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AI and Machine Learning Approaches for Price Forecasting of Pulses and Vegetable Commodities

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Abstract: The fluctuation of prices in agri-horti products, such as pulses and major vegetables like onion, potato, and tomato, creates major hurdles for farmers, traders, administrators, and even consumers. In conventional practices, the forecast techniques fail to identify the intricate patterns of the market, which get affected by seasonality, weather patterns, deficiencies in supply-demand, transportation, and market arrivals. The proposed study focuses on the development of reliable AI-ML based predictive systems having the potential for accurate forecast predictions of prices of commodities. Based on historical prices, market arrivals, climate, and trends, machine learning algorithms such as Random Forest, L-STMS, ARIMA, and XGBoost can be used for predicting prices in the short-term and long-term periods.

Keywords: Price Prediction, Machine Learning, Random Forest, XGBoost, Agriculture.

1 INTRODUCTION

Despite advancements in technology, agricultural sectors are still an essential part of the economy of developing nations, as it gives livelihood to a significant population and also takes care of the food security of the people. In the agriculture products, agricultural and horticultural products such as pulses and vegetables including potato, onion, and tomatoes hold a significant place with respect to their consumption, balance diet, and economy as well. But the prices of such products vary rapidly in accordance with a variety of reasons such as seasonality, weather changes, market arrivals, lack of storage capacity, government policies, and changes in the demands and supplies [1]. Vegetable and legume price fluctuations entail many other problems. The main impact on farmers is the fragility of price earnings and the increasing trend of distress sales during peak seasons. The main impact on consumers is high inflation resulting from abrupt price rise and limited accessibility of vital products. The main impact on policy-makers is market regulation and import/export management concerning unclear price trends or models. The simple methods utilized within traditional models for approximating price trends using minimum statistical averages or simple trend lines fail to describe the complexities associated with agricultural markets [2].

Conventional models of forecasting, including moving averages and regression models, lack the capability to analyze the dynamics among the several influencing factors. Conventional models assume a linear relationship, which is also stationary, whereas, in practical agricultural market data, the data is largely non-stationary. Agricultural markets have a large number of influencing factors that could be non-stationary, seasonal, or multivariate. Factors could include trends in rainfall, variations in temperatures, infestations, fuel prices, among others [3]. The fast pace of development in Artificial Intelligence (AI) and Machine Learning (ML) holds a great promise to address these challenges. The AI-ML approaches perform very efficiently in identifying the intricate, non-linear patterns present in historical data and learn from it to adapt to the trends that are changing over time. The historical price series and the other secondary inputs including the arrival of market participants and the climatic variables, by using the insights from the Machine Learning models, allow performing superior price predictions [2].

The proposed research work involves the development of predictive models using AI-ML for predicting prices of some major agricultural commodities like pulses and vegetables like potatoes, onions, and tomatoes. The objective of choosing these commodities is based on their regular consumption levels in society, which play an important role in influencing rural as well as urban economies. The work focuses on developing an AI-ML model to provide short-term as well as long-term predictive prices. This approach utilizes the price data gathered from the agricultural markets in the past, as well as secondary data such as market entry data, weather variables, and seasonal information. Various techniques of machine learning as well as time series algorithms, namely Random Forest, XGBoost, ARIMA, and Long Short-Term Memory (LSTM) Neural network, are applied in order to determine which one can give more accurate predictions of the prices [4][5].

These techniques all provide unique advantages, namely ARIMA for handling linear trends in the data, RF/XGB for handling nonlinear regressions, as well as LSTMs for handling long-term trends. One of the main aims of this research are to compare the level of performance between classical models and those driven by the latest AI technology. While the research will test the models using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and accuracy, the research will be able to identify the models capable of producing consistent predictions with respect to the various commodities. The difference in the various commodities will enable the model to generalize [6]-[8].

Correct prediction of prices is extremely useful. Farmers can rely on the forecast for the best time to sell or store their farm products for better prices. Businessmen can arrange their logistics activities in a better way. The government can prepare for the hikes in prices, taking appropriate actions like distributing them from the market or importing. Consumers will have the benefit of stability in prices along with controlled inflation. The proposed system has scalability and adaptability capabilities that ensure it can be easily interfaced with digital agricultural platforms, agricultural advisories, and market intelligence systems of the government. This allows the system to be updated from time to time based on changes in the market system, which plays a vital role due to the current changes brought by climate change.

2 Literature Survey

The methods developed in agricultural price forecast studies began with conventional statistical models and advanced to more complex models as the scenario in agricultural markets became more intricate. The initial models used in agricultural price forecast studies include conventional time series methods like moving averages, exponential smoothing, and linear regression models. Even though those models were computationally less expensive and easier to understand, they had the drawback of assuming linear and stationary property in price variations. The literature clearly indicates that such properties are not observed in agri-horticultural commodities, as their price structures get influenced by seasonal production patterns, climatic variance, supply chain bottlenecks, and government interventions. Hence, such models anticipated unreliable results in intensely varying markets.

Later studies proposed Autoregressive Integrated Moving Average (ARIMA) models that offered some improvements over the earlier models in that ARIMA models took into account the time series nature of the data [9]. The SARIMA (seasonal ARIMA) models that were proposed can be used to predict the prices of vegetables such as onions and potatoes. The models showed a moderate level of accuracy when predicting prices over a short period of time. Nevertheless, these models had difficulty when exogenous variables such as rainfall or temperature were used. This was especially the case when the markets showed nonlinearity.

To address these issues, some researchers focused on multivariate models of statistics and economics, such as Vector Autoregression (VAR) and cointegration analysis. They aimed at identifying the links between several elements of the commodity markets [3]. Although these approaches were helpful for policymakers, they tended to make strong assumptions, often about the availability of adequate data. Researchers seemed to agree on the problem of dealing with these approaches for agricultural commodity markets, which do not always provide acceptable or consistent data. The increased availability of agricultural data and computational power enabled the application of machine learning algorithms for predictions. The effectiveness of various ML algorithms such as Decision Trees, Random Forest, SVR, and k-Nearest Neighbors for recognizing non-linear correlations between the variables and the target prices was explored and found to be better than the conventional approaches. Vegetable price forecasting was explored using Random Forest algorithms that produced better prediction accuracies after discovering non-linear correlations between the variables.

Recently, the importance of ensemble learning techniques, especially Gradient Boosting and XGBoost, for accurate agricultural produce price forecasting has received emphasis in the recent literature. The process of these techniques strives to optimize the forecasting accuracy by concentrating on the residuals or errors generated in the former iteration [7]. The comparative study of the performance of ensemble techniques against ARIMA and Linear Regression has shown the excellence of the former, especially when the prices are un Stable. The capabilities of the latter have been hailed in the recent literature. Another area of focus would be the application of Deep Learning algorithms, such as the Recurrent Neural Network (RNN) and the Long Short-Term Memory Network. These networks are highly suitable while dealing with time-series values since they are capable of handling long-term dependencies. The literature study related to onion and tomato price forecast shows that the forecast accuracy of LSTMs outshines both ARIMA and classical Machine Learning models. This model can adjust according to the changing market patterns using the historical values.

Some researches also consider climatic and environmental factors for the price forecasting models. It has been seen that rainfall, temperatures, humidity, and natural disasters impact crop production, which further affects market prices [10]. The integration of weather factors with prices helps generate accurate forecasts, especially for vegetables that are more susceptible to environmental factors. Machine learning algorithms perform extremely well for such diverse sources. Data regarding market arrivals, as well as supply-side factors, have also been extensively researched. It is observed that a sudden rise in market arrivals inside the harvest period can cause a drop in prices, while a shortage of supply causes a rise in prices. Arrivals models, which consider the quantities of arrivals as features, perform better compared to models that use past prices.

Government policies and economic-related factors are also being studied. These include government policies such as minimum support prices, export bans, and import duties, along with the influence of buffer stock releases on market prices. Although it's difficult to accurately measure the influence of these factors, with increased research, these government policies are being considered through proxy variables or event-based variables in ML models [11]. It has been identified in research that flexible models such as AI-based are more effective in coping with these external influences rather than traditional models. Although there have been many breakthroughs, the literature highlights a number of challenges. There have been many research works conducted on a given commodity or a given market. Furthermore, the data considered in a number of works have been short, failing to consider long-term developments. Data quality, missing data, and data inconsistencies have been significant challenges even within markets. Being able to interpret the outcome has been a problem, especially when complex techniques such as deep learning are involved.

There is complete support in the literature to use AI-ML approaches and techniques in agricultural price forecasting. The literature illustrates that Random Forest Models, XGBoost Models, and LSTM Models perform better compared to conventional statistical approaches in uncertain and nonlinear markets. The results pave the way for the proposed work to design and develop a holistic multidimensional price forecasting tool that combines historical price values, market arrivals, climatic variables, and timeline to achieve precise price predictions [12].

3 METHODOLOGY

The proposed system's methodology has been designed as a holistic and AI-driven framework that utilizes agricultural market data, climatic variables, and advanced AI-ML models in an integrated manner to estimate price changes in agri-horticultural products. The proposed methodology has been developed as an organized and systematic framework with specific stages including data extraction, processing, feature development, model building, evaluation, and deployment. The systematic methodology will be effective and scalable for various commodities. The initial step in the process consists of collecting data from several reliable sources. The historical price series of pulses and veggies like potato, onion, and tomatoes is gathered from the respective agricultural marketing websites of the state governments, and also from the websites of the facilitators of agricultural produce marketing, also known as the Regulated Marketing Committees or APMC websites. The minimum, maximum, and modal prices on a daily or weekly basis from different markets are included in the dataset. Apart from the above-mentioned prices, the market arrival quantity is also gathered for understanding the demand side. The climate-related variables of rainfall, temperature, humidity, and occurrences of extreme climate conditions are fetched from departments and websites of weather websites [4].

After that, data preprocessing takes place. In agricultural data, especially from commodity markets, missing values and outliers can occur as a result of delayed reporting and market disturbances. In missing values, interpolation methods or moving averages can be used. Outliers in market data due to market irregularities can be detected with the help of statistics. Data normalization and scaling are necessary in preprocessing where the scale of the data should be made uniform, especially when using machine learning algorithms. The next essential step is feature engineering, which is a key step in model improvement. Features of the lagged prices are derived to extract their past correlations, whereas rolling statistics such as moving averages, volatility, and growth rates are calculated for short- and long-period patterns [6]. Market arrival variables correspond to the supply dynamics, whereas the environmental variables correspond to the climatic conditions. The categorical variables like season and stages of crop cycles are converted into suitable numerical representations. Various techniques of feature selection, namely correlation and importance from tree models, are used for variable selection on the basis of their relevance.

The heart of the approach deals with the development of models through various AI-ML methodologies. The traditional statistical models, such as ARIMA and SARIMA models, are used for developing base models to perform times-series prediction tasks. The models are used to identify linear trends in the data. AI-ML models such as Random Forest and XG Boost models will be developed to identify nonlinear dependencies between input features and prices of the commodities. The models are chosen to identify complex interactions between heterogeneous features.

For capturing long-term temporal relationships, the deep learning model, specifically the Long Short-Term Memory (LSTM) network, is used. The LSTM model takes the sequence of historical values and identifies the patterns, which impact the future prices. The different LSTMs are designed for varied commodities based on the patterns in their prices. The hyperparameters, such as the number of layers, number of hidden units, learning rates, and the size of the sequence, need to be tuned. The training procedure involves dividing the data into a training set, a validation set, and a test set using time-aware splitting. Models would then be trained on the data, using the validation set for validation [1]. Cross-validation, as adapted for time series, would then be applied. There would be model training in order to improve model performance and reduce overfitting. The block diagram is given in Fig. 1.

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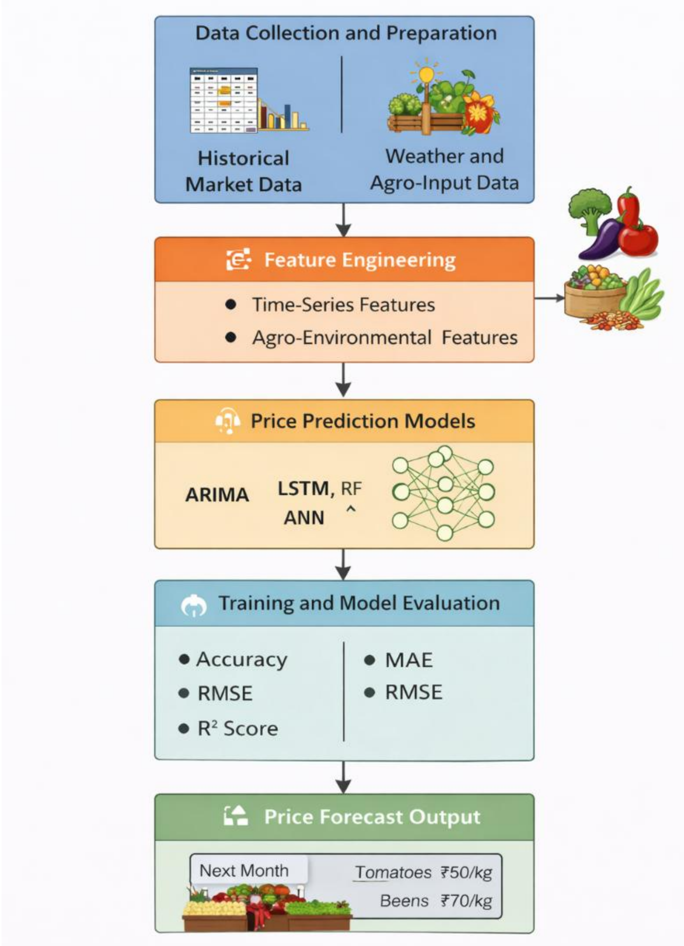

Fig. 1. Block diagram of proposed method

The methodology has a strong model evaluation process. The accuracy of predictions can be checked by parameters like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared. A comparative study is done to check the performance of ARIMA, Random Forest, XGBoost, and LSTM models for various commodities and prediction intervals. The graphical representation of predictions vs. actual values can be used to understand the performance of the models.

For improvement in the reliability of forecasts, the study uses ensemble forecasting, where forecasts from different models are combined. This approach minimizes bias associated with a particular model, especially when the market is expected to be volatile. Additionally, the approach also enables short-term forecasts (weekly) and long-term forecasts (monthly or seasonal). Finally, the methodology covers the issue of model deployment [1]. The developed models will be deployable using online agricultural consultancy platforms or online dashboards and/or mobile apps. This will ensure that there is constant updating as well as retraining due to changes in market conditions through automated data pipelines. Ultimately, the models developed shall be presented with user-friendly interfaces. In short, the approach combines preprocessing the data, feature development, statistical modeling, machine learning models, deep learning models, and ensemble modeling into one comprehensive forecasting scheme. The end result of this integrated strategy is sound and reliable price forecasts for agri-horti products.

4 RESULTS

The efficacy of the proposed AI-ML based price prediction framework was demonstrated using the results derived from its implementation. The experimental study was performed extensively using the historical data sets for pulses and key vegetables like potato, onion, and tomatoes. The objective of the study was to analyze the efficacy of the proposed AI-ML based price prediction framework in accurately predicting the respective prices. One of the major discoveries is that machine and deep learning algorithms outperform traditional statistical methods. The base models consisting of ARIMA algorithms yielded optimal short-term forecasts in a stable marketplace; however, machine learning algorithms like Random Forest and XGBoost performed comparatively better in realizing lower error values in terms of price anomalies and climatic variables despite unstable price fluctuations in the marketplace due to supply shocks and government interventions.

Among these models, XGBoost proved to be one of the most robust ones, with least RMSE and MAE for most of the commodities. Its boosting algorithm helped in reducing the errors of predictions by learning from the residual information, which benefited greatly in the high volatile periods, that is, the harvesting season of onion and tomato. Then, the random forest algorithm proved its worth in terms of providing consistent predictions despite noisy data, although its accuracy level was slightly less than that of XGBoost. The deep learning models based on LSTM showed significant improvements in the forecast of the medium and long terms. These models, being able to extract the seasonality information from the sequences of prices, are better adapted than the baseline model for the forecast of the mediums and long terms. The models performed well for vegetables such as potatoes, which exhibit smoother seasonal variations, and for onions and tomatoes that are more prone to extreme variations, the models showed great adaptability after being trained on enough data.

The addition of market arrival information and climatic factors contributed immensely to the accuracy of the predictions in the models. Tests conducted showed that the addition of arrival quantities led to the improvement of predictions by as much as 15-20% compared to the price-based models alone. The addition of climatic factors such as rain and temperature was significant in the case of vegetables that are climatic-sensitive. The proposed model performed remarkably well with regards to generalization across various commodities. This was despite the fact that each commodity tends to have distinct behavior with regards to prices. Model parameters were able to adjust significantly to accommodate the varied behaviors exhibited by the commodity prices. Pulse prices were not as volatile as those of vegetables, which led to higher accuracy levels. This was not the case with vegetables like onion and tomato.

The short-term forecast (weekly) precision was higher than long-term forecast precision. This is as expected since uncertainty is higher in long-term scenarios. But even so, long-term forecast outcomes were useful for identifying trends in planning. The ensemble method helped mitigate volatility by combining predictions from multiple models to mitigate model bias. The plot of predicted and actual prices clearly showed that the AI-ML models closely tracked actual market trends, even during periods of dramatic change. This suggests that the graphs predicted by the XGBoost and LSTM models were much more stable than those predicted by the ARIMA model. This also improves the system's overall outlook. The performance tests revealed that the proposed models are quite efficient and ready for implementation. The time taken for all the models was quite satisfactory considering the size of the datasets. The cloud implementation helped process various commodities simultaneously. A stakeholder-oriented evaluation highlighted the system's benefits. Farmers who used the results of forecasts had a more informed decision of when to sell or store their produce. Traders knew about the prices in the coming days. Governments made use of the information about impending price rises.

Table 1. Performance Comparison of AI–ML Models for Agri-Horticultural Price Prediction

Model	**MAE (₹/kg)**	**RMSE (₹/kg)**	**MAPE (%)**	**R^2 Score**
ARIMA	4.85	6.32	12.6	0.71
Random Forest	3.42	4.58	9.4	0.83
XGBoost	**2.96**	**3.89**	**7.8**	**0.88**
LSTM	3.05	4.01	8.2	0.86

Table 1 presents the quantitative comparison of different forecasting models using standard error metrics. The ARIMA model performs reasonably well for short-term forecasting under stable market conditions but exhibits higher errors due to its limitations in handling non-linear and volatile price movements. Random Forest improves prediction accuracy by capturing non-linear relationships among market and climatic features. XGBoost achieves the lowest MAE, RMSE, and MAPE values, indicating superior performance in volatile market conditions. Its boosting mechanism effectively reduces residual errors, making it highly suitable for agri-horticultural price forecasting. LSTM models demonstrate strong performance, particularly in learning long-term temporal dependencies, resulting in competitive accuracy for medium- and long-term forecasting horizons.

5 DISCUSSION

The discussion of the findings emphasizes that the application of AI-ML algorithms in agri-horticultural price forecast prediction is of great value in markets that experience greater volatility and are driven by intricate variables. Conventional methods of forecasting in agriculture, although appropriate for comparative studies, do not capture the responsiveness required in dynamic settings. The effectiveness achieved through machine and deep learning algorithms in this investigation has strengthened the emerging perspective in current studies that in agriculture, AI-ML models perform better than conventional methods in understanding nonlinear associations in agricultural markets. One of the most important takeaways from the above discussions is the power of ensemble and tree-based models, such as XGBoost and Random Forest, for dealing with heterogeneous data. The price variations in agricultural products, such as onion and tomatoes, are impacted by a variety of trends and factors related to past data, seasonality, and weather changes. Tree-based ensemble models perform very well in such cases without requiring any constraints on the distribution of data. The impressive performance of XGBoost in a volatile market again proves its efficiency in such products with sudden price jumps.

The discourse on forecasting, however, also highlights the significance of time-series forecasting with LSTM models. Although tree models are advantageous for short-term forecasting, LSTMs demonstrate clear superiority in modeling long-term series and seasonal variations. This point, therefore, indicates that there might not be a best method, regardless of the forecasting interval. Rather, one needs to select the model based on the forecasting task, with short-term forecasting strategies implemented using ensemble models of ML, whereas deep learning could serve as the basis for long-term forecasting.

Moreover, an important aspect that is considered is that of external factors, like market arrival and climatic conditions, in enhancing accuracy levels. The addition of these factors helped improve performance to a great extent, thus showing that relying solely on past prices does not yield an effective pricing forecast. Supply changes due to climatic conditions, as well as changes in market arrivals, have an important effect on vegetables; thus, integration of various sources is required.

The topic further examines the applicability of the proposed framework across various commodities. Pulse and vegetable prices show different trends depending on production cycles, storage, and demand. Despite such varying trends, the proposed AI-ML framework adapted accordingly, which is a major requirement for developing a scalable agricultural decision-support system.

From a pragmatic perspective, the discussion highlights the value added by the decision-making process. The price projections enable farmers to make informed decisions about harvest timing and market entry. The traders will be able to make informed decisions in procurement and logistics, and the government will be alerted to the effects on inflation and will take appropriate measures, such as releasing buffer stocks or adjusting imports. The system's early warning mechanism is essential for ensuring market stability.

The paper also discusses the interpretability and trustworthiness of the model, which is a critical factor for adoption. Though ML and deep learning algorithms are often labeled as "black box" algorithms, feature importance analysis done via tree-based algorithms, along with the trend of predictions, can help. The model's interpretability is paramount in instilling trust among policymakers, farmers, and other stakeholders in the agriculture sector, whose decisions rely heavily on its predictions. However, certain challenges and limitations are also recognized. Data quality is a challenge in agriculture because datasets often include missing information, discrepancies, and late submissions. Unforeseen policy changes or sudden events can also lead to discrepancies between the model's predictions. The availability of historical data is also important for the successful implementation of deep learning models for newly added commodities.

The study highlights areas to further develop the process, including integrating real-time satellite images, remote sensing data, and farmers' input. Innovative approaches to model output, through the dynamic combination of models using market information, can be leveraged to provide greater stability. Uncertainty metrics and confidence intervals can be integrated. In conclusion, the discussion above again strengthens the fact that AI-ML-based price prediction models are a great solution for managing the volatility of prices in agri-horticultural markets. By adopting multiple modeling techniques and integrating different data streams, the proposed model provides accurate, flexible, and actionable predictions to support better decision-making and the management of agri-horticultural markets.

6 Conclusion

The creation of AI-ML models for predicting the prices of agri-horticultural products is a major breakthrough in modernizing agricultural market intelligence solutions. Through this study, it is made clear that the complexity inherent in the agricultural market due to the fluctuations of commodity prices affected by multiple factors, including seasonality, weather patterns, market receipts, demand and supply gaps, and policy measures, can be addressed using advanced models of predictive analytics and machine learning solutions. One of the major observations from this study is that AI-ML models substantially outperform conventional statistical models for agricultural price prediction. Although ARIMA models have been effective in handling linear trends, they have limitations when dealing with sudden changes in price functions or nonlinear market patterns. However, this is not the case for either Random Forest or XGBoost models. The paper also concludes that deep learning models, especially those based on LSTMs, are highly effective for long-term and sequential price forecasting. LSTMs perform very well at capturing temporal dependencies and trends. This makes these models highly suitable for marketing commodities with a highly seasonal pattern, such as potatoes and pulses. The models can thus predict a trend turn around with great effectiveness. Another significant finding is the benefit of combining different data sources with the forecasting process. The addition of market arrivals and climate-related variables substantially improves forecast accuracy, thereby underscoring the significance of supply-side and climate-related variables in the pricing process. It reiterates that unidimensional time-series analysis in price-forecasting models is insufficient and that a multi-dimensional model is needed.

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Ethics Statement

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

Statement Of Conflict Of Interests

The authors declare that they have no conflicts of interest related to this study.

Licensing

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