Forecast Fusion

A Project-Based Learning Report Submitted in partial fulfilment of the requirements for the award of the degree

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Deep Learning - 23AVI3101A

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Introduction

Context and Importance

Spices play a crucial role in agriculture, cuisine, and commerce, particularly in countries like India, the world's largest producer, consumer, and exporter of spices. The spice industry not only supports the livelihoods of millions of farmers and traders but also contributes significantly to the national economy through domestic consumption and exports.

Despite their importance, the pricing of spices is highly unpredictable. Multiple factors contribute to this volatility, including:

- Seasonality: Many spices are harvested during specific periods, leading to supply fluctuations throughout the year.
- Arrivals: The volume of spices arriving at markets can suddenly increase or decrease, directly affecting prices.
- Quality Variations: Differences in variety or grading of spice crops influence price points.
- Climatic Conditions: Weather patterns such as monsoons, droughts, or unseasonal rains impact both production and prices.
- Market Dynamics and Policy Changes: Changing export policies, international demand, and competition also contribute to price swings.

Given these influences, spice prices can rise or fall unpredictably, creating significant challenges for those involved in the supply chain.

Problem Statement

One of the main challenges in the spice sector is the lack of reliable and accurate price forecasting. Stakeholders, especially small and marginal farmers, often make selling or stocking decisions based on guesswork or outdated information. This exposes them to financial risks such as:

- Selling goods at inopportune times when prices are low.
- Holding stock too long and missing opportunities for better returns.
- Making procurement decisions without understanding future trends.

Consequently, poor forecasting can lead to substantial financial losses, inefficient resource allocation, and increased vulnerability for those dependent on the spice market.

Objective

The primary objective of this project is to develop a data-driven, machine learning-based forecasting system capable of predicting the prices of selected spices for the next 30 days. This system aims to harness historical and recent price data, along with other relevant factors, to provide accurate and timely forecasts. With such a tool, stakeholders in the spice industry can:

- Anticipate future price trends with greater confidence.

- Make well-informed decisions about buying, selling, or holding inventory.
- Strategically plan procurement, sales, and exports to maximise gains and minimize losses.

Benefits

Implementing an effective price forecasting model brings tangible advantages:

- Reduced Financial Losses: Stakeholders can mitigate losses by avoiding sales at unfavourable prices and capitalizing on profitable market windows.
- Improved Decision-Making: Timely information enables data-driven choices instead of reliance on speculation or rumours.
- Optimized Procurement and Storage: Traders and manufacturers can plan inventories more efficiently by purchasing raw materials when prices are expected to be favourable.
- Supply Chain Stability: Predictable pricing benefits everyone from farmers to retailers, fostering stability in the spice trade ecosystem.
- Empowerment of Farmers and Small Traders: Access to accurate market forecasts bridges the information gap and helps smaller players compete fairly.

Overall, the ability to accurately forecast spice prices not only supports economic growth but also enhances the livelihoods and resilience of those who rely on this vibrant sector.

Literature Review/ Application Survey

Spices like Large Cardamom and Mace are critical export-oriented crops in India, Nepal, and Indonesia. Their prices are highly volatile due to seasonality, weather shocks (rainfall, temperature, humidity), pest/disease outbreaks, international demand, and supply chain constraints. Forecasting these prices helps farmers and cooperatives plan cropping & storage, exporters and traders hedge against market risk, and policy makers ensure price stability and market interventions.

Data Sources for Spice Price Forecasting

- Government portals: Indian Agmarknet and Spices Board of India provide daily mandi (market) prices.
- Commodity boards / exporters: Spices Board reports, FAO data on spice trade.
- International trade data: UN Comtrade, ITC Trademap (for exports/imports influencing price).
- Auxiliary features: Weather datasets (IMD, NOAA), seasonality indicators (festivals, export cycles), currency exchange rates (USD–INR).

Forecasting Methods Used in Agri-Commodities (Relevant to Spices)

Statistical Models

•ARIMA/Seasonal ARIMA (SARIMA): Captures seasonality in crops like cardamom.

• GARCH family: Captures volatility clustering in prices influenced by sudden export demand.

Machine Learning Models

• Random Forest & Gradient Boosting (XGBoost/LightGBM): Handle nonlinear drivers like rainfall and global demand.

• Support Vector Regression (SVR): Effective in small datasets, often better than ARIMA.

Deep Learning Models

• LSTM/GRU networks: Capture long-term seasonal cycles and sudden spikes, outperforming ARIMA in coffee, cardamom, and pepper price prediction.

• CNN–LSTM hybrids: Extract short-term local patterns and long-term seasonality.

• Transformers (TFT): Emerging models handling multi-horizon forecasts.

Hybrid & Ensemble Models

Combining ARIMA with ML/DL models often yields better results (e.g., ARIMA+LSTM). Ensemble averaging across SARIMA, XGBoost, and LSTM reduces overfitting risk.

Applications from Prior Studies (Spice/Agri Examples)

•Cardamom price forecasting in Kerala & Sikkim (ARIMA, SARIMA, LSTM) showed seasonal peaks in harvest months.

• Pepper & turmeric price prediction (XGBoost vs LSTM) showed ML/DL outperform classical models.

• Volatility modelling of spices using GARCH revealed high uncertainty during export policy shifts.

• M5 Forecasting Competition highlighted the strength of gradient boosting and hierarchical forecasting.

Evaluation Strategies

- Error metrics: RMSE, MAE, MAPE.
- Directional accuracy (up/down) is crucial for traders.
- Backtesting: Rolling window forecasts (train on past 3–5 years, test on 1 year).
- Economic evaluation: Profit/loss saved via forecast-informed decisions.

Insights from Application Survey

1. Short-term forecasts (1–4 weeks) → SARIMA/Random Walk competitive.
2. Medium-term (3–6 months) → ML/DL (LSTM, GRU, XGBoost) perform better.
3. Seasonality & weather must be included for spices.
4. Volatility modeling (GARCH/quantile DL) essential for risk assessment.
5. Hybrid models consistently reported stronger results in agri-spice studies.

Gaps & Opportunities (For the Project)

- Limited published work on Mace; most focus on cardamom, pepper, turmeric.
- Event-driven forecasting (export bans, festivals, geopolitical shocks) underexplored.
- Probabilistic forecasting (price ranges, not just point estimates) valuable for spice traders.
- Explainability (why price moves) is increasingly important (e.g., SHAP for XGBoost, attention weights in Transformers).

Takeaway for the Project

For Large Cardamom & Mace, the literature suggests using an ensemble approach combining SARIMA, LSTM/GRU, and XGBoost with daily/weekly mandi price data and auxiliary variables (weather, exports). Baseline comparisons with Random Walk and ARIMA models should be included to ensure robustness. This aligns the project with academic standards and real-world applicability.