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Procedia Computer Science 171 (2020) 699–708

Procedia Computer Science

www.elsevier.com/locate/procedia

Third International Conference on Computing and Network Communications (CoCoNet'19)

Predictive analytics in Agriculture: Forecasting prices of Arecanuts in Kerala

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Abstract

The fluctuations in prices of agricultural commodities have an adverse effect on the GDP of a country. The farmers are emotionally and financially affected as their years of hard work go in vain. Prediction of the prices may help the agriculture supply chain in making necessary decisions in minimizing and managing the risk of price fluctuations. As a result of the reduction in agricultural production due to unstable climatic conditions, global warming etc., predictive analytics is expected to solve the problems of the common man. Arecanut is an important crop cultivated in India, with Kerala being second in terms of production. In recent years farmers in Kerala are shifting from arecanut cultivation to other crops because of price fluctuations and climate change. In this work, the monthly prices of arecanut in Kerala are predicted using time-series and machine learning models. The models SARIMA, Holt-Winter's Seasonal method, and LSTM neural network were used, and their performance was evaluated based on the RMSE value on the arecanut dataset with prices from 2007 to 2017. LSTM neural network model was found to be the best model that fits the data.

Keywords: Predictive analytics; SARIMA; Holt-Winter's Seasonal method; LSTM; RMSE

1. Introduction

Agriculture and cultivation have been part of human civilization for centuries and is evolving with technology, giving rise to smart farms. The agriculture sector is the backbone of the economy and prosperity of a nation. India is the second-largest producer of agriculture commodities, and the agriculture sector contributes to 17.32% of the countries GDP [1], which signifies the importance of the agriculture market. The data collected can be commodity

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10.1016/j.procs.2020.04.076

prices, satellite images, coordinates of farms, etc. and with the application of IoT devices like sensors, data such as temperature, moisture, soil fertility, rainfall, etc. are generated from various fields. The analysis of these data provides valuable insights- known as Precision agriculture(PA)- that can help the farmers to increase productivity, reduce cost, restrict the use of chemical fertilizers and water, increase revenue, understand the seasonal trend demand, etc.[2], which has an impact on the agricultural market. The agriculture markets contribute a significant portion to the economic prosperity of a nation.

Analytics in the agriculture market is expected to grow because of the application of modern technology, rising population and, improved productivity. The competition among the business organizations- from the input suppliers to retailers in the supply chain is ever increasing, and analytics has provided a means for the competitors in getting ahead. FieldScripts- a prescription service for farming, owned by Monsanto, an agrochemical and agricultural biotechnology corporation in the United States - provides a farming plan based on the two-year historical field data provided by the farmers[3]. IoT (Internet of Things) has found immense application in agriculture analytics as a means for data collection. In[4], the integration of IoT devices in the agriculture farms is proposed, and based on the data produced from these devices, predictions will be made for increased crop production and control of expenses.

The quality of soil is one of the critical factors that influence the quality of the crop produced. The soil data from sensors can be used for testing soil fertility, based on which the farmers can decide on the fertilizer and the plant to seed[5]. The wheat yield from the fields in Bedfordshire, UK were predicted based on soil data and satellite images of crop growth, using Supervised Kohonen Networks[6]. The increasing global food demand, pollution, degradation of soil, etc. influence the quality and quantity of crops produced, affecting the agriculture supply chain. Understanding their influence is used for prediction, which provides the farmers, suppliers, and the government to reduce risk and make better decisions for sustainable agriculture. In [7], the grain crop yield of China was predicted using Artificial Neural Network by understanding the influence of various factors such as climate, labour, irrigation, etc. using Grey Relational Analysis(GRA). In India, Microsoft uses AI sensors that allow the farmers to make timely decisions in farming. In the villages of Telangana, Maharashtra, and Madhya Pradesh, farmers, receive automated voice calls in case of any pest attack, based on weather and crop stage[8]. The prices of crops are volatile, especially for tree crops and the crops cultivated annually. Unpredictable events such as drought and flood can affect the prices of agricultural commodities, thus affecting the entire market; the farmers, suppliers, exporters, and stakeholders face huge losses. In [9], the demand and share price of coffee in the stock market of the Indian coffee supply chain was predicted using the Weighted Moving Average model that allows the exporters and stakeholders to make timely decisions to reduce financial loss and maximize profit. The farmers are most affected in the year of a bad crop, which leads to a massive amount of debt. Based on a forecast, the insurance companies and government can support the farmers financially by providing insurance policies and loans at affordable interest rates. The prices of agricultural commodities are forecasted using various time-series, machine learning, and deep learning models.

Arecanut is an important commercial tree crop mainly cultivated in Karnataka, Tamil Nadu, Kerala, Assam, West Bengal, Meghalaya and Maharashtra[10]. Price volatility of these crops is a major issue faced by the farmers. Although there exist numerous online platforms such as *commodityonline*, that provides details of prices of arecanuts from various districts and taluks, there have not been much research and application of data analytics in fore-casting the prices of arecanuts in Kerala.

In this work, the monthly prices of arecanuts in the markets of Kerala are predicted using SARIMA, Holt-Winter's Seasonal method, and LSTM neural network. The performance of these models was evaluated for fitting the best model.

The rest of the paper is organised as follows. In Section 2, a brief review of the application of analytics and usage of time series forecasting in the agricultural domain is given. Section 3 discusses the proposed techniques. Section 4 presents the experimental setup and the results, and Section 5 concludes the paper.

2. Literature Survey

The prices of agricultural commodities such as crops, livestock, and dairy are affected by numerous factors such as climate, government policies, crop diseases, availability, etc. The prices of these commodities are volatile and can either turn for the good or bad. According to the 2018 Indian economy survey[11], agricultural employs 50% of the workforce and contributes to 17-18% of the nation's GDP, signifying the importance of agricultural markets. It is important to ensure the financial security of the agricultural supply chain for a stable economy.

Arecanut is a valuable tropical cash crop cultivated in India. Over the past few years, the prices of arecanuts had its peaks and valleys affecting the farmers and suppliers as a whole. India has the largest production of arecanut based on the FAO statistics of 2013, with Kerala and Karnataka being the leading producers in the country, in terms of area and production. Climate change and government policies have affected the production and prices of crops.

In Meghalaya, the production of arecanuts is being affected due to increase in temperature[12]. Back in 2011, the prices of arecanuts in India took a hit when the supreme court banned some of the arecanut products[13]. As a result, the farmers couldn't pay back the loan or interest. Farmers fall into huge debt, which results in increased suicide rates in the country. It is necessary to provide a solution to these price variations, as farmers are the driving force of the nation.

Understanding the price fluctuations can provide an insight for the government and organisations in taking necessary decisions for managing risk. The government can provide loans and insurance at reduced interest rates. The farmers can also take timely actions in improving the production of the crop.

The 2018 Kerala floods had affected the agricultural sector especially the arecanut plantations resulting in huge losses for the government and producers[14] and farmers in Kerala are switching from arecanut farming to various other crops because of price fluctuations and diseases[15]. Being second in terms of production, Kerala is facing a decline in Arecanut production.

Analytics are currently dominating the financial markets. Predicting price fluctuations allows the organizations to take necessary actions for ensuring economic stability. Price variation is a common phenomenon in the agricultural markets. Predictive analytics using various data mining techniques helps in understanding the trends and seasonality of the price data. The importance of data mining in agriculture for crop price prediction is discussed in [16] where the prices of different types of agricultural commodities in national and international markets were predicted using time-series models such as ARIMA, naive, exponential smoothing, etc. with better accuracy. The application of price forecasting in agriculture was discussed in [17] using exponential smoothing, ARIMA, expert judgement, econometric model and composite forecasting for predicting the prices of hogs in the US with forecasts from ARIMA models responding quickly to price variation. In [18], the prices of cocoa beans in Malaysia were predicted using exponential smoothing, ARIMA, GARCH, variation of the ARMA model based on error variance, and a hybrid ARIMA-GARCH model. The hybrid model outperformed the performance-based on RMSE, MAPE, MAE, and Theil Statistics. In [19], the prices of paddy from Punjab, West Bengal, Uttar Pradesh, Andhra Pradesh, Tamil Nadu, and India were predicted using the ARIMA model. ARIMA models were used for forecasting onion prices in Hubli of Northern Karnataka [20] and Kolhapur of Western Maharashtra [21]. Based on the forecast, the prices were expected to increase. The Box-Jenkins model was used for forecasting coriander seed prices in Rajasthan [22]. The minimum, maximum, and averages prices of arecanuts in the markets of Assam and Meghalaya were predicted using Box- Jenkins ARIMA models [23]. The proposed models were ARIMA (1, 0, 1), ARIMA (1, 1, 1), ARIMA (0, 1, 1) for the Assam markets and log ARIMA (0, 1, 1), log ARIMA (1, 0, 1) with a linear trend and a man-made intervention and log ARIMA (0, 1, 1) with a linear trend and a man-made intervention for the Meghalaya market. Machine learning models such as Artificial Neural Network (ANN), Support Vector Machine (SVM) and Relevance Vector Machines (RVM) are mostly used for forecasting non-linear time-series models. In [24], SVM is used to predict the stock price in the Indian markets. The prices of cattle, hogs, and corn were predicted in [25], using Multivariate Relevance Vector Machines (MVRVM); an extension of RVM.

ANN allows the machine to learn the fluctuations and give better forecast results. Artificial Neural Network performed better than the statistical methods- Exponential Smoothing and ARIMA model in predicting the rice exports of Thailand [26]. RNN models were also used for predicting crude oil futures [27], stock prices [28]. As the time-series data is sequential and has temporal dependence, a variant of Recurrent Neural Network, LSTM, is used. LSTM was found to be a better model in forecasting retail compared to the ARIMA model in [29]. Wheat production in Pakistan was predicted using the LSTM forecasting model [30]. A hybrid of linear and non-linear models is also extensively used. In [31], a combination of ARIMA and Elmann neural network(ENN) were used for forecasting the hog prices and canola prices in Germany. Based on research findings, machine learning models were found superior to statistical methods.

3. Proposed Techniques

In this work, a model is fit for predicting the prices of arecanuts. The performance of classical time-series models- Holt-Winter's Seasonal Method, SARIMA model- and Machine learning model- LSTM were compared for finding out the most parsimonious model. Exploratory analysis indicated the presence of trend and seasonality in the time-series data of prices. ARIMA and Holt-Winter's seasonal method is the commonly used statistical method in forecasting data with trend and seasonality. These models are capable of producing forecasts with relatively good performance. LSTM model was selected as it has the ability to capture the non-linear dependence of the data points that makes it favourable for time-series forecasting.

3.1. ARIMA

ARIMA (Auto-Regressive Integrated Moving Average) model is a variation of Box Jenkins models used for predicting or understanding stationary or non-stationary time-series data. The Box Jenkins model plays a vital role in the area of time-series analysis and forecasting. ARIMA consists of three parts- the AR part, lag-difference(integrated), and the MA part, denoted as ARIMA (p, d, q) where p is the number of AR terms, d is the order of lag difference, and q is the number of MA terms.

- AR: The forecast value will be dependent on the previously lagged value, i.e., lagged value as the predictor variable.
- Integrated: In order to make the time-series stationary, the lag difference is applied to non-stationary time- series for parameter estimation and model selection.
- MA: The predictor values are past lagged error values.

The seasonal variation model of ARIMA is the SARIMA denoted as SARIMA (p, d, q) (P, D, Q), used for data with trend and seasonality. Also, it consists of seasonal AR, seasonal lag difference, and seasonal MA terms. Here P is the number of seasonal AR terms, D is the order of seasonal lag difference, and Q is the number of seasonal MA terms.

- Seasonal AR: The values corresponding to the previous year are the predictor variables.
- Seasonal lag difference: The difference in observed value to the value in the corresponding previous year. Seasonal MA: The predictor values are error values of the previous corresponding year.

SARIMA model equation [32] is written as follows:

$$\psi(B_h)\psi(B)\nabla_D^H \nabla_d X_t = \alpha + \theta(B_h)\theta(B)Z_t \tag{1}$$

3.2. Holt-Winter Seasonal Method

Holt-Winter Seasonal Method is one of the variation of Exponential Smoothing used for seasonal data. It consists of a forecast equation(Eq.2) and three smoothing equations:

$$y_{T+h|T} = l_t + hb_t + s_{t+h-m(k+1)} \tag{2}$$

- Trend

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \tag{3}$$

- Seasonal

$$l_t = \alpha y_t + (1-\alpha)(l_t - 1 + b_t - 1) \tag{4}$$

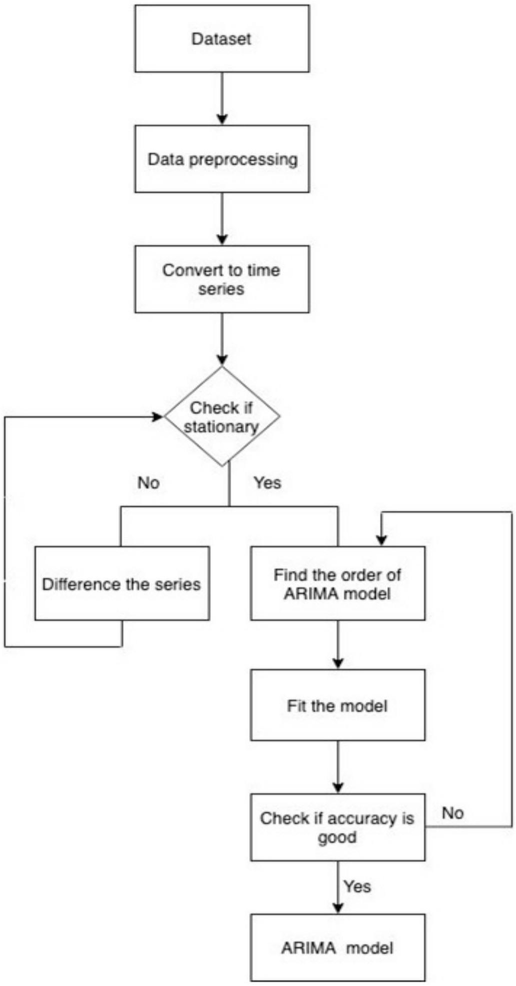


Fig. 1: *Steps for Box-Jenkins model selection*

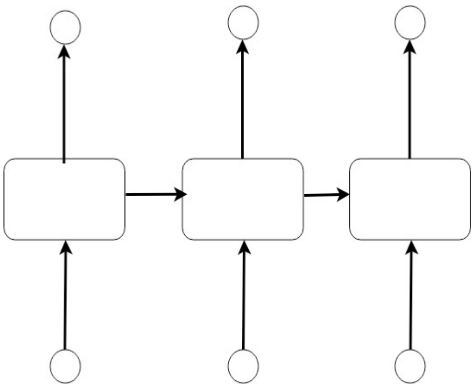
- Level

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m} \tag{5}$$

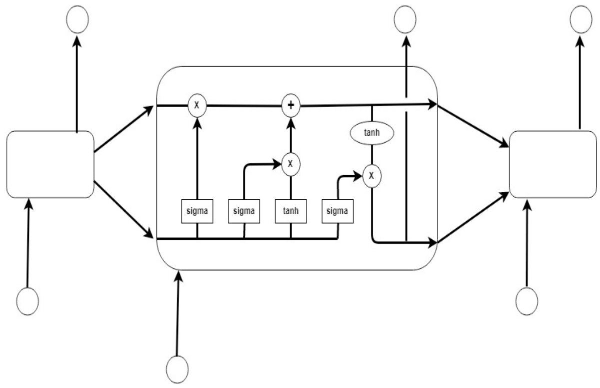
3.3. LSTM

Deep learning model-LSTM was the machine learning model used for forecasting. The long-term temporal dependence is an important aspect to be considered in a time series data. Although there exists several other feedforward control neural network and machine learning models such as Elmann Neural Network, Support Vector Machine, etc. for time series forecasting, feedback control network are found to be useful as they have a memory state for considering the correlation in lagged values.Since RNN can use sequence data as input, it is very much useful for time series forecasting.

The main drawback of traditional RNN is the vanishing gradient problem where the gradient diminishes and finally becomes close to zero[33]. This problem is overcome using the LSTM network model;a type of RNN, which has a memory and forget cell. LSTM consists of read, write and delete operation using different cells in the hidden layers enabled by the three gates: input gate, output gate and forget gate. The information passes from one layer to another through the *cell state*. The first step is to allow necessary information to pass through the cell state using the forget gate. The forget gate consists of a sigmoid layer and a point-wise multiplication. As the sigmoid function outputs values between 0 and 1, the relevant information are kept if the value is 1 and removed if the value is 0. The update state allows new information to be added using the tanh layer, which creates new set of values for updation and a sigmoid layer decides the values that require updation. Now the new cell state is the combination of the forget and update state. The sigmoid layer in the output state determines the information in the new cell state- normalized using the tanh layer- that are necessary for output.



(a) Simple RNN



(b) LSTM

Fig. 2: RNN and LSTM model

4. Experimental Setup and Performance Analysis

4.1. Data

The dataset was obtained from the Department of Economics and Statistics, Kerala. It consisted of the monthly price of arecanuts from 14 districts in Kerala for the period 2007-2017. Observations from 2007-2016 were used as the training set, and the values from 2017 were used for testing. Since the amount of data available was limited, it was not possible to allocate data-points for validation set as it would affect learning.

4.1.1. Data preprocessing

The dataset contained missing values for most of the districts. For districts having missing values less than 50%, the linear interpolation method was used. Wayanad district had the most number of missing values, which resulted in data inconsistency. These missing values were filled using the multiple linear regression method. The predictor variables were selected using the correlogram, a plot that consists of correlation between the predictor and forecast variable. Districts having a correlation greater than or equal to 0.7 were selected as the predictor variable. The dataset was simplified by taking the average of district-wise monthly data. The price of arecanuts is per 100 numbers. Forecasting was done using ARIMA and Holt-Winter Seasonal method, and their performances were compared.

4.1.2. Exploratory analysis

The increase in prices of arecanuts with time in Fig. 4., indicates the presence of an increasing trend, and the presence of seasonality is indicated from the box plot in Fig. 5., with the prices increasing and decreasing during particular months. The scalloped shape and slow decrease in the ACF plot in Fig. 6. confirms the presence of both seasonality and trend in the series.

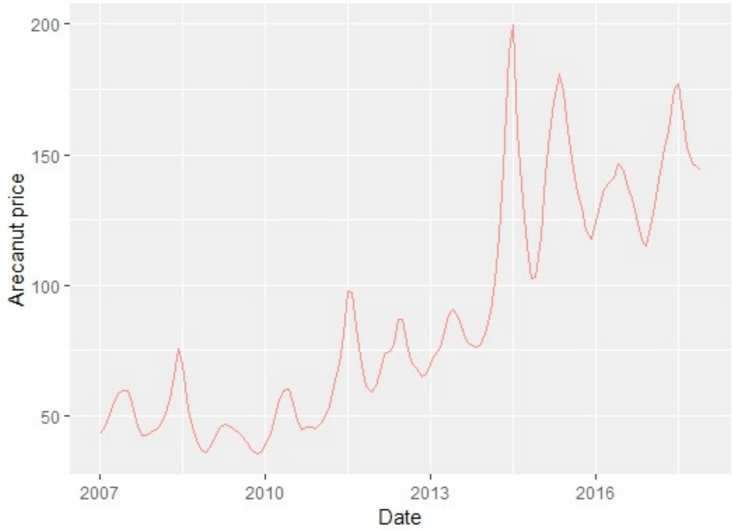


Fig. 3: *Monthly prices of arecanuts from 2007-2017*

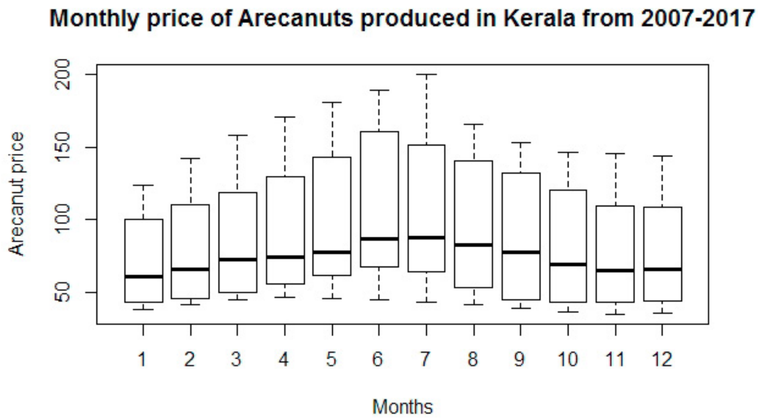


Fig. 4: *Box plot of Monthly prices*

4.1.3. Stationary analysis

Augmented-Dickey Fuller test was used to check the stationarity. It is a hypothesis test in which the null hypothesis is that the series is non-stationary, and the alternate hypothesis is set to series is stationary. Based on the test, the p-value was found to be 0.1644, the alternate hypothesis implying the stationarity is rejected.

4.2. Model Fitting

The dataset was divided into training and test set. The training set consisted of 120 observations and the observations from the year 2017 was taken as the test set.

4.2.1. Time-Series model

Classical time-series models, SARIMA, and Holt-Winter Seasonal Method were used for forecasting the prices of arecanuts. SARIMA (1,0,0) (0,1,2) was fit based on the AIC, BIC and AICc values.

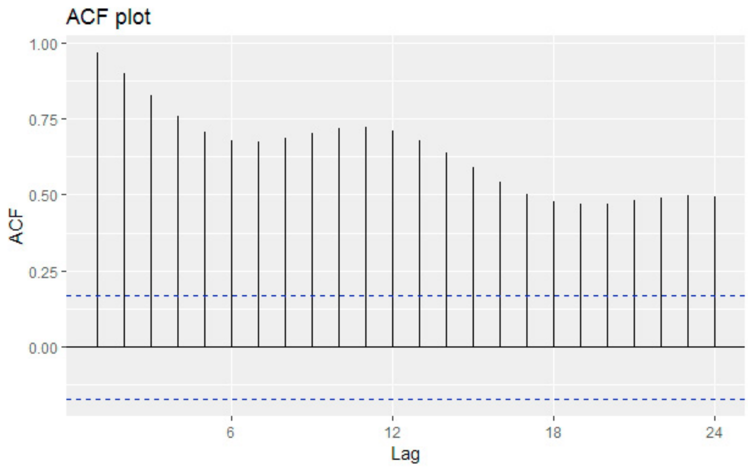


Fig. 5: *ACF plot*

4.2.2. Machine-Learning model

LSTM model was used for the prediction of prices with seasonality. As LSTM is able to consider the complex temporal dependence , the model was fit for stationary and non-stationary data . Their performance were compared based on RMSE value. A lag difference of one was used to make the series stationary and the data was scaled to the range of -1 to 1. A quadratic cost function with Adam optimization algorithm was found to produce better results. Table 1. shows that LSTM model performed well on stationary data.

Table 1: Performance Evaluation of LSTM models

Model	RMSE
LSTM(Non-stationary data)	146.8620
LSTM(Stationary data)	7.2780

4.3. Performance Analysis

Based on the results in Table 2, it can be concluded that LSTM is the most parsimonious model that fit the data for predicting the price of arecanut in Kerala. The expected and predicted values in the test set show much less deviation in Table 3

Table 2: Performance Evaluation

Model	RMSE
SARIMA (1,0,0)(0,1,2)	16.5475
Holt-Winter's Seasonal Method	18.0589
LSTM(Stationary data)	7.2780

5. Conclusive Remarks

Time series forecasting plays a vital role in the agricultural markets. The volatility in the prices of commodities makes it hard to take timely decisions based on intuition. Based on this work the judgements can me made with

Table 3: Expected v/s Forecast values

Month	Actual	Predicted
January	116.62	122.2
February	131.55	130.48
March	134.42	143.11
April	157.76	152.41
May	151.39	159.55
June	157.39	174.91
July	189.15	177.34
August	165.53	165.23
September	153.88	153.12
October	147.57	146.62
November	140.39	145.37
December	146.61	143.94

support for a better economic outcome. As Kerala is second in terms of production of arecanuts, the work will help the arecanut producers in managing their resources for better production of crops with maximum profit based on the forecast of prices. Based on a number of previous works, statistical methods were dominating in predicting the variation of prices. But in this work, LSTM was found to be a better model in forecasting the prices of arecanuts in Kerala. The one drawback will be the lack of data available for training as LSTM is a deep learning algorithm that requires a lot of data.

Acknowledgements

We extend our sincere gratitude to the Department of Economics and Statistics, Kerala for providing the dataset

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