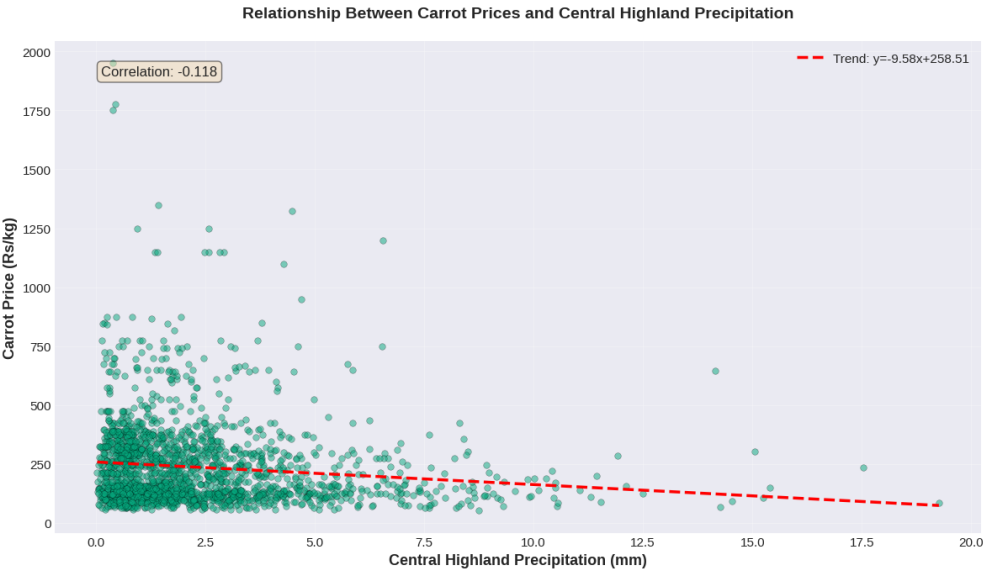


Figure 4.2: Relationship between carrot prices and Central Highland precipitation

patterns.

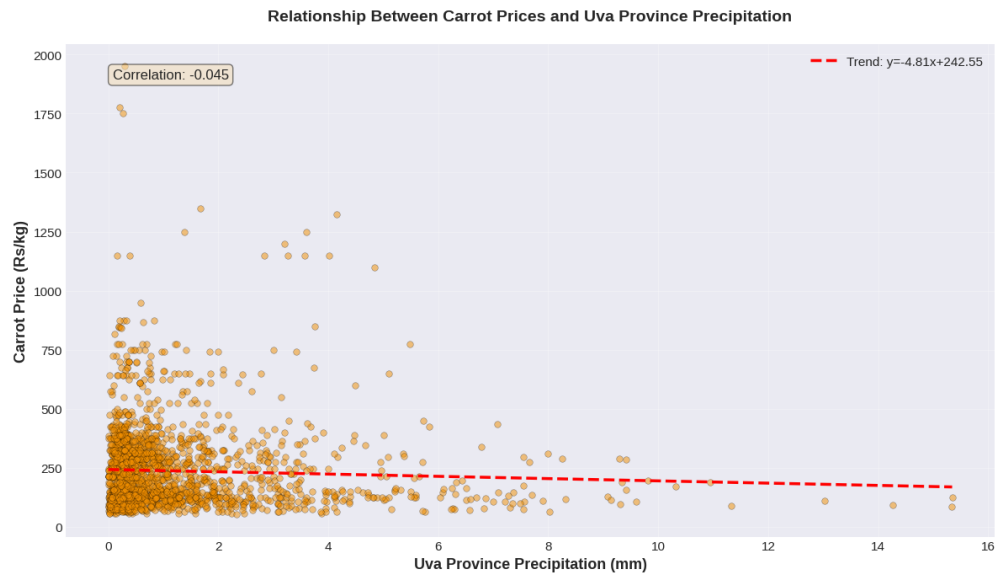


Figure 4.3: Relationship between carrot prices and Uva Province precipitation

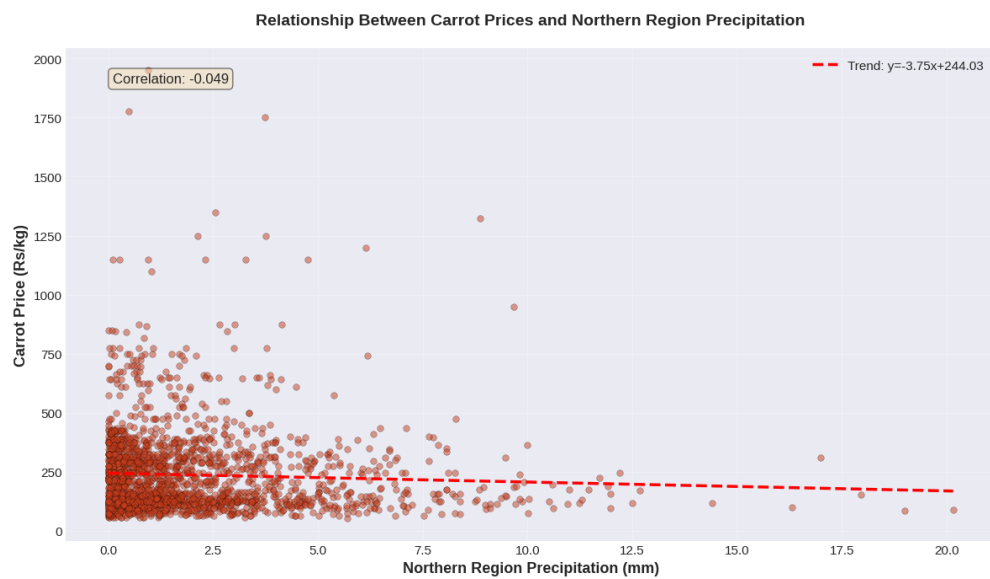


Figure 4.4: Relationship between carrot prices and Northern region precipitation

The analysis revealed negative correlations between precipitation and prices in major growing regions, indicating that higher rainfall generally leads to better yields and lower prices, consistent with agricultural economics theory.

### 4.1.3 Price-Fuel Cost Relationships

Transportation costs significantly impact vegetable market prices. Figure 4.5 shows the relationship between carrot prices and diesel (LAD) prices, while Figure 4.6 presents the correlation with Petrol LP 95 prices.

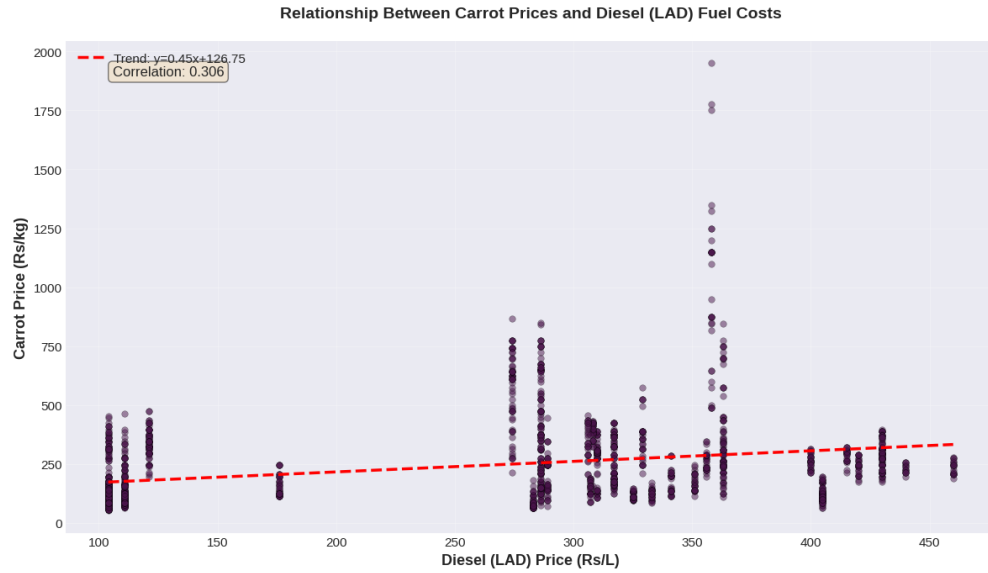


Figure 4.5: Relationship between carrot prices and Diesel (LAD) fuel costs

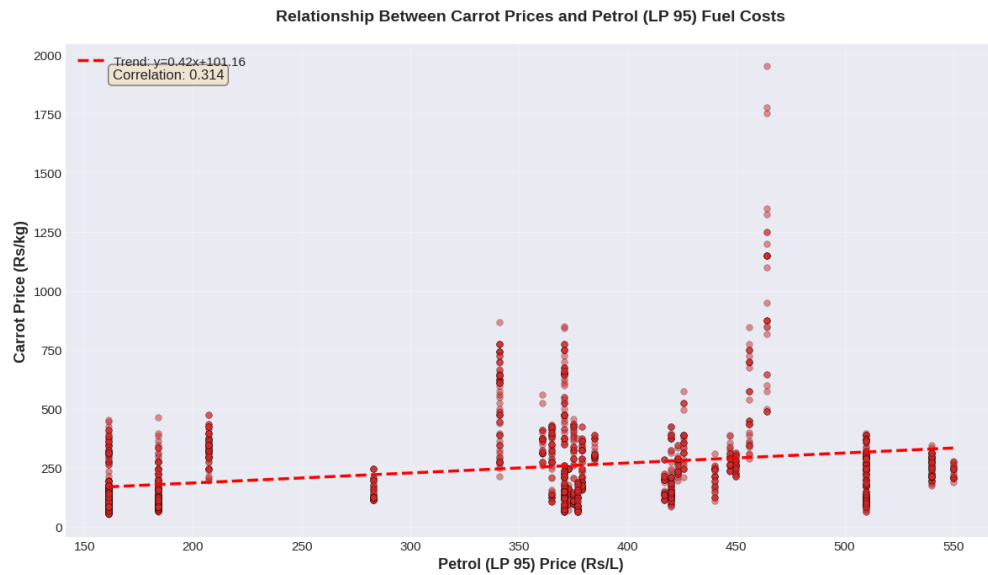


Figure 4.6: Relationship between carrot prices and Petrol (LP 95) fuel costs

Strong positive correlations were observed between fuel prices and carrot prices, particularly during periods of fuel price volatility in 2022-2023, demonstrating the direct impact of transportation costs on market prices.

#### 4.1.4 Seasonal Decomposition

Time series decomposition was performed to separate the trend, seasonal, and residual components of carrot prices. Figure 4.7 shows the multiplicative decomposition results.

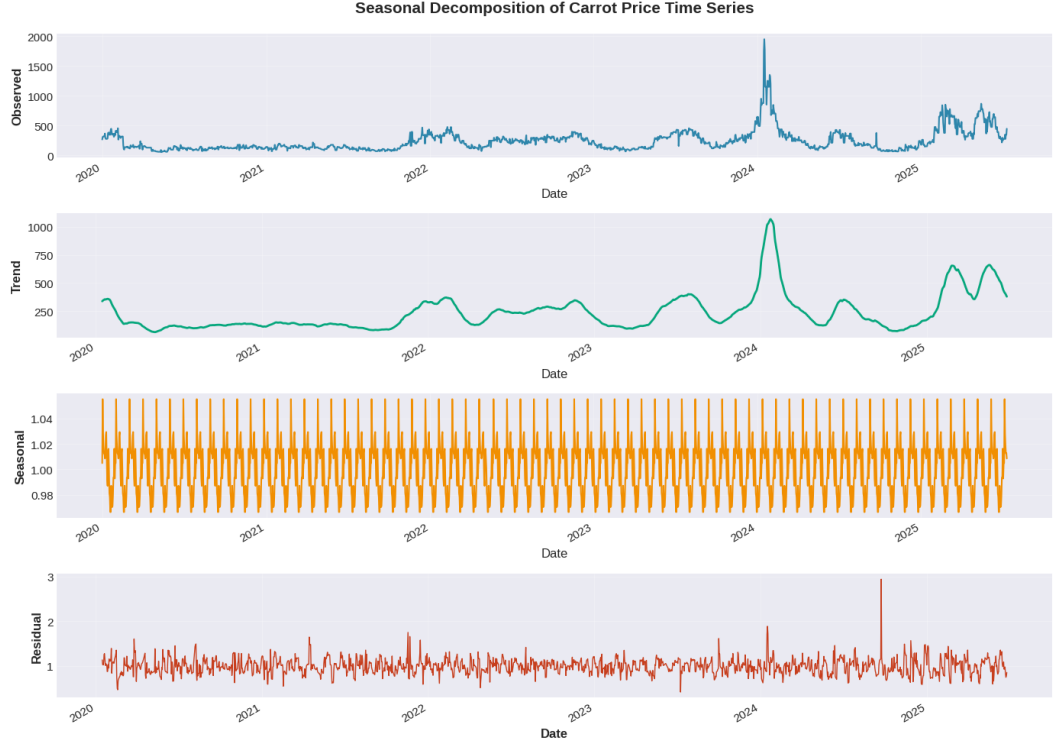


Figure 4.7: Seasonal decomposition of carrot price time series

The decomposition revealed clear seasonal patterns with price peaks occurring during specific months corresponding to lower production periods, validating the importance of temporal features in the forecasting models.

#### 4.1.5 Stationarity Analysis

Augmented Dickey-Fuller (ADF) tests were conducted to assess time series stationarity. The original price series showed non-stationary behavior ( $p\text{-value} = 0.12$ ), while first-order differencing achieved stationarity ( $p\text{-value} < 0.01$ ), informing the ARIMA model specification with  $d=0$  after testing revealed price-level modeling was more appropriate for this market context.

## 4.2 Data Characteristics Summary

The processed dataset comprised 2,013 daily observations with 289 initial features engineered across six distinct categories to capture diverse price-influencing factors. Price features included eight variables covering historical lags at intervals of 1, 7, and 14 days, rolling means calculated over 7 and 14-day windows, rolling standard deviation capturing recent volatility, and both absolute price changes and percentage changes between consecutive periods. Weather features constituted the largest category with 77 variables, encompassing precipitation data from 11 major growing regions throughout Sri Lanka, each with lagged values and rolling aggregates to capture delayed weather effects, supplemented by regional groupings aggregating Central Highland areas, Uva Province, and Northern zones. Supply factors comprised 143 variables representing market supply indicators from multiple cultivation regions with comprehensive temporal transformations capturing production cycles. Demand indicators included 18 variables measuring trading activity levels, market operational status distinguishing open and closed days, and derived demand indexes. Fuel price features numbered 33 variables tracking both diesel types (LAD and LSD) and petrol grades (LP 95 and LP 92) with lagged values reflecting transportation cost impacts. Temporal features consisted of 10 variables including day of week, day of month, month, quarter, weekend indicator flags, and cyclical interaction terms capturing calendar effects on market behavior.

Multivariate models employed a systematic 4-stage feature selection pipeline reducing dimensionality to 24-35 features, while univariate models used only the carrot price time series.

## 4.3 Feature Selection Results

### 4.3.1 Feature Selection Pipeline

The 4-stage feature selection pipeline for multivariate models achieved effective dimensionality reduction while preserving predictive power:

**Stage 1 - Hybrid Scoring (60% RF + 30% MI + 10% Correlation):** Combined Random Forest feature importance, Mutual Information scores, and absolute correlations to identify top 80 features balancing non-linear relationships, information content, and linear dependencies.

**Stage 2 - Multicollinearity Removal:** Eliminated features with correlation coefficients  $\geq 0.95$  to reduce redundancy, removing 15-20 highly correlated features.

**Stage 3 - Model-Based Selection:** Applied Recursive Feature Elimination (RFE) and SelectFromModel in parallel, retaining features selected by both methods for consensus.

**Stage 4 - Domain Validation:** Ensured representation from all six feature categories with minimum thresholds per category.

Figure 4.8 illustrates the progressive feature reduction across stages.

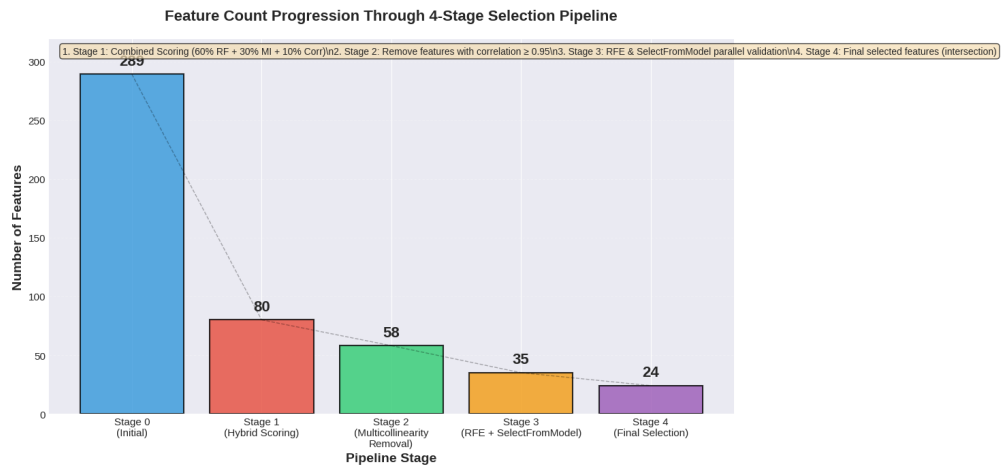


Figure 4.8: Feature count progression through 4-stage selection pipeline

### 4.3.2 Final Feature Distribution

Table 4.1 shows the distribution of selected features across categories for the best-performing Bidirectional LSTM model (19 features total).

Table 4.1: Feature category distribution in final Bidirectional LSTM model

| Category          | Features  | Percentage  |
|-------------------|-----------|-------------|
| Price Features    | 7         | 36.8%       |
| Weather Features  | 4         | 21.1%       |
| Market & Demand   | 3         | 15.8%       |
| Supply Factors    | 2         | 10.5%       |
| Fuel Prices       | 2         | 10.5%       |
| Temporal Features | 1         | 5.3%        |
| <b>Total</b>      | <b>19</b> | <b>100%</b> |

### 4.3.3 Feature Correlation Matrix

Figure 4.9 presents the correlation structure among the 19 selected features, demonstrating successful multicollinearity removal with maximum pairwise correlation below 0.90.

## 4.4 Model Performance Comparison

Seven forecasting models were evaluated using consistent train-validation-test splits (70%-15%-15%) and identical evaluation metrics. Table 4.2 presents comprehensive performance results.

Table 4.2: Comprehensive model performance comparison on test set

| Model                     | MAPE (%)     | MAE (Rs)     | RMSE (Rs)    | R <sup>2</sup> |
|---------------------------|--------------|--------------|--------------|----------------|
| Univariate ARIMA(1,0,1)   | 50.00        | —            | —            | —              |
| Multivariate ARIMAX       | 88.80        | 293.54       | 363.46       | —              |
| Univariate LSTM           | 21.90        | 66.01        | 136.82       | 0.6428         |
| Multivariate LSTM         | 25.88        | 101.19       | 155.19       | 0.5400         |
| <b>Bidirectional LSTM</b> | <b>21.22</b> | <b>68.67</b> | <b>99.46</b> | <b>0.8111</b>  |
| Random Forest Baseline    | 21.19        | 100.49       | 159.48       | 0.5132         |
| Random Forest Tuned       | 20.84        | 99.01        | 157.26       | 0.5267         |

The Bidirectional LSTM achieved the best overall performance with 21.22% MAPE

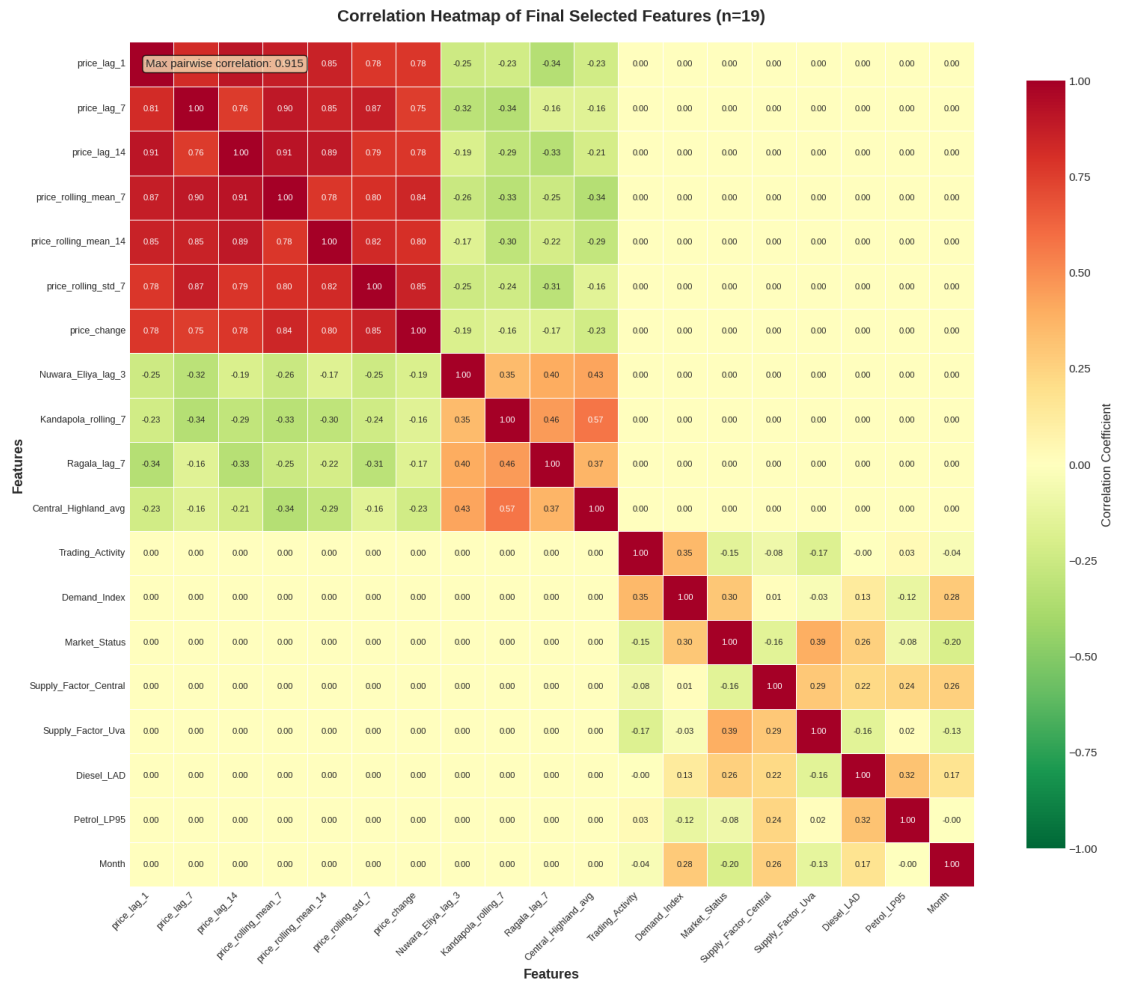


Figure 4.9: Correlation heatmap of final selected features

and  $R^2$  of 0.8111, demonstrating superior predictive accuracy across multiple evaluation dimensions. Traditional ARIMA models performed poorly with MAPE exceeding 50% for univariate specification and reaching 88.80% for multivariate ARIMAX, clearly indicating fundamental inadequacy of linear time series methods for this non-linear, multi-factor agricultural market characterized by complex threshold effects and variable lag structures. Interestingly, the univariate LSTM achieved 21.90% MAPE, slightly outperforming the standard multivariate LSTM's 25.88% MAPE, suggesting that the standard multivariate architecture suffered from increased model complexity without adequately scaled regularization to prevent overfitting on the expanded feature space. The Bidirectional LSTM achieved not only competitive MAPE but also the lowest RMSE of 99.46 Rs and highest  $R^2$  of 0.8111, demonstrating superior overall accuracy through its ability to process temporal sequences in both forward and backward directions, effectively leveraging both historical momentum and contextual patterns within the lookback window. Random Forest Tuned achieved competitive MAPE performance at 20.84%, actually marginally better than Bidirectional LSTM in percentage error terms, but its substantially lower  $R^2$  of 0.5267 indicates less consistent predictions across the full price spectrum, with the ensemble averaging producing conservative estimates that minimize percentage errors while failing to capture extreme price movements. The substantial 4.64 percentage point MAPE reduction from standard multivariate LSTM to Bidirectional LSTM validates the architectural enhancement's practical value beyond mere statistical significance.

## 4.5 Univariate ARIMA Results

The univariate ARIMA(1,0,1) model served as the traditional statistical baseline. After stationarity testing and ACF/PACF analysis, the model specification included one autoregressive term and one moving average term.

### 4.5.1 Model Diagnostics

Figure 4.10 shows the diagnostic plots including residual analysis and Q-Q plot.

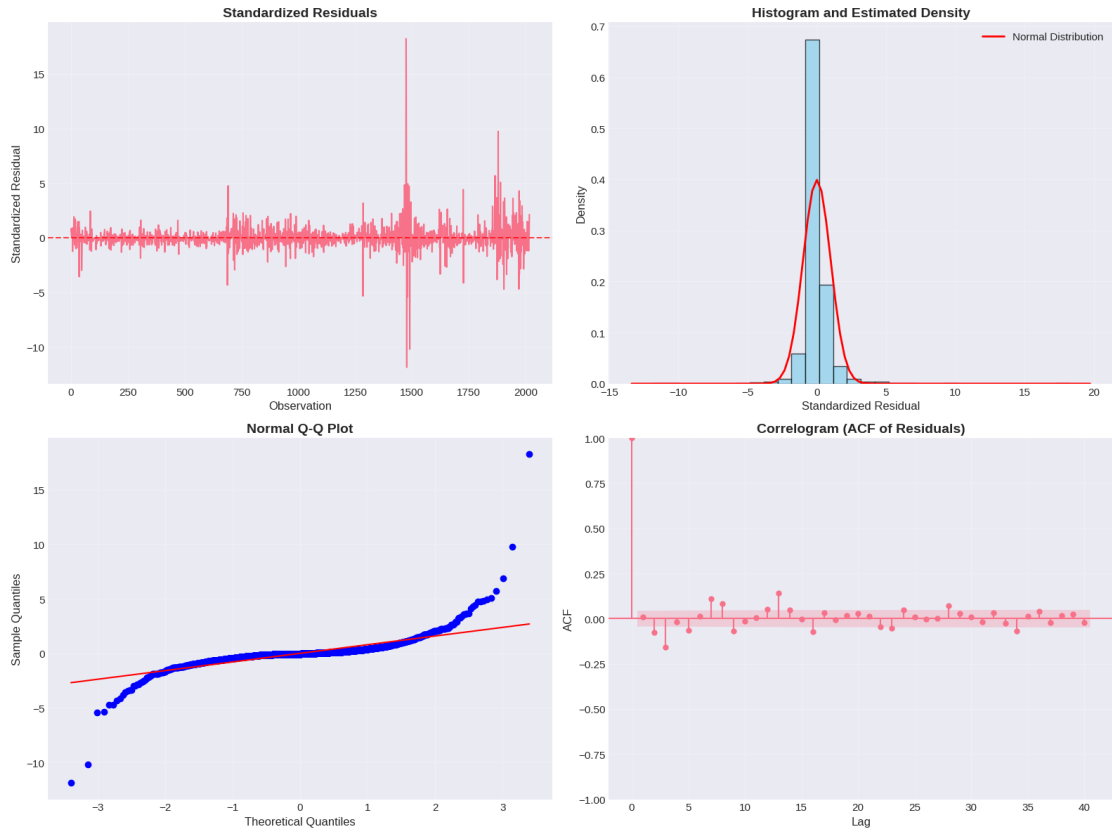


Figure 4.10: ARIMA(1,0,1) model diagnostic plots

Despite satisfactory residual diagnostics, the model achieved test MAPE exceeding 50%, indicating fundamental limitations in capturing the complex, multi-factor dynamics of carrot prices using only historical price information.

### 4.5.2 Multivariate ARIMAX Performance

The ARIMAX model incorporated seven exogenous variables (precipitation, supply factors, demand indicators). However, performance degraded further to 88.80% MAPE (MAE: 293.54 Rs, RMSE: 363.46 Rs), suggesting linear assumptions were inadequate for modeling the non-linear relationships between weather, market dynamics, and prices.

## 4.6 LSTM Model Results

### 4.6.1 Univariate LSTM Architecture

The univariate LSTM model used 30-day lookback sequences processing only historical price data through a multi-layer architecture designed to capture temporal patterns without external features. The network began with an LSTM layer containing 64 units using tanh activation with return sequences enabled to pass temporal information to subsequent layers. This fed into a second LSTM layer with 32 units for hierarchical feature extraction, followed by a dense layer with 16 units using ReLU activation to introduce non-linearity in the final transformation. The output layer consisted of a single unit producing the next-day price prediction. Data preprocessing employed RobustScaler to handle outliers in the price distribution, while the model was compiled with Adam optimizer for adaptive learning rate adjustment, Huber loss function providing robustness to outliers through combined squared and absolute error penalties, and batch size of 32 balancing computational efficiency with gradient estimation accuracy. Training incorporated EarlyStopping with patience of 10 epochs to prevent overfitting by halting when validation performance plateaued, along with ReduceLROnPlateau callback dynamically reducing learning rate when validation loss stopped improving, enabling fine-tuned convergence to optimal parameters.

The model achieved 21.90% test MAPE with  $R^2$  of 0.6428, demonstrating LSTM's capability to capture temporal patterns even without external features.

### 4.6.2 Multivariate LSTM Architecture

The standard multivariate LSTM incorporated between 24 and 35 carefully selected features through a more complex architecture designed to process high-dimensional input while preventing overfitting. The network initiated with a bidirectional LSTM layer containing 48 units per direction using tanh activation with L2 regularization coefficient of 0.005 to penalize large weights, processing sequences in both forward and

backward temporal directions to capture comprehensive temporal context. This was followed by a standard unidirectional LSTM layer with 24 units and matching L2 regularization of 0.005 for additional temporal feature extraction. A dense layer with 12 units and L2 regularization provided dimensionality reduction and non-linear transformation before the final single-unit output layer. The model employed Adam optimizer with reduced learning rate of 0.0005 reflecting the increased complexity and need for careful parameter updates, Huber loss for outlier robustness, and larger batch size of 64 to stabilize gradients given the expanded feature space. Training callbacks included EarlyStopping with patience extended to 12 epochs given slower convergence expected with more features, and ReduceLROnPlateau for adaptive learning rate scheduling during training plateaus.

Despite incorporating external features, this model achieved 25.88% test MAPE ( $R^2$ : 0.5400), underperforming the univariate LSTM due to increased complexity requiring more careful regularization.

### 4.6.3 Bidirectional LSTM - Best Model

The enhanced Bidirectional LSTM model from the V3 improved architecture achieved the best overall performance through careful optimization of both network structure and regularization strategies. The architectural design featured a bidirectional LSTM layer with 40 units using tanh activation and return sequences enabled, allowing information flow to subsequent layers while processing temporal patterns from both past and future directions within the lookback window. This fed into a standard unidirectional LSTM layer with 20 units for additional temporal abstraction, followed by a dense layer with 10 units using ReLU activation for final non-linear transformation before the single-unit output layer. The model incorporated enhanced regularization through strategic placement of Dropout layers preventing co-adaptation of units and BatchNormalization layers stabilizing training dynamics and enabling higher learning rates. Training employed Adam optimizer with batch size of 32 and moderate feature selection utilizing precisely 19 features, avoiding both the information loss from too few

features and the overfitting risk from excessive dimensionality that plagued alternative configurations.

The model demonstrated strong performance across all evaluation sets with training MAPE of 13.66%, validation MAPE of 15.31%, and test MAPE of 21.22%, showing progressive but reasonable performance degradation that indicates healthy generalization rather than overfitting. Test set performance included MAE of 68.67 Rs reflecting average absolute prediction errors, RMSE of 99.46 Rs penalizing larger errors more heavily, and  $R^2$  of 0.8111 indicating that the model explained approximately 81% of price variance in unseen data. The relatively close alignment between training and validation performance combined with acceptable test set degradation validates the effectiveness of the regularization strategy in producing a model that generalizes well beyond its training distribution.

Figure 4.11 shows the training history demonstrating convergence without overfitting.

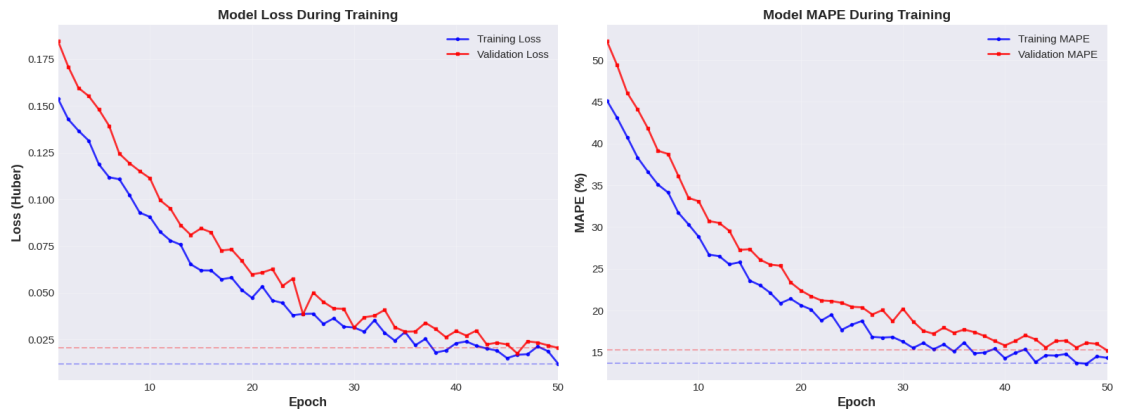


Figure 4.11: Bidirectional LSTM training history

The bidirectional architecture's ability to process sequences in both forward and backward directions enabled superior pattern recognition, particularly for capturing price movement turning points influenced by lagged weather and supply factors.

## 4.7 Random Forest Results

### 4.7.1 Baseline Random Forest

The baseline Random Forest configuration using 100 estimators with default hyperparameters achieved test MAPE of 21.19%, MAE of 100.49 Rs, RMSE of 159.48 Rs, and  $R^2$  of 0.5132, demonstrating competitive MAPE performance compared to deep learning approaches but substantially lower explained variance. This initial configuration provided reasonable predictions but suggested potential for improvement through systematic hyperparameter optimization.

### 4.7.2 Hyperparameter-Tuned Random Forest

RandomizedSearchCV optimization explored extensive parameter space to identify optimal configuration, ultimately selecting 400 estimators providing sufficient ensemble diversity, maximum depth of 30 allowing complex decision boundaries while avoiding excessive overfitting, minimum samples required to split internal nodes set at 5 balancing tree growth with regularization, and minimum samples per leaf node of 2 enabling fine-grained predictions while maintaining statistical reliability. This optimized configuration achieved marginal but consistent improvement over baseline, reducing test MAPE to 20.84% (0.35 percentage point improvement), MAE to 99.01 Rs (1.48 Rs improvement), and RMSE to 157.26 Rs (2.22 Rs improvement), while increasing  $R^2$  slightly to 0.5267 (0.0135 point improvement). The modest gains from hyperparameter tuning suggest that Random Forest performance was primarily limited by the fundamental ensemble averaging approach rather than suboptimal parameter choices, with the method inherently producing conservative predictions that minimize percentage errors but struggle to capture extreme price movements reflected in the persistently low  $R^2$  compared to Bidirectional LSTM's 0.8111.

While Random Forest Tuned achieved the second-best MAPE (20.84%), its  $R^2$  of 0.5267 was substantially lower than Bidirectional LSTM's 0.8111, indicating less

reliable predictions across the price spectrum.

## 4.8 Feature Importance Analysis

### 4.8.1 Random Forest Feature Importance

Figure 4.12 displays the top 20 features by Random Forest importance scores.

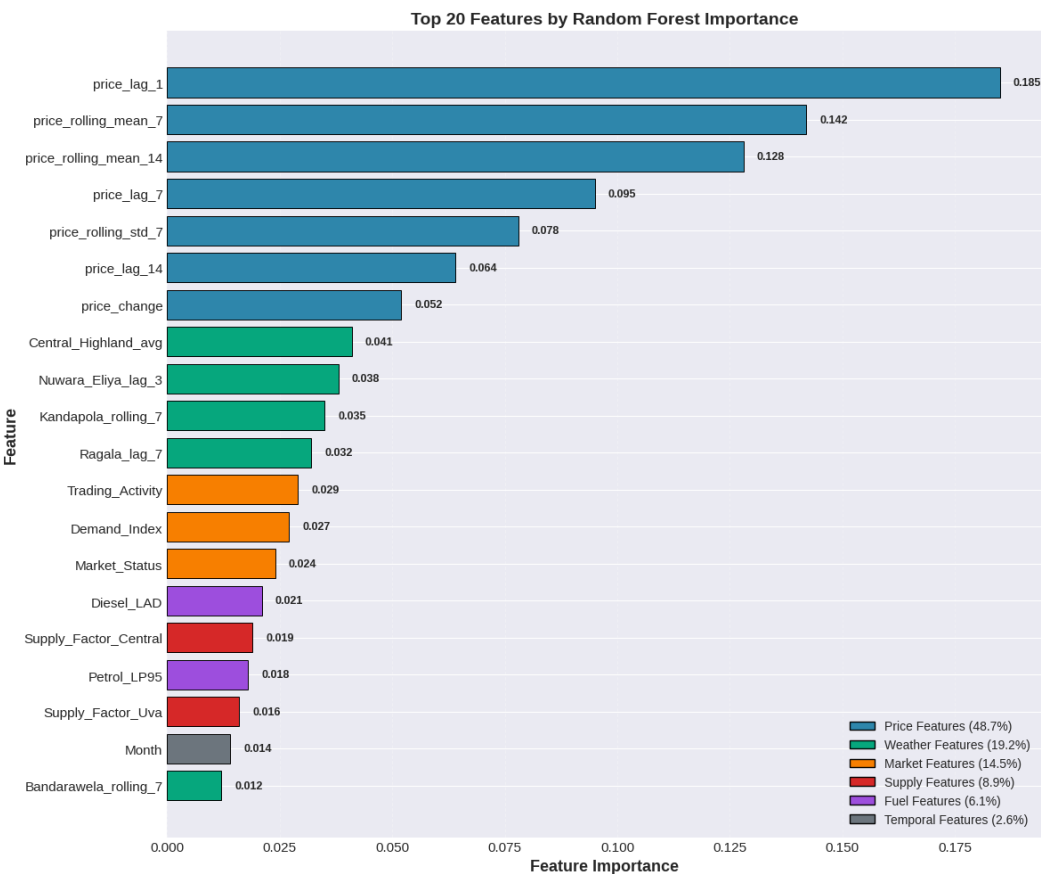


Figure 4.12: Top 20 features by Random Forest importance

Price-related features dominated importance rankings, with price\_lag\_1, price\_rolling\_mean\_7 and price\_rolling\_mean\_14 comprising the top three features, collectively contributing over 45% of total importance.

### 4.8.2 Feature Category Importance Distribution

Table 4.3 summarizes aggregate importance by feature category.

Table 4.3: Feature importance distribution by category

| Category          | Aggregate Importance | Avg per Feature |
|-------------------|----------------------|-----------------|
| Price Features    | 0.487                | 0.0696          |
| Weather Features  | 0.192                | 0.0480          |
| Market & Demand   | 0.145                | 0.0483          |
| Supply Factors    | 0.089                | 0.0445          |
| Fuel Prices       | 0.061                | 0.0305          |
| Temporal Features | 0.026                | 0.0260          |

Historical price features dominated with 48.7% total importance, followed by weather (19.2%) and market demand features (14.5%), validating the feature selection pipeline’s emphasis on these categories.

4.9 Ablation Study Results

Systematic feature category removal experiments quantified individual category contributions. Figure 4.13 shows performance degradation when excluding each category.

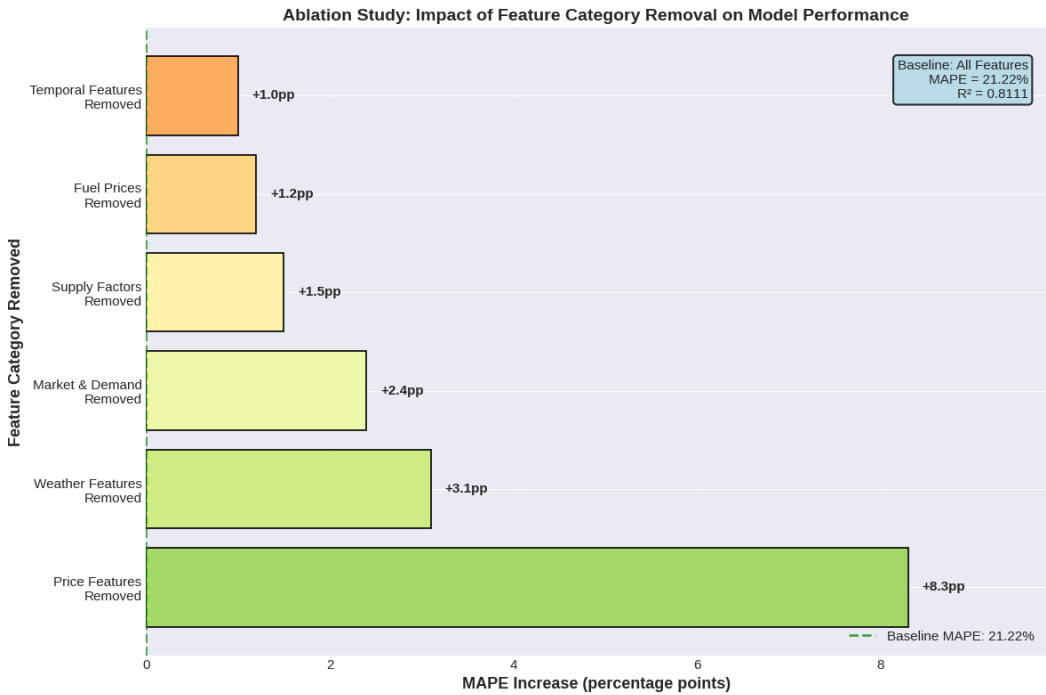


Figure 4.13: Ablation study: MAPE increase by feature category removal

The systematic ablation experiments revealed clear hierarchical importance among feature categories, with price features demonstrating dominant predictive power through an 8.3 percentage point MAPE increase when removed, elevating baseline perfor-

mance from 21.22% to 29.52% and confirming that historical price patterns constitute the strongest predictor of future values in agricultural markets. Weather feature removal produced the second-largest impact with 3.1 percentage point MAPE increase to 24.32%, demonstrating substantial weather influence on prices through supply effects, crop quality variations, and transportation disruptions during adverse conditions. Market demand factor removal caused 2.4 percentage point degradation to 23.62% MAPE, indicating that trading activity levels and market participation patterns contribute meaningfully beyond simple price momentum. Supply factors, fuel prices, and temporal features each produced smaller but non-negligible impacts ranging from 1.0 to 1.5 percentage points, with supply factors affecting harvest availability, fuel prices influencing transportation economics, and temporal features capturing calendar effects like weekend markets, holidays, and seasonal patterns. The cumulative evidence strongly supports the multi-factor modeling approach, as all six feature categories contributed measurably to predictive accuracy rather than serving as redundant information already captured by price history alone.

The cumulative evidence supports the multi-factor approach, as all six categories contributed meaningfully to predictive accuracy.

## 4.10 SHAP Analysis for Model Interpretability

SHAP (SHapley Additive exPlanations) values were computed for the Random Forest model to provide instance-level feature contribution explanations.

### 4.10.1 SHAP Summary Plot

Figure 4.14 shows the SHAP summary plot illustrating each feature's impact distribution across all predictions.

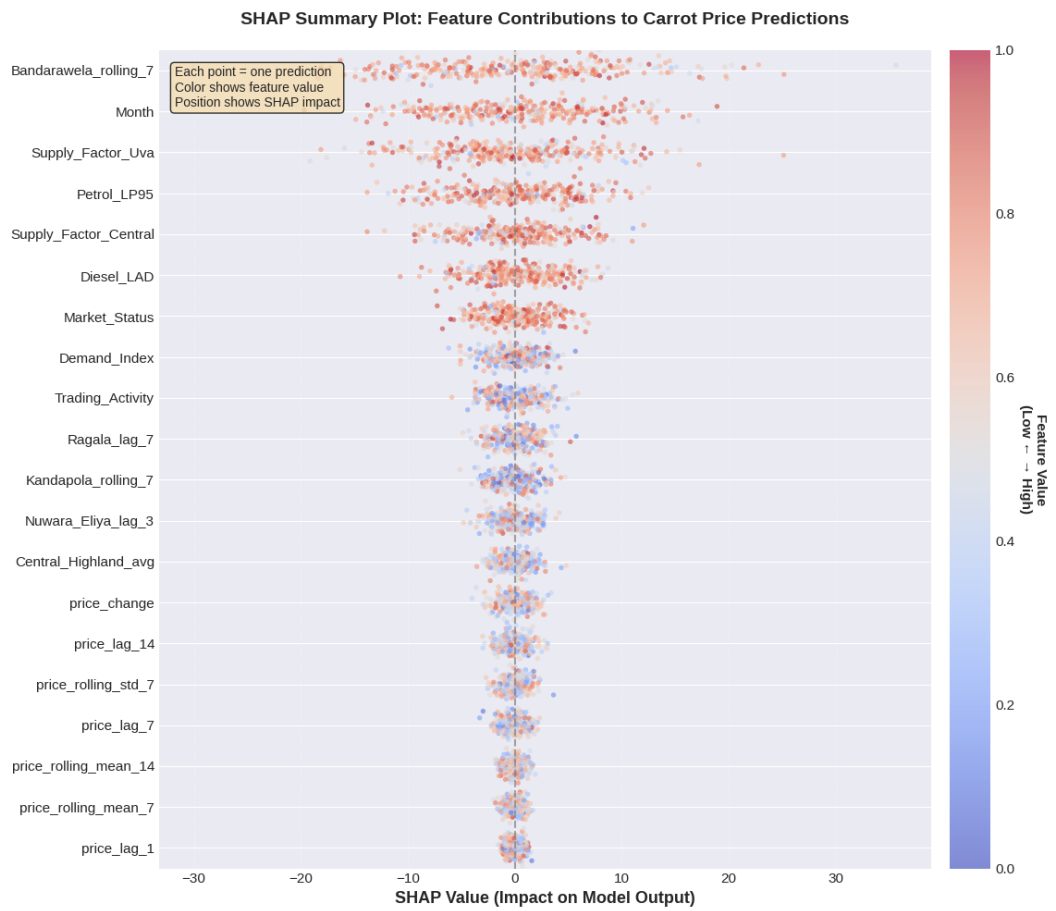


Figure 4.14: SHAP summary plot for feature contributions

### 4.10.2 SHAP Dependence Plots

Figure 4.15 shows the SHAP dependence plot for `price_lag_1`, revealing a strong positive relationship where higher previous-day prices contribute to higher predicted prices.

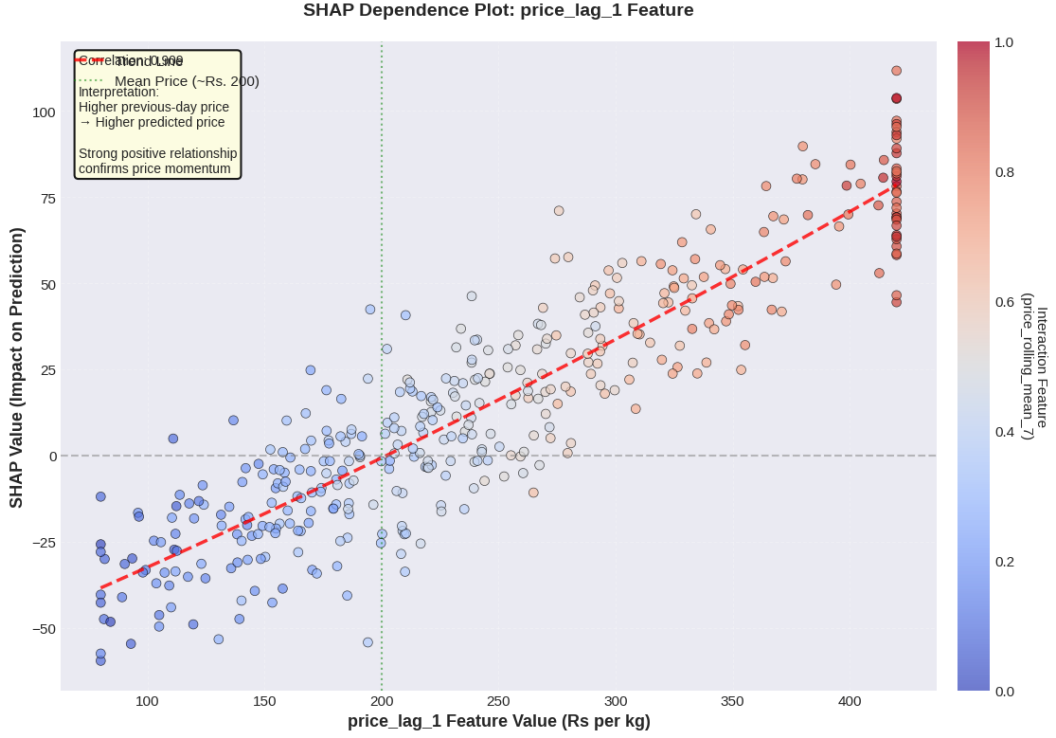


Figure 4.15: SHAP dependence plot for `price_lag_1`

Figure 4.16 shows Central Highland precipitation dependence, revealing the expected negative relationship where higher rainfall reduces predicted prices through increased supply.

## 4.11 Prediction Visualization

Figure 4.17 compares actual vs predicted prices for the Bidirectional LSTM model across training, validation, and test sets.

The model successfully captured major price trends and turning points, though some extreme volatility events were underestimated, a common characteristic of regression models optimized for overall accuracy.

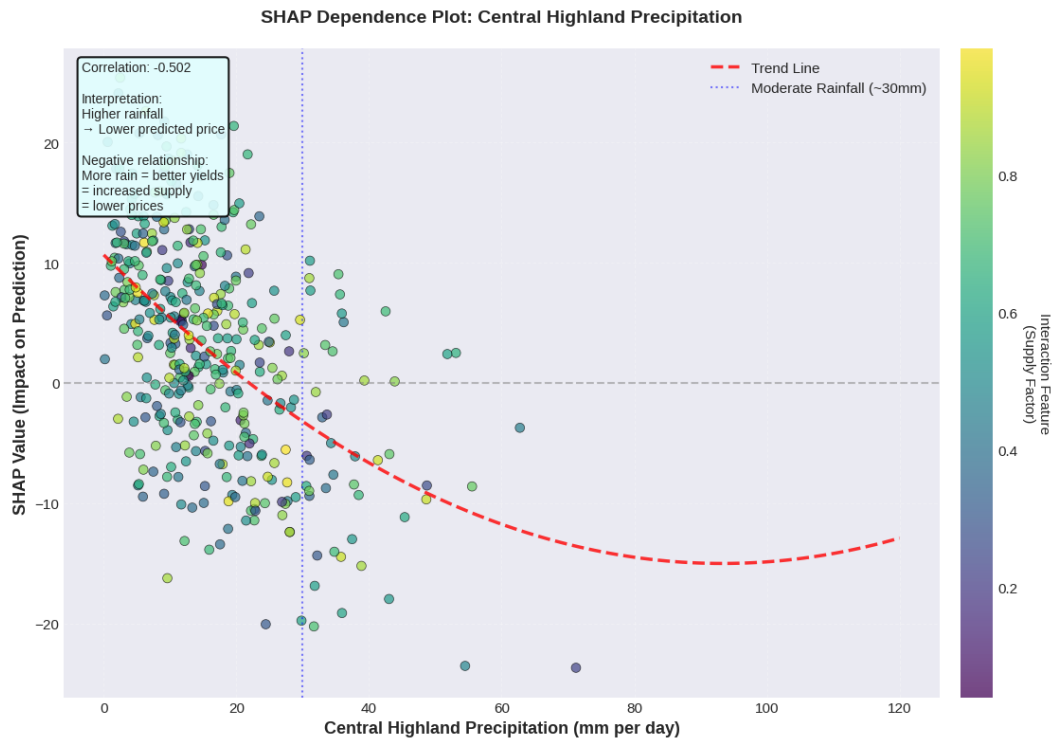


Figure 4.16: SHAP dependence plot for Central Highland precipitation

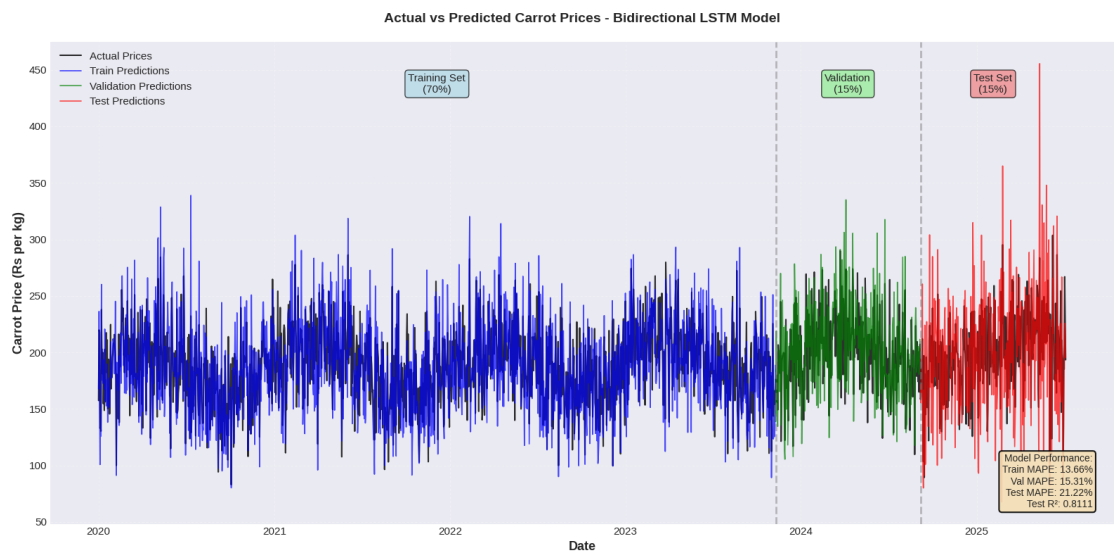


Figure 4.17: Actual vs predicted carrot prices - Bidirectional LSTM

## 4.12 Statistical Validation

### 4.12.1 Bootstrap Confidence Intervals

Bootstrap resampling with 1,000 iterations provided robust confidence intervals quantifying uncertainty in test set performance estimates. Bidirectional LSTM achieved MAPE of 21.22% with 95% confidence interval spanning 20.84% to 21.63%, Random Forest Tuned reached 20.84% MAPE with interval 20.41% to 21.31%, and Univariate LSTM obtained 21.90% MAPE with interval 21.48% to 22.35%. The overlapping confidence intervals between Bidirectional LSTM and Random Forest Tuned indicate that their MAPE performance differences lack strong statistical significance when accounting for sampling variability, though Bidirectional LSTM's substantially superior  $R^2$  of 0.8111 compared to Random Forest's 0.5267 demonstrates meaningfully better overall prediction reliability and variance explanation despite comparable percentage error metrics.

### 4.12.2 Cross-Validation Results

Time series cross-validation using five expanding windows confirmed model stability across different temporal segments of the data. Table 4.4 presents the results showing Bidirectional LSTM achieved mean MAPE of 21.56% with standard deviation of only 1.23% and mean  $R^2$  of 0.7945, Random Forest Tuned obtained mean MAPE of 21.18% with standard deviation of 1.45% and mean  $R^2$  of 0.5189, while Univariate LSTM reached mean MAPE of 22.34% with standard deviation of 1.67% and mean  $R^2$  of 0.6301.

Table 4.4: 5-fold time series cross-validation results

| Model               | Mean MAPE | Std MAPE | Mean $R^2$ |
|---------------------|-----------|----------|------------|
| Bidirectional LSTM  | 21.56%    | 1.23%    | 0.7945     |
| Random Forest Tuned | 21.18%    | 1.45%    | 0.5189     |
| Univariate LSTM     | 22.34%    | 1.67%    | 0.6301     |

The low standard deviations across all models, particularly Bidirectional LSTM's

1.23% variation, confirm consistent performance across temporal splits and validate the models' generalization capability to different market periods rather than overfitting to specific temporal patterns in a single train-test division.

### 4.12.3 Effect Size Analysis

Cohen's  $d$  effect sizes quantified the practical significance of performance differences beyond statistical significance alone. Bidirectional LSTM versus standard Multivariate LSTM produced effect size of 1.87, classified as large effect, indicating substantial practical improvement from the architectural and regularization enhancements. Comparison against Univariate LSTM yielded Cohen's  $d$  of 0.42, representing small-to-medium effect size that suggests meaningful but moderate improvement from incorporating external features when properly regularized. Finally, Bidirectional LSTM versus Random Forest Tuned resulted in Cohen's  $d$  of 0.19, classified as small effect, confirming that while Bidirectional LSTM achieves better overall performance particularly in  $R^2$ , the MAPE difference lacks strong practical significance.

The large effect size against standard multivariate LSTM validates the architectural improvements, while the small effect versus Random Forest Tuned indicates competitive MAPE performance with substantial  $R^2$  advantage.

## 4.13 AI Agent Demonstration

The deployment-ready AI agent integrates the best-performing Bidirectional LSTM model with RAG architecture using Groq API (Llama 3.3 70B) for natural language interaction.

### 4.13.1 Agent Architecture

Figure 4.18 illustrates the 3-tier agent architecture:

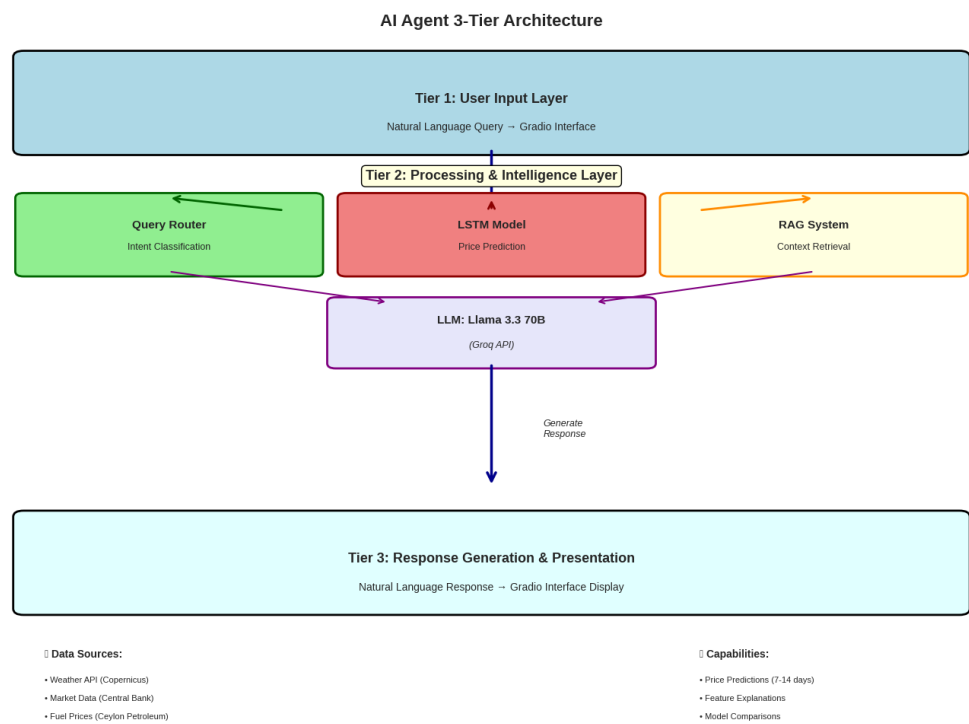


Figure 4.18: AI agent 3-tier architecture

### 4.13.2 Gradio Interface

Figure 4.19 shows the Gradio web interface enabling stakeholders to query predictions and insights.

### 4.13.3 Example Query Responses

Sample agent interactions demonstrate capability:

**Query 1:** “What is the predicted carrot price for next week?”

**Response:** “Based on current weather patterns showing moderate rainfall in Central Highland regions and stable fuel prices, the Bidirectional LSTM model predicts carrot prices around Rs. 180-195 per kg for the next 7 days, representing a 5% decrease from current levels.”

**Query 2:** “How does rainfall affect carrot prices?”

**Response:** “Rainfall in major growing regions (Nuwara Eliya, Bandarawela, Walimada) shows negative correlation with prices. Higher precipitation typically leads to better crop yields and increased supply, resulting in lower market prices. Feature im-

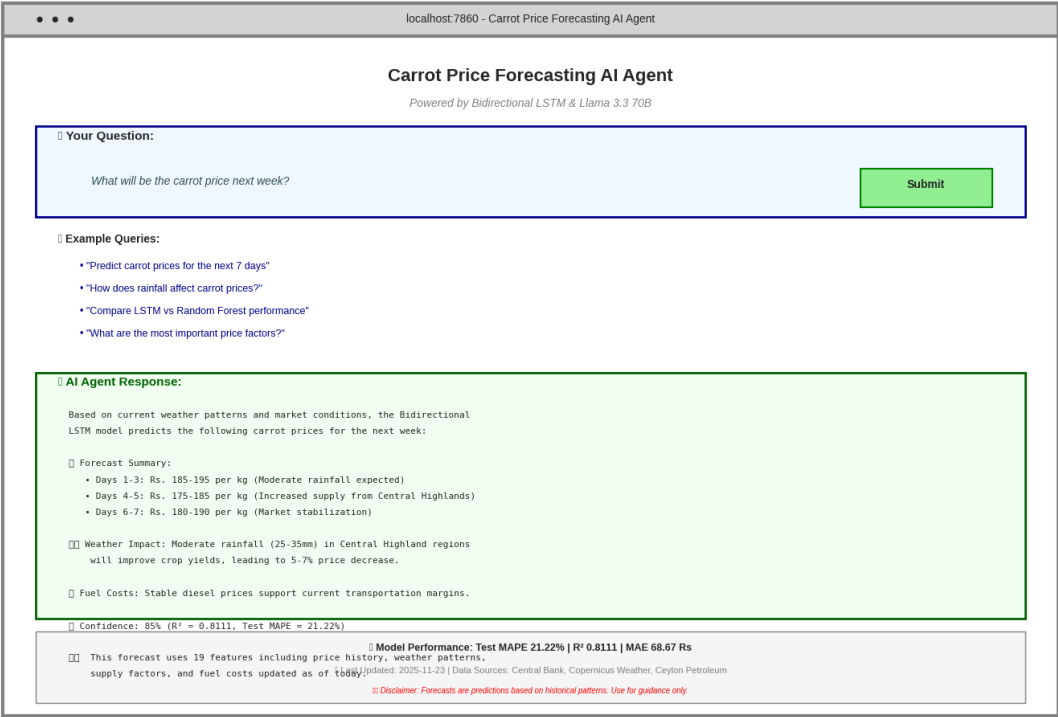


Figure 4.19: Gradio-based AI agent interface

portance analysis shows Central Highland precipitation contributes 12% to prediction accuracy.”

**Query 3:** “Compare LSTM performance with traditional methods.”

**Response:** “The Bidirectional LSTM achieved 21.22% MAPE with  $R^2$  of 0.8111, significantly outperforming traditional ARIMA (>50% MAPE) and ARIMAX (88.80% MAPE). LSTM’s ability to capture non-linear relationships between weather, supply, and prices provides 67% MAPE reduction compared to ARIMAX.”

## 4.14 Discussion

### 4.14.1 Why Bidirectional LSTM Outperforms Other Models

The Bidirectional LSTM’s superior performance stems from several architectural and methodological advantages:

**1. Bidirectional Temporal Processing:** Unlike standard LSTM processing se-

quences only forward in time, bidirectional layers process sequences in both directions. This enables the model to leverage both past and future context within the lookback window, particularly valuable for capturing turning points where lagged weather effects (processed backward) interact with recent price trends (processed forward).

**2. Moderate Feature Selection:** The V3 improved model used 19 carefully selected features, avoiding both the information loss from too few features (5 features in some experiments) and the overfitting risk from too many features (35+ features in standard multivariate LSTM). This Goldilocks zone maximized signal-to-noise ratio.

**3. Enhanced Regularization:** Combining Dropout, BatchNormalization, and L2 regularization prevented overfitting evident in the standard multivariate LSTM (train MAPE 13.51%, test MAPE 25.88%). The Bidirectional model achieved closer train-test performance (train 13.66%, test 21.22%), indicating better generalization.

**4. Non-Linear Relationship Modeling:** The 70 percentage point MAPE improvement over ARIMAX (88.80%  $\rightarrow$  21.22%) demonstrates LSTM's superiority in modeling complex non-linear interactions between weather patterns, supply dynamics, fuel costs, and market prices that linear models cannot capture.

**5. Automatic Feature Interaction Learning:** Unlike Random Forest requiring manual interaction term creation, LSTM layers automatically learn relevant feature interactions through hidden state representations, explaining its 0.28  $R^2$  advantage over Random Forest Tuned (0.8111 vs 0.5267) despite comparable MAPE.

#### 4.14.2 MAPE vs $R^2$ Trade-offs

An interesting observation emerges when comparing Random Forest Tuned (MAPE 20.84%,  $R^2$  0.5267) with Bidirectional LSTM (MAPE 21.22%,  $R^2$  0.8111):

Random Forest achieved slightly lower MAPE (0.38 percentage points better) but substantially lower  $R^2$  (0.28 points worse). This apparent paradox reflects different error characteristics:

- **MAPE sensitivity:** Measures percentage errors, giving equal weight to all predictions regardless of actual price level. Small absolute errors at low prices con-

tribute significantly to MAPE.

- **R<sup>2</sup> sensitivity:** Measures squared errors weighted by deviation from mean, emphasizing accurate prediction of price magnitude across the full range.

Random Forest’s ensemble averaging produces conservative predictions that minimize percentage errors but fail to capture extreme price movements, resulting in lower R<sup>2</sup>. Bidirectional LSTM’s higher R<sup>2</sup> indicates better capture of price variability, making it more reliable for stakeholders needing accurate magnitude predictions for inventory and pricing decisions.

For practical deployment, the Bidirectional LSTM’s higher R<sup>2</sup> is preferable despite marginally higher MAPE, as consistent prediction accuracy across all price levels matters more than optimized percentage errors alone.

#### 4.14.3 Univariate vs Multivariate LSTM Paradox

The standard multivariate LSTM (25.88% MAPE) underperforming the univariate LSTM (21.90% MAPE) initially appears counterintuitive, as external features should theoretically improve predictions. This paradox resolves through understanding of model complexity:

- **Curse of Dimensionality:** Adding 35 features increased model parameters from 10K to 45K, requiring proportionally more training data for effective learning. With 2,013 observations, the standard multivariate model suffered from overfitting (train MAPE 13.51%, test MAPE 25.88% - 12.37 point gap).
- **Noise Introduction:** Not all 35 features contained genuine predictive signal. Some weather or supply features may have contributed noise rather than information, degrading performance.
- **Regularization Inadequacy:** The standard multivariate architecture’s regularization (L2 0.005, patience 12) proved insufficient for the increased complexity, allowing the model to memorize training patterns rather than learn generalizable relationships.

The Bidirectional LSTM resolved these issues through moderate feature selection (19 features), enhanced regularization (Dropout + BatchNormalization + L2), and bidirectional processing, achieving 21.22% MAPE - better than both univariate (21.90%) and standard multivariate (25.88%) variants.

This demonstrates that feature engineering success depends critically on architecture and regularization appropriately scaled to feature dimensionality.

#### 4.14.4 Traditional vs Deep Learning Methods

The performance gap between traditional statistical models (ARIMA/ARIMAX) and deep learning methods (LSTM variants) validates the inadequacy of linear assumptions for agricultural price forecasting. Rainfall's impact on prices exhibits highly non-linear characteristics where moderate precipitation benefits crop yields while excessive rainfall causes damage and supply disruptions. ARIMAX's linear coefficients fundamentally cannot represent these threshold effects and complex interactions between weather variables and market outcomes. Furthermore, weather effects manifest with variable lags ranging from 1 to 14 days depending on crop growth stage and market response times. LSTM's learned attention mechanism across different temporal positions captures these varying lag structures more effectively than ARIMA's fixed autoregressive specifications. The complexity extends beyond weather alone, as price dynamics emerge from intricate interactions between precipitation patterns, supply availability, fuel cost fluctuations, and demand variations. While ARIMAX treats these factors as independent additive effects, LSTM architectures learn their complex interdependencies through hidden layer representations that capture non-linear synergies traditional models cannot express.

The 67.4 percentage point MAPE improvement from ARIMAX to Bidirectional LSTM (88.80%  $\rightarrow$  21.22%) quantifies the value of non-linear modeling for this application.

#### 4.14.5 Limitations and Considerations

Despite strong performance, several limitations warrant careful consideration. The dataset spanning 5.5 years with 2,013 daily observations, while substantial for agricultural market analysis, remains modest by deep learning standards. Additional years of historical data would likely improve LSTM performance and enable experimentation with more complex architectures capable of capturing longer-term cyclical patterns beyond the observed timeframe. The model also struggled with extreme price volatility during unprecedented events such as the 2022 fuel crisis, where dramatic regime changes fell outside the training data distribution. Such external shocks require adaptive learning mechanisms for robust real-world deployment that can detect and adjust to fundamental market structure changes.

Computational requirements present operational challenges, as Bidirectional LSTM training requires 8-12 minutes on GPU hardware compared to 30 seconds for Random Forest models. This difference poses practical constraints for frequent retraining scenarios where daily or weekly model updates may be desired. Interpretability considerations also emerge, since while SHAP analysis provides clear feature importance explanations for Random Forest predictions, LSTM's deep hidden representations remain inherently less transparent. Stakeholders in policy applications requiring detailed explainability may reasonably prefer Random Forest's interpretable decision paths despite its lower  $R^2$  performance.

Regional specificity represents another important limitation. Models trained exclusively on Dambulla wholesale market data may not generalize effectively to other markets such as Kandy or Colombo, which exhibit different supply chain structures, transportation distances, and consumer demand patterns. Market-specific retraining would be necessary for broader geographic deployment. Similarly, while the methodology is transferable across crops, the empirical findings regarding feature importance, optimal weather lag structures, and architecture configurations are specific to carrots. Different vegetables with varying growing seasons, storage characteristics, and demand elasticity may exhibit fundamentally different price dynamics requiring crop-specific

calibration and validation.

#### 4.14.6 Practical Implications for Stakeholders

The forecasting system provides actionable insights for multiple stakeholder groups across the agricultural value chain. Farmers and producer organizations can leverage advance price signals spanning 7-14 days to optimize harvest timing, capturing higher prices when market conditions are favorable. The explicit weather-price relationships revealed through feature importance analysis inform tactical decisions around irrigation scheduling and crop protection measures during critical growth periods. Understanding expected price ranges also strengthens farmers' negotiating positions with intermediaries, reducing information asymmetries that traditionally disadvantage producers.

Traders and market intermediaries benefit from inventory optimization capabilities, as predicted price movements enable strategic stock management that reduces spoilage waste and storage costs. Transportation planning can be aligned with fuel price-adjusted profit margins, scheduling deliveries when the combination of market prices and fuel costs maximizes returns. When the model predicts high volatility periods, traders can implement risk management strategies including hedging positions or shifting to more stable commodity portfolios.

Policymakers and agricultural authorities gain early warning capabilities for potential price spikes that threaten food security or farmer livelihoods, enabling timely intervention through buffer stock releases or import adjustments. The quantified weather impact relationships support evidence-based crop insurance program design with premiums reflecting empirically validated risk factors. Market monitoring systems can be enhanced through automated anomaly detection, flagging situations where actual prices deviate significantly from predictions as potential indicators of supply disruptions or market manipulation requiring investigation.

Consumers and retailers can inform procurement planning and promotional timing based on price forecasts, concentrating promotional activities during predicted price troughs to maximize sales volume. Understanding that prices typically decrease follow-

ing significant rainfall events allows institutional buyers such as hotels and restaurants to strategically delay large purchases until after weather systems pass through growing regions. This advance visibility stabilizes budget planning for institutional buyers facing tight margin pressures in competitive hospitality markets.

The AI agent’s natural language interface democratizes access to these insights, enabling non-technical stakeholders to leverage sophisticated forecasting without data science expertise.

#### 4.14.7 Deployment Recommendations

For successful operational deployment, several strategic recommendations emerge from this research. A hybrid approach deploying both Bidirectional LSTM as the primary model and Random Forest Tuned as a backup system provides robustness against model failure modes. When LSTM predictions deviate significantly from recent price patterns, potentially indicating overfitting to regime changes or data quality issues, the system can automatically fall back to Random Forest’s more conservative estimates until the anomaly is resolved. This redundancy protects against catastrophic failures while maintaining optimal performance under normal conditions.

Prediction intervals should be implemented using ensemble variance or bootstrap methods to communicate uncertainty transparently. Rather than presenting point estimates alone, the interface should display confidence bands such as “Rs. 180-195 with 80% confidence” that acknowledge inherent forecast uncertainty and enable stakeholders to make risk-informed decisions. Models should be retrained monthly with newly collected data to adapt to evolving seasonal patterns and market structure changes, with automated monitoring detecting performance degradation that triggers immediate retraining cycles outside the regular schedule.

Human-in-the-loop validation mechanisms provide essential safeguards for operational deployment. Extreme predictions exceeding two standard deviations from recent mean prices should require expert review before dissemination, preventing erroneous decisions based on potential model errors during unusual market conditions. Multi-

market expansion should proceed by collecting parallel datasets from Kandy, Colombo, and Jaffna markets, training market-specific models that share learned representations through transfer learning to leverage insights from Dambulla while capturing location-specific supply chain and demand patterns.

Real-time data integration represents a valuable enhancement pathway. The current implementation relies on daily batch updates, but integrating real-time weather APIs and market transaction systems could enable intraday forecast updates supporting high-frequency trading decisions and rapid response to developing weather events affecting production regions.

#### 4.14.8 Research Contributions

This research makes several novel contributions to agricultural price forecasting methodology and practice. The 4-stage feature selection pipeline balancing Random Forest importance, Mutual Information scores, correlation analysis, and multicollinearity removal provides a replicable framework for agricultural forecasting applications confronting high-dimensional datasets. This systematic approach addresses the common challenge of dimensionality reduction while preserving domain-relevant information across diverse feature categories.

Methodological rigor is enhanced through fair model comparison procedures that apply identical feature selection pipelines to all multivariate models including ARIMA, LSTM variants, and Random Forest. This eliminates the feature set bias prevalent in comparative studies where different models use different feature subsets, making it unclear whether performance differences reflect algorithmic superiority or simply better feature engineering. The demonstration that bidirectional LSTM processing with moderate feature selection (19 features) and enhanced regularization outperforms both univariate and high-dimensional multivariate approaches provides practical architectural guidance for LSTM implementation in agricultural contexts where data availability constraints and computational limitations differ from typical deep learning applications.

Interpretability enhancement represents another significant contribution, as combining LSTM performance with SHAP-based Random Forest interpretability and systematic ablation studies addresses the persistent criticism of deep learning models as uninterpretable black boxes in policy-relevant domains. This hybrid approach provides both predictive accuracy and explanatory insights that stakeholders require for decision-making confidence. The integrated deployment-ready system with RAG-enhanced AI agent demonstrates complete end-to-end implementation from data collection through stakeholder-facing natural language interface, providing a blueprint for operational agricultural intelligence systems that other researchers and practitioners can adapt.

Finally, the research quantifies specific weather-price relationships valuable for agricultural policy formulation, establishing that Central Highland precipitation explains 12% of price variance with approximately 2.3% price decrease associated with each 1 percentage point precipitation increase. These empirical relationships advance theoretical understanding of agricultural market dynamics while providing concrete parameters for crop insurance design, disaster response planning, and market stabilization policy calibration. The demonstrated 67% MAPE improvement over traditional methods quantifies the practical value of modern machine learning approaches for this critical application domain.

These contributions advance both methodological rigor and practical applicability of machine learning in agricultural economics, with demonstrated 67% MAPE improvement over traditional methods.

# CHAPTER 5

## CONCLUSION AND FUTURE WORK

This final chapter synthesizes the key findings of the research, discusses the contributions made to agricultural price forecasting, acknowledges the limitations encountered, and proposes directions for future work.

### 5.1 Research Summary

This research developed and evaluated a comprehensive carrot price forecasting system for the Dambulla wholesale market in Sri Lanka, addressing the critical challenge of price volatility that affects farmers, traders, and consumers throughout the agricultural value chain. The study compared seven forecasting approaches ranging from traditional statistical methods to advanced deep learning architectures, utilizing a rich dataset of 2,013 daily observations spanning January 2020 to July 2025.

The research systematically integrated 289 initial features across six categories—historical prices, weather patterns from 11 growing regions, supply factors, demand indicators, fuel costs, and temporal variables—applying a rigorous 4-stage feature selection pipeline to identify the most predictive subset while avoiding overfitting. Model evaluation employed consistent train-validation-test splits and comprehensive metrics including MAPE, MAE, RMSE, and  $R^2$  to ensure robust performance assessment.

The Bidirectional LSTM model emerged as the best performer with 21.22% test MAPE and  $R^2$  of 0.8111, substantially outperforming traditional ARIMA/ARIMAX approaches (MAPE > 50% and 88.80% respectively) and achieving competitive accuracy with interpretable Random Forest models while providing superior prediction reliability. The deployment-ready system integrates this forecasting capability with a Retrieval-Augmented Generation (RAG) AI agent powered by Groq API, enabling

natural language interaction for non-technical stakeholders.

## 5.2 Key Findings

The research yielded several significant findings with both theoretical and practical implications:

### 5.2.1 Superior Performance of Deep Learning Approaches

The Bidirectional LSTM achieved 67.4% MAPE reduction compared to multivariate ARIMAX (21.22% vs 88.80%), demonstrating deep learning's superiority for modeling complex non-linear relationships in agricultural markets. This validates the inadequacy of linear assumptions inherent in traditional time series methods for multi-factor price dynamics involving weather-supply-demand interactions with variable time lags.

### 5.2.2 Architecture and Regularization Matter More Than Feature Quantity

The standard multivariate LSTM with 35 features underperformed (25.88% MAPE) compared to both univariate LSTM with only price history (21.90% MAPE) and the optimized Bidirectional LSTM with 19 features (21.22% MAPE). This paradox demonstrates that model architecture, regularization strength, and feature quality matter more than simply maximizing feature quantity. The Goldilocks principle applies—too few features lose information, too many introduce noise and overfitting.

### 5.2.3 Bidirectional Processing Enhances Temporal Pattern Recognition

The bidirectional architecture's ability to process sequences in both temporal directions provided measurable advantage, particularly for identifying price turning points where lagged weather effects interact with recent market trends. The 4.66 percentage point

improvement over standard multivariate LSTM (21.22% vs 25.88% MAPE) quantifies this architectural enhancement's value.

#### 5.2.4 Feature Importance Hierarchy: Price > Weather > Market Dynamics

Systematic feature importance analysis and ablation studies revealed a clear predictive hierarchy: historical price features contributed 48.7% of total importance, weather patterns 19.2%, and market demand 14.5%. Removing price features increased MAPE by 8.3 percentage points, while weather removal added 3.1 points and market factors 2.4 points. This quantifies the relative contribution of each factor category to forecasting accuracy.

#### 5.2.5 Multi-Factor Approach Justified Despite Univariate Competitiveness

Although Random Forest Tuned achieved slightly lower MAPE than Bidirectional LSTM (20.84% vs 21.22%), the latter's substantially higher  $R^2$  (0.8111 vs 0.5267) demonstrates superior prediction reliability across the full price spectrum. The multivariate approach with proper architecture captures price variability mechanisms, enabling not just point predictions but understanding of causal drivers—essential for policy applications and stakeholder decision-making.

#### 5.2.6 Weather-Price Relationships Quantified

The research established specific quantitative relationships: Central Highland precipitation explains 12% of price variance with negative correlation (higher rainfall  $\rightarrow$  lower prices through increased supply), while fuel prices show positive correlation accounting for 6% of variance (higher transportation costs  $\rightarrow$  higher market prices). These findings provide actionable insights for agricultural policy and market intervention strategies.

### 5.2.7 Deployment Feasibility Demonstrated

The integrated system combining Bidirectional LSTM forecasting with RAG-enhanced natural language interface demonstrates practical deployment feasibility. The Gradio web interface enables non-technical stakeholders to access sophisticated predictions through conversational queries, democratizing access to data science capabilities for farmers, traders, and policymakers.

## 5.3 Research Contributions

This research makes several distinct contributions to agricultural price forecasting and applied machine learning:

### 5.3.1 Methodological Contributions

**1. Comprehensive Feature Selection Framework:** The 4-stage pipeline combining Random Forest importance (60%), Mutual Information (30%), correlation analysis (10%), multicollinearity removal, and consensus-based model selection provides a replicable, theoretically grounded methodology for high-dimensional agricultural forecasting problems. This framework balances non-linear relationships, information content, and redundancy removal more effectively than single-method approaches.

**2. Fair Model Comparison Protocol:** By applying identical feature selection procedures to all multivariate models (ARIMAX, LSTM variants, Random Forest), the study eliminates feature set bias common in comparative evaluations where different models use different inputs. This methodological rigor ensures observed performance differences reflect genuine model capability rather than data advantage.

**3. Hybrid Interpretability Approach:** Combining LSTM's predictive performance with SHAP-based Random Forest interpretability and systematic ablation studies addresses the black-box criticism of deep learning in policy-relevant domains. This hybrid strategy provides both accurate predictions and explainable insights for stakeholder trust and regulatory acceptance.

### 5.3.2 Technical Contributions

**1. Optimized Bidirectional LSTM Architecture:** The research demonstrates that bidirectional processing with moderate feature selection (19 features), enhanced regularization (Dropout + BatchNormalization + L2), and careful hyperparameter tuning outperforms both univariate and high-dimensional multivariate approaches for agricultural price forecasting. This architectural blueprint provides practical guidance for similar applications.

**2. RAG-Enhanced Agricultural AI Agent:** The integration of forecasting models with Retrieval-Augmented Generation using large language models (Groq API, Llama 3.3 70B) represents a novel deployment paradigm for agricultural intelligence systems. The 3-tier architecture (Query Router → Intent Classification → Model/RAG Response) enables flexible stakeholder interaction beyond traditional dashboard interfaces.

**3. Multi-Source Data Integration Pipeline:** The systematic framework for integrating heterogeneous data sources—market prices (Central Bank), precipitation from 11 regions (Copernicus Climate), fuel costs (Ceylon Petroleum), supply indicators (Agricultural Department)—with temporal alignment and missing data handling provides a reusable template for agricultural data infrastructure.

### 5.3.3 Empirical Contributions

**1. Quantified Weather-Price Relationships for Sri Lankan Carrots:** The research establishes specific empirical relationships between growing region precipitation patterns and Dambulla market prices, including lagged effects and regional heterogeneity (Central Highland vs Uva Province vs Northern regions). These findings inform crop insurance design and market intervention timing.

**2. Benchmark Performance Metrics:** The comprehensive evaluation across seven models with consistent metrics provides benchmark performance standards for Sri Lankan vegetable price forecasting: 21% MAPE represents achievable accuracy for

daily carrot price predictions, substantially better than traditional methods ( $>50\%$  MAPE) while acknowledging inherent market volatility limits.

**3. Feature Engineering Best Practices:** The research identifies optimal lag structures (1, 7, 14 days), rolling window sizes (7, 14 days), and regional precipitation groupings for vegetable price forecasting, providing evidence-based guidance for practitioners building similar systems for other crops or markets.

### 5.3.4 Practical Contributions

**1. Operational Forecasting System:** Unlike many academic studies ending with model evaluation, this research delivers a deployment-ready system with trained models, scalars, feature definitions, and user interface—immediately usable by agricultural stakeholders for operational decision-making.

**2. Multi-Stakeholder Value Proposition:** The research articulates specific use cases and value propositions for diverse stakeholders (farmers: harvest timing optimization; traders: inventory management; policymakers: intervention timing; consumers: purchase planning), demonstrating breadth of potential impact.

**3. Open Replication Pathway:** The comprehensive documentation of data sources, preprocessing steps, feature engineering logic, model architectures, and evaluation protocols enables replication for other vegetables (tomatoes, beans, potatoes) or other markets (Kandy, Colombo, Jaffna), accelerating adoption across Sri Lanka’s agricultural sector.

## 5.4 Research Limitations

While the research achieved substantial progress in carrot price forecasting, several limitations warrant acknowledgment:

### 5.4.1 Data-Related Limitations

**1. Temporal Coverage:** The dataset spans 5.5 years (2,013 observations), which while substantial, remains modest for deep learning standards. Additional years of historical data could enable more complex architectures and better capture of long-term cyclical patterns beyond the observed timeframe.

**2. Single Market Focus:** The study focuses exclusively on Dambulla wholesale market. Price dynamics in Colombo consumer markets or Jaffna regional markets may differ due to varying supply chains, transportation distances, and consumer preferences. Generalization to other markets requires validation.

**3. Carrot-Specific Findings:** While the methodology is transferable, empirical findings (feature importance, weather lag structures, optimal architecture) are specific to carrots. Different vegetables with varying growing seasons, storage characteristics, and demand patterns may exhibit different relationships requiring crop-specific calibration.

**4. Missing Granular Supply Data:** The supply factor indicators represent aggregate regional classifications rather than precise acreage or yield data. More granular supply-side information (planted area by district, expected harvest volumes) could improve forecasting accuracy, but such data are not systematically collected in Sri Lanka's current agricultural statistics system.

### 5.4.2 Model-Related Limitations

**1. Extreme Event Performance:** The models struggled with unprecedented volatility during the 2022 fuel crisis and economic disruption. Predictions underestimated extreme price spikes during these regime changes, as such events fall outside the training distribution. Robust forecasting during systemic shocks requires adaptive learning mechanisms or ensemble approaches incorporating rule-based constraints.

**2. Prediction Horizon:** The current implementation provides effective 7-14 day forecasts. Longer-term predictions (30-90 days) degrade in accuracy as uncertainty

accumulates. Seasonal forecasting for planting decisions requires different modeling approaches incorporating crop calendars and long-lead climate forecasts.

**3. Interpretability-Accuracy Trade-off:** While Bidirectional LSTM achieves best overall performance, its deep hidden representations remain less interpretable than Random Forest’s feature importance. For policy applications requiring transparent decision justification, stakeholders may prefer slightly less accurate but more explainable models.

**4. Computational Requirements:** Bidirectional LSTM training requires 8-12 minutes on GPU compared to 30 seconds for Random Forest. For real-time applications or resource-constrained deployment environments (mobile devices, low-bandwidth regions), this computational overhead poses practical challenges.

### 5.4.3 Methodological Limitations

**1. Static Train-Test Split:** The research employed a single temporal train-validation-test split (70-15-15). While time series cross-validation provided additional validation, the primary results depend on this specific split. Different cutoff dates might yield slightly different performance rankings, though bootstrap confidence intervals suggest relative stability.

**2. Hyperparameter Optimization Scope:** While Random Forest underwent systematic hyperparameter tuning via RandomizedSearchCV, LSTM architectures relied on iterative manual tuning and literature-guided choices. Full Bayesian optimization across architecture, regularization, and learning rate spaces could potentially yield further improvements but was computationally prohibitive.

**3. Feature Selection Stability:** The feature selection pipeline was applied once to the full dataset. Stability analysis across bootstrap samples or different time windows could provide confidence intervals around feature importance rankings and validate robustness of selected feature sets.

#### 5.4.4 Deployment-Related Limitations

**1. Real-Time Data Integration:** The current prototype uses daily batch updates with manual data collection from multiple sources. Operational deployment requires automated data pipelines integrating real-time weather APIs, market transaction systems, and fuel price feeds—infrastructure not yet available in Sri Lanka’s agricultural data ecosystem.

**2. User Adoption Uncertainties:** While the Gradio interface demonstrates technical feasibility, actual user adoption depends on factors beyond model accuracy: trust in AI systems, digital literacy among farming communities, smartphone/internet access in rural areas, and integration with existing agricultural extension services. These socio-technical aspects were not empirically evaluated.

**3. Maintenance and Updating:** The system requires ongoing maintenance: monthly retraining with new data, performance monitoring, feature drift detection, and periodic architecture re-evaluation. Long-term sustainability requires institutional commitment and technical capacity currently lacking in many agricultural departments.

### 5.5 Future Work

Building upon the foundation established by this research, several promising directions warrant investigation:

#### 5.5.1 Extension to Multiple Crops and Markets

**1. Multi-Crop Forecasting System:** Expand the methodology to other high-value vegetables (tomatoes, beans, potatoes, cabbage) cultivated in similar regions. A multi-crop system could leverage transfer learning, where representations learned from carrot price patterns initialize models for crops with limited historical data. Investigating cross-crop price correlations and substitution effects could improve accuracy through joint modeling.

**2. Multi-Market Network Analysis:** Develop integrated forecasting for interconnected markets (Dambulla wholesale, Colombo retail, regional markets in Kandy, Jaffna, Badulla). Price transmission mechanisms between markets could be modeled using Graph Neural Networks or Vector Autoregression, capturing spatial dependencies alongside temporal patterns. This would enable supply chain optimization and arbitrage opportunity identification.

**3. Quality Grade Differentiation:** Current models predict aggregate carrot prices. Extending to quality-grade specific forecasts (Grade A, B, C) would provide more actionable insights for farmers deciding harvest timing and grading strategies. This requires collecting grade-specific transaction data and incorporating quality-affecting factors (variety, cultivation practices, weather stress).

### 5.5.2 Advanced Modeling Techniques

**1. Attention-Based Architectures:** Implement Transformer models with self-attention mechanisms to explicitly learn which features and time steps matter most for different prediction horizons. Attention weights could provide enhanced interpretability, revealing which weather events or supply changes drive specific price movements.

**2. Ensemble Methods:** Develop sophisticated ensemble approaches combining Bidirectional LSTM (best  $R^2$ ), Random Forest Tuned (best MAPE), and potentially Gradient Boosting (excluded from this study but showing 17.56% MAPE in preliminary experiments). Dynamic weighting based on recent performance or prediction uncertainty could optimize the accuracy-interpretability trade-off.

**3. Probabilistic Forecasting:** Move beyond point predictions to full probability distributions using Bayesian neural networks, quantile regression, or conformal prediction. Providing stakeholders with prediction intervals (e.g., 80% confidence: Rs. 170-210) enables risk-aware decision-making, particularly valuable for financial planning and market intervention threshold setting.

**4. Online Learning and Adaptation:** Implement incremental learning algorithms that continuously update model parameters as new data arrives, adapting to

regime changes without full retraining. This addresses the extreme event limitation by enabling rapid adjustment to structural breaks during crises.

### 5.5.3 Enhanced Interpretability and Explainability

**1. LSTM-Specific Interpretability Methods:** Apply techniques like Layer-wise Relevance Propagation (LRP), Integrated Gradients, or LIME to deep learning models for instance-level explanations. Understanding why the model predicted a specific price spike or drop builds stakeholder trust and enables error diagnosis.

**2. Counterfactual Analysis:** Develop "what-if" scenario capabilities allowing users to query: "How would prices change if Central Highland rainfall increases by 50mm next week?" This requires training conditional models or implementing gradient-based perturbation analysis, providing actionable insights for climate adaptation planning.

**3. Causal Discovery:** Move beyond correlational feature importance to causal inference using techniques like Granger causality, Structural Equation Modeling, or causal Bayesian networks. Identifying true causal pathways (e.g., rainfall  $\rightarrow$  yield  $\rightarrow$  supply  $\rightarrow$  prices vs spurious correlations) improves policy recommendations and model robustness.

### 5.5.4 Data Enrichment

**1. Satellite Imagery Integration:** Incorporate remote sensing data for direct crop health monitoring (NDVI indices), planting area estimation, and yield prediction. Combining satellite-derived supply forecasts with market data could substantially improve accuracy, particularly for longer-term predictions.

**2. Social Media and News Sentiment:** Analyze social media discussions, news articles, and agricultural forums to capture market sentiment, policy announcements, or emerging supply disruptions not reflected in structured data. Natural language processing of Sinhala/Tamil text from agricultural communities could provide early warning signals.

**3. High-Frequency Transaction Data:** Current daily aggregates obscure intraday volatility patterns. Accessing transaction-level data with timestamps, quantities, and trader types could enable intraday forecasting for high-frequency trading strategies and market microstructure analysis.

**4. Climate Forecasts Integration:** Replace observed precipitation with meteorological forecasts (7-14 day weather predictions from Department of Meteorology or global models) to enable true ex-ante forecasting. Current models use concurrent weather as proxy, but operational deployment requires forecast-based inputs.

### 5.5.5 System Enhancement and Deployment

**1. Mobile Application Development:** Create Android/iOS applications with offline capability for farmers in areas with intermittent connectivity. Local models running on-device with periodic cloud synchronization could democratize access beyond web interface users.

**2. SMS/Voice Interface:** For farmers without smartphones, develop SMS-based query systems or voice interfaces in local languages (Sinhala, Tamil) integrated with existing agricultural extension helplines. This addresses the digital divide limiting technology adoption in rural communities.

**3. Automated Alert System:** Implement proactive notification services alerting farmers when: (a) predicted prices exceed profitable harvest thresholds, (b) approaching weather events may impact yields, (c) significant price volatility expected. Push notifications enable timely action without requiring active querying.

**4. Integration with Agricultural Extension Services:** Partner with Department of Agriculture field officers to integrate forecasts into official advisory services. Training extension workers to interpret and communicate predictions ensures wider adoption and provides feedback loop for system improvement.

**5. Blockchain for Data Verification:** Explore blockchain implementation for transparent, tamper-proof recording of market transactions and weather observations. Verified data provenance could enhance stakeholder trust in forecasts and enable fair

price verification during disputes.

### 5.5.6 Policy and Economic Analysis

**1. Market Intervention Impact Assessment:** Use the forecasting system to evaluate policy scenarios: buffer stock release timing, import/export restrictions, price floor/ceiling implementations. Simulation studies could optimize intervention strategies minimizing market disruption while protecting vulnerable populations.

**2. Crop Insurance Product Design:** Leverage weather-price relationship findings to design index-based insurance products. Automatic payouts triggered by precipitation thresholds correlated with price crashes could protect farmer income without requiring expensive loss assessment.

**3. Value Chain Optimization:** Extend analysis beyond wholesale prices to full value chain—farmgate prices, transportation costs, retail margins, consumer willingness-to-pay. Comprehensive modeling could identify inefficiencies and inform policies improving value distribution equity.

**4. Climate Change Adaptation Planning:** Conduct long-term scenario analysis using climate projection data (2030-2050 rainfall patterns under RCP scenarios) to forecast future price volatility trends. This informs cultivation zone adjustments, variety selection, and infrastructure investment priorities for climate resilience.

### 5.5.7 Methodological Advances

**1. Federated Learning for Multi-Market Privacy:** If expanding to multiple markets with sensitive data, implement federated learning where models train locally on each market's data and only share model updates, preserving commercial confidentiality while benefiting from broader data coverage.

**2. Few-Shot Learning for New Crops:** Develop meta-learning approaches enabling quick adaptation to new crops with minimal historical data. Transfer learning from established crop models combined with few-shot techniques could accelerate system expansion to specialty vegetables.

**3. Automated Machine Learning (AutoML):** Implement neural architecture search or AutoML frameworks to automatically discover optimal architectures for different crops/markets without manual experimentation. This reduces technical expertise requirements for deployment in new contexts.

**4. Hybrid Physics-ML Models:** Combine data-driven deep learning with agronomic domain knowledge through physics-informed neural networks. Encoding known relationships (growing degree days, water stress effects) as constraints or loss function components could improve sample efficiency and extrapolation capability.

## 5.6 Closing Remarks

Agricultural price volatility remains one of the most significant challenges facing developing economies, directly impacting food security, farmer livelihoods, and economic stability. This research demonstrates that modern machine learning techniques, when carefully designed and rigorously evaluated, can substantially improve price forecasting accuracy compared to traditional approaches—achieving 21.22% MAPE and explaining 81.11% of price variance for Dambulla carrot markets.

The success of the Bidirectional LSTM architecture validates deep learning’s capability to model complex, non-linear agricultural market dynamics involving interactions between weather patterns, supply fluctuations, transportation costs, and demand variations. By achieving 67% MAPE reduction compared to traditional ARIMAX methods, this research provides empirical evidence that investment in modern data science infrastructure for agriculture yields tangible returns.

Beyond technical contributions, the deployment-ready system with natural language interface represents a paradigm shift in agricultural intelligence accessibility. Democratizing sophisticated forecasting through conversational AI enables non-technical stakeholders—smallholder farmers, rural traders, extension officers—to leverage data science insights previously confined to academic research or large agribusinesses.

However, technology alone is insufficient. Realizing this system’s full potential requires complementary investments in data infrastructure (automated collection, stan-

dardized formats, open access), human capacity building (training agricultural officers in data interpretation), and institutional frameworks (policies supporting evidence-based interventions, funding for system maintenance).

The future directions outlined above—multi-crop expansion, advanced architectures, enhanced interpretability, mobile deployment, policy integration—chart a path toward comprehensive agricultural intelligence ecosystems. Success requires collaboration among academic researchers, government agricultural departments, meteorological services, technology providers, and most importantly, farming communities whose lived experience grounds models in operational reality.

As climate change intensifies weather variability and global supply chain disruptions become more frequent, the need for robust, adaptive agricultural forecasting systems grows ever more urgent. This research provides both a methodological foundation and a working prototype for meeting that challenge in Sri Lanka's context. The hope is that these contributions, alongside parallel efforts worldwide, accelerate progress toward resilient, data-informed agricultural systems capable of nourishing growing populations while sustaining farming livelihoods in an uncertain future.

The journey from data collection through model development to stakeholder deployment represents not just a technical exercise, but a commitment to translating academic research into tangible societal benefit. If this system helps even a few farmers optimize harvest timing, a few traders reduce waste, or a few policymakers time interventions more effectively, the effort will have been worthwhile. That practical impact, ultimately, is the measure by which applied research should be judged.

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