

# Forecasting Prices of Black Pepper in Kerala and Karnataka using Univariate and Multivariate Recurrent Neural Networks

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**Abstract**—Our country has a high level of agricultural employment. Price swings harm the economy of our country. To combat this impact, forecasting the selling price of agricultural products has become a need. Forecasts of agricultural prices assist farmers, government officials, businesses, central banks, policymakers, and consumers. Price prediction can then assist in making better selections in this area. Black pepper, sometimes known as the "King of Spices," is a popular spice farmed and exported in India. The largest producers of black pepper are Karnataka and Kerala. For black pepper in Kerala and Karnataka, this study provides a univariate and multivariate price prediction model using Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). The data is denoised using Singular Spectral Analysis (SSA). The most accurate method is the multivariate variate LSTM technique, which uses macroeconomic variables. It has a Mean Absolute Percentage Error (MAPE) of 0.012 and 0.040 for Kerala and Karnataka, respectively.

**Index Terms**— Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Singular Spectral Analysis (SSA), Black Pepper, Macroeconomic, Time series.

## I. INTRODUCTION

The price of black pepper, a trade-dependent commodity, fluctuates a lot. The prices of black pepper exhibit nonlinear patterns. Because of the greater connection with the foreign markets, price volatility might be directly conveyed to domestic pricing. Agriculture analytics is projected to expand in the modern era. Big data and artificial intelligence are two instances of extensively used technologies. These instruments can be used to diagnose crop diseases, manage crops, control pests, monitor disease transmission, monitor irrigation, control soil nutrients, monitor production, and ensure the preservation of agricultural products. Several statistical methods are used in traditional time series prediction methodologies, including auto-regressive integrated moving averages (ARIMA) and seasonal auto-regressive integrated moving averages (SARIMA). It has been proven that these tactics work. These methods can be used only when the data has been transformed to stationary. RNNs are used to reveal and forecast volatile nonlinear data. For the Price Prediction of Black Pepper in Karnataka, univariate techniques with high accuracy have already been developed. In this paper, univariate models are implemented using RNN, and macroeconomic variables are included as part of the multivariate model for price prediction in prominent black pepper-producing states; Kerala and Karnataka. SSA has also been used to denoise the data.

Macroeconomic factors in a multivariate manner tend to produce better prediction scores. Previous research on the problem will be discussed, the proposed model, experiments and results, and a conclusion.

The remainder of the paper is laid out as follows: Section 2 discusses similar studies on the research issue, Section 3 describes the proposed model's entire architecture and includes descriptions of the approaches employed in this work, and Section 4 details model implementation and findings for univariate and multivariate models. Section 5 ends and summarizes the research work.

## II. RELATED WORKS

Agricultural price prediction has employed statistical, mathematical, machine learning, data mining, and deep learning methodologies. Ahumada et al. [7] proposed a stochastic tactical planning model for modern agricultural production and distribution. Forecasting the weather and demand fluctuations is integral to establishing fresh produce growing and distribution strategies. The findings imply that the suggested stochastic technique outperforms deterministic models in planning recommendations. Farmers' high holding costs, uncertain procurement capabilities, and a lack of easily accessible financing contribute to distressed selling. A tractable stochastic dynamic programming model predicted a significant decrease in farmer welfare [10]. Thanks to the model, policymakers may readily analyze the relative impact of changes in the significant drivers of distressed sales. This research [14] by Widodo et al. uses many mathematical models. To improve profitability, it addresses dynamic pricing for Fruit Supply Chain players. Data mining in agriculture has been studied in [9] and [18]. Recent data mining approaches include K-Means, K-Nearest Neighbour (KNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM). A decision-support model for predicting agricultural commodity prices is presented in [15] by Vohra et al. This work offers a decision-support model for farmers. By analyzing 2014-2019, Bandung rice prices, Mukhlisin et al. [24] proposed a data mining technique for projecting rice prices. For testing, the KNN regression method is used. Rice prices from 2014 to 2019 can be successfully predicted using the KNN technique combined with a regression model in this study.

An algorithm for estimating agricultural commodity prices has been devised in [19] by Varun R et al. In addition to the date, yield, maximum and minimum trades, the algorithm also evaluates wind speed, humidity, maximum and minimum temperatures, and pesticide usage. Onion prices were forecasted using machine learning [20]. Bangladesh's Ministry of Agriculture provided the estimate. To create predictions, machine learning techniques such as KNN, Naive Bayes, Decision Tree, Neural Network, and SVM were used. The work tested five algorithms and discovered the best system for predicting onion prices. Onion demand and supply were determined based on this forecasted price. For price prediction, M.L. Shiha et al. [1] suggested using a weighted case-based reasoning (CBR) method. CBR feature weights were determined using an evolutionary algorithm model. According to the experiments, the proposed CBR technique outperformed linear regression, regression trees, and neural nets in prediction performance. Lia et al. [2] developed and verified a model for forecasting the short-term egg market. Each predictor component's and eggs' monthly prices were assessed and tested for relevance and long-term stability. A regression model was built utilizing Reviews analysis software. Finally, the regression model's validity and applicability were tested statistically. The short-term price changes of pork, chicken, and egg in the Chinese market were analyzed in by Gan-qiong et al. [4]. They use a linear quantile technique to investigate data heteroscedasticity and construct confidence bands. A groundbreaking agricultural commodity price forecasting approach was proposed using fuzzy information granulation, Mind Evolutionary Algorithm (MEA), and SVM in [13]. The MEA-SVM model is more accurate and takes less time to calculate than other models. Adaptive learning forecasting enables forecast averaging and error learning [17]. Theoretical properties were studied and showed a priori Mean Squared Error (MSE) improvements. By learning from past forecast failures, this technique improves the performance of any input forecast.

The Grey Prediction approach was proposed in the study to forecast agricultural commodity prices [5]. Ten agricultural items were selected from the Agricultural Bank of China from January to December 2011 to forecast prices for four weeks and compare Mean Percentage Error via Grey Method (GM) and Radial Basis Function (RBF) Neural Network. The RBF neural network outperformed the GM in agricultural product predictions. It offers a higher prediction accuracy for collected data. Nasira et al. [6] suggested a backpropagation neural network model for predicting vegetable prices. According to the study, a neural network can estimate the nonlinear time series pricing of vegetables. In this study, a Quantile Regression-Radial Basis Function (QR-RBF) neural network model with two features is presented [12]. Nonlinear components of RBF neural networks are approximated by RBF neural networks, while quantile regression methods represent the range of soybean prices. GDGA, an algorithm that combines genetic algorithms (global search) with gradient descent methods (local search), is presented to optimize QR-RBF neural network parameters. Based on China's monthly domestic soybean price

statistics, the suggested hybrid GDGA appears effective. Compared to multivariate linear regression and pure GA, the proposed hybrid GDGA algorithm outperforms forecasting and convergence. From January 2008 to December 2012, a chaotic neural network was used to predict weekly egg retail prices in China [8]. The chaotic neural network outperforms the linear in terms of nonlinear fitting and precision. In the short term, the chaotic neural network can also predict agricultural prices. In the short term, the chaotic neural network can also predict agricultural prices. Aziz et al. [3] advocated combining the Auto Regressive Moving Average (ARMA) family and an artificial neural network to anticipate CPO price. Every forecasting method has drawbacks. Such is ARIMA, which cannot be used with nonlinear time series data. A more accurate forecasting mistake in linear time series data. Worst case scenario, determining the linearity of time series data for Box-Jenkins and ANN is challenging. As a result, unreliability and predicting errors occur. Data reported at high frequencies such as daily, hourly, minutely, and second are better suited to the artificial neural network. Vegetable price forecasting uses a similar method [11]. The study by Mallikarjuna1 et al. [25] attempted to predict black pepper's price in one of Karnataka's key markets. For its size and productivity, the Gonikoppal market in the Kodagu district was selected. Prices were analyzed using the ARIMA and Autoregressive Conditional Heteroskedasticity (ARCH) models with SPSS, Gretl, and EViews. A best-forecast model was selected based on the lowest values of the Akaike information criterion (AIC) and Schwartz Bayesian Information Criterion (SBIC). Based on the lowest Root Mean Square Error (RMSE) and MAPE, they assessed the model's predictability, power, and performance. ARIMA outperformed ARCH family models in terms of prediction accuracy. The ARIMA (0,1,1) model works well for forecasting black pepper prices.

Based on the Artificial Bee Colony (ABC) Algorithm [16], this study by Wang et al. proposes a strategy using soybean and corn futures prices; three noise removal techniques were utilized in the original price series to remove external noise: SSA, Empirical Mode Decomposition (EMD), and Variational Mode Decomposition (VMD). In the second phase of the study, the researchers combined denoising techniques with five widely used forecasting algorithms: ARIMA, Support Vector Regression (SVR), RNN, GRU, and an LSTM. An ABC technique is used for three forecasting combinations: heterogeneous, semi homogeneous, and homogeneous. In tests, the semi-heterogeneous forecast combo surpasses the competition. The research by Hui Li1 et al. [21] proposes DP-MAELS, a robust forecasting paradigm for multiple global agricultural commodities futures. This project applies deep neural networks to multivariate time series data to address three significant issues. In the recurrent-skip component, short- and very long-term repetitions are combined. A certified noise injection mechanism is presented using differential privacy to increase prediction robustness and accuracy. This study shows that DP-MAELS outperforms comparisons for multivariate time series forecasting and is a viable alternative. A software tool with price predicting features was introduced in [22] by *Yuan et al.* This study analyses ARIMA, LSTM, SVR, Prophet, and XGBoost. It is then tested to find the best algorithm for a software model. Difficulty in managing large amounts of complex data is LSTM's strongest suit. Aside from forecasting, the software integrates weather, agriculture news, and third-party suppliers to provide a trading platform for farmers. Kerala areca nut prices are forecast using time-series and machine learning approaches [23]. Models included SARIMA, the Holt-Winter Seasonal Method, and the LSTM neural network. The RMSE of the areca nut price dataset from 2007 to 2017 was used to evaluate their performance. An LSTM neural network was the best model for the data.

### III. PROPOSED MODEL

To predict Black Pepper prices in Kerala and Karnataka, a univariate and multivariate model is utilized in this study. For both univariate and multivariate models, the performance of LSTM and GRU was compared. The trend and seasonality in pricing data were revealed through exploratory data analysis. The residual part of the data was eliminated using SSA. The most accurate method was determined to be multivariate LSTM, which uses macroeconomic variables. To determine the nonlinear dependence of the data points, the data was not converted to stationary. The LSTM and GRU recurrent neural networks were chosen because they could represent the nonlinear dependency of the data points. The steps for model implementation are given in Figure 1.

#### A. LSTM

LSTM is a RNN design. There are feedback connections in the LSTM. It has the ability to process completedata sequences. A cell state, an input gate, an output gate, and a forget gate make up an LSTM. The cell state stores values for arbitrary time intervals, while the other three gates regulate information flow into and out of the cell. At the forget gate, any information from the preceding time step that should be forgotten is erased. In the input gate, new data is requested. The data produced by the output gate is really useful. The architecture of LSTM is given in Figure.2. Multiple LSTM layers are stacked in a stacked LSTM architecture (Figure.3). The LSTM

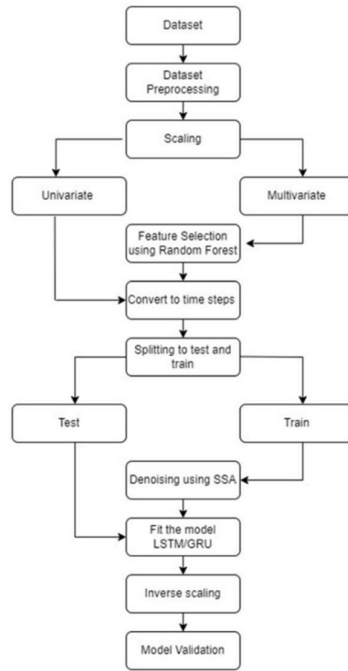


Figure. 1. Steps for Model Implementation

layer above sends a sequence of values rather than a single value to the LSTM layer below. Each input time step has its output time step, rather than one output time step for all input time steps.

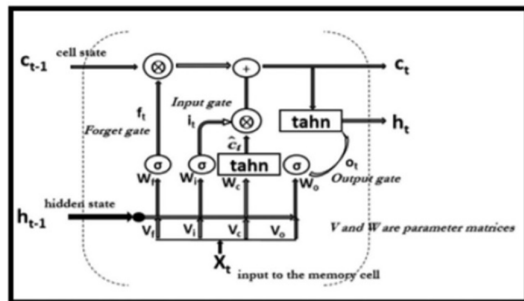


Figure. 2. LSTM cell Diagram [27]

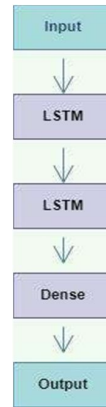


Figure. 3. Stacked LSTM

### B. GRU

Except for the operations and gates associated with each GRU unit, the Gated Recurrent Unit follows the same flow as the RNN. GRU uses two gate operating strategies to tackle the issue posed by regular RNN: Update gate and Reset gate. The update gate, which is the same as the output gate in the LSTM recurrent unit, regulates how much past knowledge should be passed on. The reset gate, similar to the Input and Forget gates of an LSTM recurrent unit, controls how much previous knowledge is forgotten. The architecture of GRU is given in Figure.4. Like a stacked LSTM, a stacked GRU architecture is a GRU with many GRU layers (Figure.5).

### C. SSA

A singular spectrum analysis is a non-parametric process for breaking down and demolishing a time series into its well-defined distinct components. Assuming that these components have a parametric structure a priori, SSA analyzes time series by separating them into explanations, such as periodic components, trend and noise.

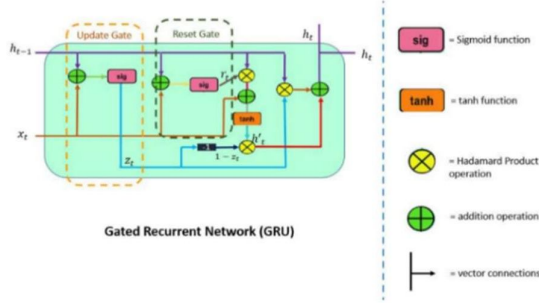


Figure. 4. GRU Cell Diagram [26]

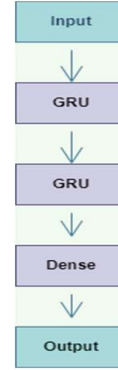


Figure.5. Stacked GRU

Consider a real time series  $X = (x_1, \dots, x_N)$  of length  $N$ . Let  $L (1 < L < N)$  be integer called the window length and  $K = N - L + 1$ . From the trajectory matrix of the series  $X$ ,

$$X = [X_1 : \dots : X_K] = (x_{ij})_{i,j=1}^{L,K}$$

Singular value decomposition (SVD) of the trajectory matrix  $X$  is performed.

$$X = \sum_{i=1}^d \sqrt{\lambda_i} U_i V_i^T \quad (2)$$

The Eigen triple of the SVD will be referred to as the collection  $\sqrt{\lambda_i}$ ,  $U_i$ ,  $V_i$ . The left singular vectors of the matrix  $X$  are  $U_i$ , and the singular values are  $\sqrt{\lambda_i}$ . The vectors  $\sqrt{\lambda_i} V_i$  are called the vectors of main components, and the rank of  $X$  is  $d$ . Reconstruct using the smoothing threshold and the relevant decompositions. Decompose the matrix diagonally by averaging ( $X_i = \sqrt{\lambda_i}$ ,  $U_i$ ,  $V_i$ ) to a series:  $\tilde{x}^k = (x_1^*, \dots, x_{T^*}^*)$ , Take the average diagonally to transfer the matrix of decomposition ( $X_i = \sqrt{\lambda_i}$ ,  $U_i$ ,  $V_i$ ) to a series:

$$x_k^* = \begin{cases} \frac{1}{k} \sum_{m=1}^k x_{m,k-m+1}^* & 1 \leq k < L^*, \\ \frac{1}{L^*} \sum_{m=1}^{L^*} x_{m,k-m+1}^* & L^* \leq k < K^*, \\ \frac{1}{T-k+1} \sum_{m=k-K^*+1}^{N-K^*+1} x_{m,k-m+1}^* & K^* < k \leq T, \end{cases} \quad (3)$$

Where  $K = T - L + 1$ ,  $L^* = \min(L, K)$  and  $K^* = \max(L, K)$ . Add the series  $\tilde{x}_1, \dots, \tilde{x}_p$ , Then, get the smoothed-out commodity futures:

$$\tilde{x}_t = \sum_{i=1}^p \tilde{x}_i \quad (4)$$

#### IV. EXPERIMENTS AND RESULTS

##### A. Data

The dataset was obtained from <https://data.gov.in>, an open government data platform. Market-wise records of Daily Black pepper prices for different varieties were present in the dataset. We chose the states' prices, Kerala and Karnataka, and the variety was as General as the other states, and varieties had fewer records. Observations from May 2002 – to August 2021 and April 2002 – to July 2021 were available for Kerala and Karnataka. The final 365 days of data were used for testing, and the rest were used for training. For the multivariate analysis, macroeconomic data, including Unemployment Rate, Interest rate, Consumer Price Index (CPI), exports rate, imports rate, debt rate, Gross Domestic Product (GDP), and foreign exchange rate, were collected for the corresponding years from the portal of Federal Reserve Economic Data (FRED). Black Pepper price and macroeconomic variables were joined using the Vertical Lookup function in excel for matching dates.

##### B. Data preprocessin

The dataset had null values for several dates. Records were not in daily wise format for the initial years. To tackle this problem, the dataset was converted to daily. The interpolation method from the panda's libraries was used to

fill in the missing values. The data set was simplified by aggregating prices for the state for the corresponding dates. For the multivariate analysis, essential features were chosen using Random Forest Regressor. Foreign exchange rate, Export rate, Import Rate, Unemployment Rate, and GDP had the higher scores and were selected for model building. Data was converted to 100 timesteps, and feature scaling was done using Minmax Scaler from the sklearn library.

### C. Exploratory Data Analysis

The rise in prices of Black Pepper with time shows that there is a growing trend but a slow decline after 2016. The presence of seasonality is also evident from these plots down the years (Figures. 6 and 7). The monthly wise price variation is plotted in the Figures. 8 and 9, respectively, for Kerala and Karnataka



Figure 6. Components of time series (Kerala)

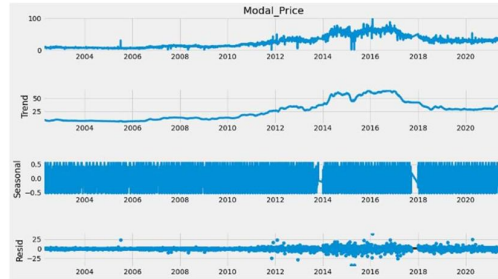


Figure 7. Components of time series (Karnataka)

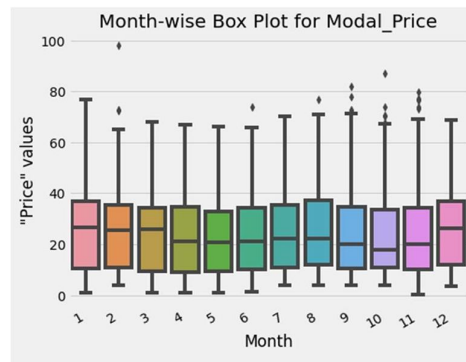


Figure 8. Monthly Black Pepper Prices in Kerala



Figure 9. Monthly Black Pepper Prices in Karnataka

### D. Denoising using SSA

SSA divides time series into three categories: trend, periodicity, and noise. It was used to eliminate noise from the records on the training set.

### E. Stationary analysis

Stationarity has been tested using the Augmented-Dicky Fuller test. A non-stationary series is a null hypothesis, while a stationary series is an alternative hypothesis. On both datasets, stationarity was rejected by the test.

### F. Model Fitting

There were two sets of data: training and testing. The test dataset contained the final 365 days of records, and the remaining were used for training

### G. LSTM and GRU models

Recurrent Neural Networks (RNN) such as LSTM and GRU can consider complicated dependencies and accommodate non-stationary data. Here, stacked LSTM and GRU are employed. Stacking hidden layers deepen the model, earning the term "deep learning" a more accurate definition. Three input layers are piled on top of one another, each with 100 hidden layers. The loss function was calculated using the mean squared error. The Adams optimizer was utilized as the optimizer. For the univariate and multivariate models, epochs were set to 30 and 50, respectively. A batch size of 32 was chosen.

## H. Results

Mean absolute error (MAE), and mean absolute percentage error (MAPE), mean squared error (MSE) were the three evaluation measures employed in model evaluation. Before comparing the predicted and actual values, inverse scaling was used. The evaluation's findings are listed below (Table 1). For both the Kerala and Karnataka datasets, multivariate LSTM produced the best results.

TABLE I. MSE, MAE, AND MAPE VALUES FOR PROPOSED MODELS

| Model Name        | MSE    |           | MAE    |           | MAPE   |           |
|-------------------|--------|-----------|--------|-----------|--------|-----------|
|                   | Kerala | Karnataka | Kerala | Karnataka | Kerala | Karnataka |
| Univariate LSTM   | 0.530  | 5.891     | 0.591  | 1.801     | 0.017  | 0.060     |
| Univariate GRU    | 2.269  | 6.708     | 1.423  | 2.128     | 0.042  | 0.067     |
| Multivariate LSTM | 0.469  | 3.383     | 0.471  | 1.102     | 0.012  | 0.040     |
| Multivariate GRU  | 1.987  | 4.681     | 1.269  | 1.893     | 0.033  | 0.045     |

## V. CONCLUSION

In agricultural markets and economies, time series forecasting is critical. Commodity price fluctuations are volatile, making intuitive decisions difficult. This research should aid Black Pepper growers and those engaged in the supply chain in increasing their earnings. Multivariate LSTMs that incorporate macroeconomic factors and are denoised with SSA provide the best accuracy score in this study. The absence of data was the only flaw in this project. With more records, LSTM tends to give even better accuracy. The relationship between macroeconomic variables and commodities prices was used to make predictions in this study. Other variables, such as climatic variables, can be utilized in the future to determine if the model can be improved.

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