Agri Watch: Predictive Surveillance for Floral Product Demand and Price Analysis

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Abstract - Farmers play the most important role in agriculture. Farmers face immense losses after harvesting due to falling in price. GDP of a country's is affected the price fluctuations of agricultural products. Flower price & demand estimation and evaluation are done to take an intelligent decision on a specific type of a flower. Predicting the price of a flower will help in taking better decisions which results in minimizing the loss and managing the risk of price fluctuations. In this paper, the price and demand of different flowers are predicted by analysing the previous WPI (Wholesale Price Index) data. The research combines historical price data, demand patterns, and various socio-economic and environmental factors to develop a robust forecasting model. Time series analysis, machine learning techniques, and econometric models are employed to predict future prices and demand for flowers, taking into consideration seasonality, festivals, and other relevant variables. In this research paper the algorithm that are used is LSTM (Long Short-Term Memory) to analyze the previous data and predict the price and demand for the latest data and forecast the price with demand.

Keywords: Predicting price, Time Series Analysis, Machine Learning, LSTM, Forecast.

I. INTRODUCTION

India, known for its agricultural prominence with over 54% relying on farming, confronts significant challenges. The primary sector of the economy heavily depends on agriculture, where farmers grapple with substantial losses from market overstock, climate change, and unproductive land. Strategic price forecasting becomes imperative for inventory management, aiding in optimizing sales for enhanced profits and mitigated losses[9]. Traditionally, farmers relied on experiential knowledge of specific crops for price predictions [2], a practice now undergoing transformation. Assume that we have access to historical data that includes a variety of corresponding price predictions that are recorded. These price predictions are then utilized to categorize price predictions that are made in the future. Farmers also benefit from price forecasting [6], as their production[18] and marketing decisions are based on anticipated prices that could have an impact on their finances months down the road.

In India, floral products have long been valued for their cultural, artistic, and commercial significance[13][16]. A thriving and dynamic floral industry has been facilitated by the nation's varied environment and rich heritage of using flowers for religious events, décor, and personal adornment. In order to shed light on the factors driving this industry, this research paper aims to investigate the intricate relationship between demand and price forecast for floral items.

The floral industry in India produces a wide variety of goods, such as potted plants, garlands, and cut flowers. These goods are used for everything from religious rites to decorative decorations, and a wide range of factors, including cultural customs, seasonal changes, agricultural practices, and financial situations, have an impact on the market for these products.

Flower producers, wholesalers, retailers, and consumers must all comprehend the dynamics of demand and price prediction [7] in the Indian floral sector. Precise prediction can aid farmers in making well-informed choices about pricing, distribution, and cultivation, eventually maximizing the use of resources and competitiveness in the market. This prediction employs machine learning techniques [8] and is based on data gathered from market and government sources. Forecasts are derived from past demand patterns and additional variables that will become available in the future. Predictive analysis's main objective is to help farmers forecast pricing[4], demand[3], and how these factors will affect production[17] in the near future.

Time series prediction is the practice of projecting future values of a time-dependent variable based on historical observations by employing statistical or machine learning models. Stated differently, time series prediction is the process of predicting future values of a variable by analyzing past patterns and trends in a time series dataset, such as sales figures, weather data, or stock prices.

Simple statistical approaches like moving averages and exponential smoothing can be used to create time series prediction models, or more sophisticated machine learning methods like neural networks or LSTM. To produce precise forecasts, these models account for seasonality, trends, and other patterns that are present in time series data. Numerous applications, such as demand forecasting, financial forecasting, and predictive maintenance, use time series prediction.

II. LITERARY REVIEW

The goal of recent research on the subject of demand and flower price prediction has been to create data-driven methods for projecting flower prices and their changes in the future

1. “Crop Price Prediction Using Machine Learning Techniques” [1] – In this research paper, discuses the forecasted price of various crops through an analysis of historical rainfall and Wholesale Price Index (WPI) data. We employed Time Series Analysis to estimate the crop price for the upcoming months, Decision Tree Regressor and Random Forest, a Supervised machine learning algorithm, to analyze the historical data.

2. “Machine Learning for demand forecasting in physical internet: a case study of agricultural products “[3]. This research proposes the use of a Long Short-Term Memory (LSTM) for physical internet supply chain network demand forecasting. To automate the tuning of the LSTM hyperparameters, a hybrid genetic algorithm and scatter search approach is presented.

3.“Flowers Sale Prediction Using Machine Learning” [7] - The primary objective of the system is to analyse upcoming flower market sales and forecast whether they will rise or fall using a variety of machine learning techniques, including Decision Trees and Gradient Boosted.

4 “Crop Price Prediction System using Machine learning Algorithms” – The aim of paper is to predict the crop price for the next rotation. This work is based on finding suitable data models that helps in achieving the price prediction of the crop.

5. ”Machine Learning Techniques for Forecasting Agricultural Prices: A case of brinjal in Odisha [6], IndiaForecasting prices for perishable crops, such as vegetables, is important for farmers, traders, and consumers alike. A timely and precise price forecast enables farmers to sell their produce at competitive prices by allowing them to choose amongst other neighboring markets. The data can be used by the farmers to make decisions about when to start marketing.

6. ”Deep learning for crop yield prediction”[9] – This paper discuses an overview of the state-of-the-art application of deep learning in the crop yield prediction.

Though the CNN is the most common algorithm and it has the best performance in terms of Root Mean Square Error.

7. “An ARIMA-LSTM model for predicting volatile agricultural price series with random forest technique” [10]. In this article, focus has been made on presenting a machine learning algorithm with special attention to deep learning model in form of a potential alternative to statistical models such as Autoregressive Integrated Moving Average (ARIMA) and ARIMA-Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models. This types of models were applied to predict the volatile monthly price of multiple pulse namely gram, moong, urad.

8. “Memory based Neural Network for Cumin Price Forecasting in Gujarat” [11] - In an ambitious bid to enhance cumin price estimation, this research emphasizes the pivotal role of deep learning models and time series forecasting, surpassing limitations posed by traditional statistical methods. For a comprehensive prediction spanning the entirety of 2022 (365 days), cutting-edge deep learning techniques—Deep Neural Network (DNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—take center stage, promising a paradigm shift in accuracy and overcoming conventional drawbacks

9.“Long Short-Term Memory Model Based Agriculture Commodity Price Prediction Application”[12] This paper introduces a novel software application integrating price forecasting capabilities, aiming to empower farmers with enhanced market insights for maximizing agricultural profits. By exploring diverse machine learning algorithms, including ARIMA, LSTM, SVR, Prophet, and XGBoost, the research conducts experiments to pinpoint the most optimal model for the software. Notably, LSTM emerges as the frontrunner, showcasing superior accuracy and efficiency, particularly adept at handling intricate and expanding datasets, as evidenced by the MSE results.

III. METHODOLOGY

Machine learning, in straightforward terms, is a data analysis technique that automates the creation of analytical models.

3.1 Data Collection

Data collection is the structured approach of collecting and measuring information about variables of interest.This crucial phase lays the foundation for research, analysis, and decision-making across various domains. It involves the careful acquisition of raw, relevant data to derive meaningful insights and support informed conclusions.
Methods of data collection vary widely, encompassing both quantitative and qualitative approaches. Quantitative methods involve numerical data, often obtained through surveys, experiments, or existing records. Qualitative methods, on the other hand, investigate into the richness of non-numerical information through techniques such as interviews, focus groups, or observations

The data that has been required for this research AGRI WATCH has been collected by surveying and meeting the intermediator for the farmers, that they have the lots of historical data’s of floral selling price and stock in the market Fig. No. 1 Data Collection represents the data that has been collected.

The data’s that contains the features of ‘Date, Season, Festival, Average rainfall of the month, Minimum price per kg, Maximum price per kg, Minimum demand in tons and Maximum demand in tons’. This are data’s that has been collected from the intermediator.

3.2 Importing Libraries and Dataset

In the initial stage, diverse libraries are imported, facilitating feature extraction, data analysis, and model building. This crucial step lays the foundation for robust and effective processes in the subsequent stages. Pandas and NumPy are installed in the Jupyter Notebook which are useful while accessing the data frame from the external environment. Matplotlib and Seaborn libraries are installed for visualisations.

SI.NO	DATE	SEASON	FESTIVAL	AVG RAINFALL	MIN PRICE/KG	MAX PRICE/KG	MIN DEMAND IN TONS	MAX DEMAND IN TONS
1	01-04-2022	Summer	yes	0.25	310	350	0.2	0.5
2	02-04-2022	Summer	yes	0.25	260	300	0.2	0.4
3	03-04-2022	Summer	no	0.25	290	330	0.2	0.4
4	04-04-2022	Summer	no	0.25	260	300	0.2	0.4
5	05-04-2022	Summer	no	0.25	310	350	0.2	0.4

Fig.No. 1 Data Collection & importing dataset

3.3 Data Preprocessing

Data preprocessing is a critical phase in the realm of data mining, playing a pivotal role in ensuring optimal performance and enhancing the overall quality of outcomes, particularly in the context of machine learning projects. The adage "garbage in, garbage out" resonates strongly in this domain, underscoring the significance of refining and preparing data before subjecting it to analysis. In the data mining and machine learning data-gathering methods often lack stringent controls, leading to issues like out-of-range values improbable data combinations, and the presence of missing values. Analyzing unscrutinized data can yield misleading results, emphasizing the paramount importance of meticulous data preprocessing. This phase is especially critical in computational biology, where the abundance of irrelevant, redundant, or noisy information can impede knowledge discovery during the training phase.

3.3.1 Data loading and Cleaning

Data preprocessing encompasses a spectrum of techniques, including cleaning, instance selection, normalization, one-hot encoding, transformation, and feature extraction and selection. These methods collectively contribute to refining the raw data into a final, optimized training set. The data cleaning process has been handled by using pandas library in the data set the variable “DATE” that is in the type of time format (DD/MM/YYYY) that variable is splitted, into three variable’s they are day, month and year.

3.3.2 Handling categorical variables

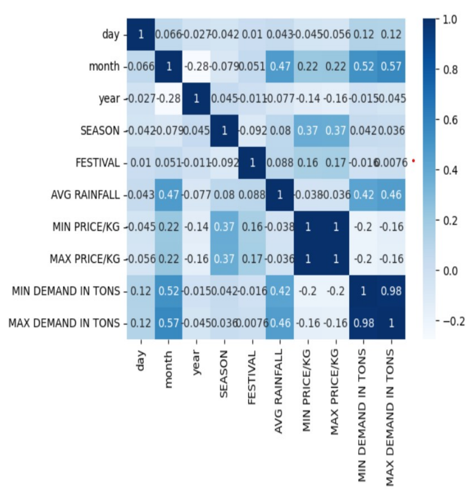
In the dataset the "Season" variable contains categorical values they are "summer, winter, monsoon, Autumn" this value has been handled by using the label encoder algorithm that converts the string values into numerical values. And the "Festival" variable contains the string values of yes and no, it is also converted into numeric value by using label encoder. After converting all the data types into integer, they are scaled between (0,1) using Min Max Scaler algorithm in machine learning. It scales the values without changing the shape of the original distribution of the dataset. More over, beyond its impact on analysis, data preprocessing also plays a pivotal role in addressing bias and ensuring fairness in machine learning models. By carefully preparing and filtering data, practitioners can mitigate potential biases, fostering a more equitable and reliable model. In essence, data preprocessing stands as the cornerstone of any successful machine learning endeavor, wielding the power to transform raw, disparate data into a refined and reliable foundation for knowledge discovery and model development.

	day	month	year	SEASON	FESTIVAL	AVG RAINFALL	MIN PRICE/KG	MAX PRICE/KG	MIN DEMAND IN TONS	MAX DEMAND IN TONS
0	1	4	2022	1	1	0.25	310	350	0.2	0.5
1	2	4	2022	1	1	0.25	260	300	0.2	0.4
2	3	4	2022	1	0	0.25	290	330	0.2	0.4
3	4	4	2022	1	0	0.25	260	300	0.2	0.4
4	5	4	2022	1	0	0.25	310	350	0.2	0.4

Fig.No 2. Data Preprocessing

3.4 Feature Engineering

Only the training dataset is used to perform data analysis. First, the correlation between Independent and dependent attributes is found out by using heatmap which is present in the seaborn library. Fig. No.3 displays the results obtained in the form of data visualisation using heatmap. This map describes the variables that how they are correlated. By using heatmap the features were selected to do further process. Some of the features has been dropped to build a effective machine learning model for the forecasting process. Model has been trained by selected features that are "day, month, year, festival, minimum price, maximum price, minimum demand, maximum demand". Feature engineering serves as a pivotal step in the realm of machine learning, acting as the transformative process that turns raw data into refined features suitable for



mod el training. In essence, it encompasses the art of selecting, extracting, and transforming pertinent features from the dataset, aiming to construct machine learning models that exhibit heightened accuracy and efficiency.

Fig.No 3. Correlation between Independent and dependent variables

3.4.1 Scaling the data

After completing the process of feature selection, they are scaled between (0,1) using Min Max Scaler algorithm in machine learning. It scales the values without changing the shape of the original distribution of the dataset. Incorporating features with diverse magnitudes and ranges results in varying step sizes for each feature during gradient descent. Ensuring smoother and quicker convergence requires careful consideration of feature scaling in the optimization process.

3.4.2 Train-Test Split

The scaled data that are splitted to train the model. It can be used for regression problems and can be used for any supervised learning algorithm.This crucial step sets the foundation for tasks such as training and testing, enabling effective model evaluation and validation.75% of the data was separated into a training dataset x_train, y_train and 25% was split into a testing dataset as x_test and y_test.

3.5 Model Selection

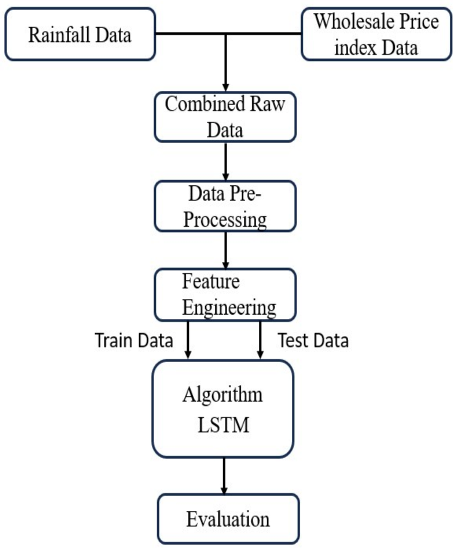


Fig.No 4. System Architecture

Following the data pre-processing step, this section presents the forecasting process with an LSTM recurrent neural network(RNN) and existing machine learning models[18]. The models were applied to the data generated for commodity floral products. The dataset for crop comprised input variables (X) and predicted outputs (Y).

The predictive of models hinges on input variables like historical daily demand and unit prices. This intricate interplay culminates in the forecasted output for the upcoming period, forming a nexus of data-driven insights to navigate the complexities of market fluctuations.

3.5.1 LSTM

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture used in the field of deep learning. It is particularly adept at handling sequential data as time series. Diverging from conventional RNNs, LSTMs incorporate feedback connections enabling the processing of entire data sequences, surpassing the limitation of handling individual data points. This distinctive feature enhances comprehensive data analysis.

The LSTM[20] algorithm makes them highly effective in understanding and predicting patterns in sequential data. LSTMs are used for time series forecasting tasks, such as predicting prices, and demand . They can learn patterns in historical data and use them to make predictions about future events.

1. $f_t = \sigma\ (W_f\ .\ [h_{t-1},\ x_t] + b_f)$
2. $i_t = \sigma\ (W_i\ .\ [h_{t-1},\ x_t] + b_i)$
3. $c_t = \tanh\ (W_c\ .\ [h_{t-1},\ x_t] + b_C\ )$
4. $o_t = \sigma\ (W_o\ .\ [h_{t-1},\ x_t]+b_o)$
5. $h_t = o_t * \tanh\ (C_t)$

6. $\mathrm{relu}(x) = \max(0, x)$

Here
X_t -- is the input at time step t,
h_{t-1} -- is the hidden state from the previous time step,
σ -- denotes the sigmoid activation function, and
tanh -- is the hyperbolic tangent activation function.
W_f -- is the weight for the input gate
b_f -- is the bias for the input gate
i_t -- is the input gate activation function
c_t -- is the cell state at time step
o_t -- it is the output gate activation at time step

First of all to train the LSTM model, some of the python libraries should be imported. They are,

1. Sequential
2. Dense
3. Dropout
4. LSTM

These libraries were imported from the Keras module.
Creating an instance of the sequential and assigns it to a variable named 'Model'. This creates an empty model with no layers. The first layer is an LSTM layer with the number of units, adding a activation function called rectified linear unit (ReLU), this activation function activates the neurons in the network that has to be passed to the next layer. The return_sequences argument set to 'True', this means that the layer will output a sequence of vectors instead of a single vector. The 'input_shape' argument specifies the shape of the input data, in this case the time step has been take as 60.

The LSTM model has defined and compiles with an optimizer and a loss function called 'Adam' and 'mse' respectively. The optimizer argument specifies the optimization algorithm to use, and the loss argument specifies the loss function to minimize. In this case, the Adam optimizer is used with a mean squared (MSE) loss function. After creating a successful machine learning model, the scaled values are transformed into inverse transform, so that the original values can be returned.

IV.RESULTS AND INFERENCES

Floral prices and demand are influenced by a variety of factors, including seasonal trends, special events, consumer preferences, and economic conditions. By understanding these factors, farmers can make informed decisions about pricing strategies, and production planning. To make informed decisions by farmers the model has been created by using the algorithm LSTM (Long Short-Term Memory).

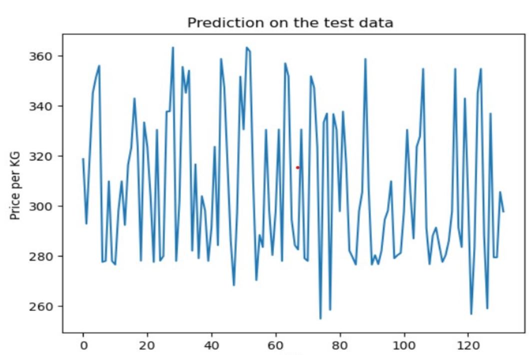


Fig.No 5. Predicted price

Captures complex patterns: LSTMs excel at identifying and leveraging long-term dependencies in data, making them suitable for capturing complex trends and seasonality. Handles non-linear relationships: Unlike traditional statistical methods, LSTMs can learn non-linear relationships between variables, leading to more accurate forecasts. Good for diverse data: LSTMs can handle various data types, including numerical, categorical, and even text data. LSTM algorithm has a mean absolute error **0.0310**, Coefficient of determination, also called as root mean square error score is used to evaluate the performance of a regression model. It refers to the extent of predictability in the output dependent attribute based on the input independent variable(s). This measure quantifies the proportion of variability captured by the model. A higher value of root mean square error is desirable as it indicates better results. The model built gives R^2 value of **0.1761**.

V. CONCLUSION

AGRI WATCH is a predictive surveillance system designed to analyze pricing and demand for floral products. It gives growers, distributors, and retailers insights into flower market trends by combining machine learning with real-time data collection. AGRI WATCH is able to assist farmers in making more informed judgments regarding marketing, pricing, and inventory control. The goal of the study is to forecast the demand for and price of the specified floral products. The training datasets so acquired offer sufficient information to forecast market prices and demand. As a result, the system assists farmers in reducing their challenges and discourages them from attempting large losses. In this paper, a prediction sales system is proposed. By utilizing both historical and present sales data for training and testing the algorithm, we integrated two widely used forecasting models and added other features to the trigger model. All in all, we were able to forecast data more accurately than we could have by just looking at the algorithms.

In the future, the system's accuracy can be increased by utilizing other datasets and advanced forecasting techniques and algorithms. The system can predict sales of flowers based on factors in the market.

VI.FUTURE WORKS

1. **Expand market coverage:** Extend AGRI WATCH's coverage to a wider range of floral products and geographies, providing insights into global floral market trends and enabling businesses to make informed decisions across diverse markets.

2. **Personalize recommendations:** Develop personalized recommendations for growers, wholesalers, and retailers based on their specific needs, market conditions, and customer preferences.

3. **Integrate with supply chain management**: Integrate AGRI WATCH with supply chain management systems to optimize inventory management, logistics, and distribution, ensuring optimal product availability and minimizing waste

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