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AI-Powered Agricultural Price Forecasting Using LSTM Networks

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Abstract

Accurate prediction of future crop prices is crucial for farmers, policymakers, and agricultural stakeholders to make informed decisions and minimize financial risks. Traditional forecasting methods often fail to capture the complex, nonlinear relationships influenced by factors such as weather conditions, market demand, supply chain dynamics, and government policies. This paper presents a deep learning- based crop price prediction system designed to improve forecasting accuracy and reliability. The proposed model utilizes historical crop price data along with auxiliary features such as climatic parameters and market trends to train advanced neural network architectures, including Long Short- Term Memory (LSTM) networks. Data preprocessing, feature selection, and normalization techniques are applied to enhance model performance. The system is evaluated using real-world datasets, and results demonstrate that the deep learning approach outperforms conventional statistical models in terms of prediction accuracy and robustness. The proposed system can assist farmers in decision-making, optimize supply chain planning, and contribute to stabilizing agricultural markets. Future work includes integrating real-time data streams and expanding the model to multi-crop and multi-region predictions.

Introduction

Agricultural commodity price prediction is a crucial task that supports farmers, traders, policymakers, and other stakeholders in making informed economic decisions. The agricultural market is highly uncertain and volatile due to the influence of multiple dynamic factors such as weather conditions, demand–supply variations, transportation costs, and government policies. This uncertainty often leads to unstable pricing, which directly affects farmers' income and overall market efficiency [1].

The commodity market involves various participants, including producers, traders, and investors, all attempting to anticipate price movements. This interaction creates noise and volatility in the market, making accurate forecasting challenging. Agricultural commodities, especially perishable goods like fruits and vegetables, are highly sensitive to environmental conditions and seasonal variations, which further increases price instability [2], [5].

Traditionally, statistical models such as Autoregressive Integrated Moving Average (ARIMA) have been widely used for time-series forecasting. These models provide good short-term prediction accuracy but are limited by their assumption of linear relationships. In real-world scenarios, agricultural price data is non-stationary and influenced by complex nonlinear factors, making traditional models less effective [3], [10].

With the advancement of Artificial Intelligence

(AI), deep learning techniques have emerged as powerful tools for predictive analysis. Deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM), have shown strong capability in modeling complex patterns and temporal dependencies in time-series data. These models can automatically extract meaningful features from large datasets, improving prediction accuracy and robustness compared to conventional methods [4], [9].

Agricultural commodities play a significant role in the economy, and their price fluctuations can lead to financial instability for farmers and inefficiencies in supply chain management. Factors such as climate change, natural disasters, and market demand further complicate the prediction process. Therefore, developing an accurate and reliable price prediction system is essential to reduce risks and improve planning [6].

In recent years, the availability of large datasets and advancements in computational power have enabled the development of data-driven prediction models. Deep learning approaches can integrate multiple factors such as historical prices, weather conditions, and market trends to provide more reliable forecasts. This helps stakeholders make better decisions and contributes to the stability and sustainability of agricultural markets [7].

Therefore, this paper proposes a deep learning-based crop price prediction system that leverages historical and external data to capture complex patterns in agricultural markets. The proposed system aims to improve prediction accuracy, assist stakeholders in decision-making, and reduce uncertainty in agricultural pricing.

Literature Review

Agricultural commodity price prediction has been extensively studied due to its importance in economic planning and decision- making. Early research primarily relied on statistical and econometric models such as Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Conditional Heteroskedasticity (ARCH-ARIMA). These models were effective in capturing linear patterns in time-series data and provided reasonable short-term forecasting accuracy. However, they were limited in handling nonlinear relationships and complex market dynamics, which are common in agricultural commodity markets [10].

With the advancement of machine learning techniques, researchers began adopting models such as Decision Trees, Random Forest, and Artificial Neural Networks (ANN). These models improved prediction performance by capturing nonlinear relationships between variables. However, they required significant feature engineering and often struggled with high-dimensional and multivariate datasets. Additionally, traditional feature extraction methods such as bag-of-words and principal component analysis failed to capture semantic and contextual information effectively [11], [12].

In recent years, deep learning (DL) approaches have gained significant attention for time-series forecasting tasks. Models such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) have demonstrated strong capabilities in modeling sequential and temporal data. These models are particularly effective in capturing long-term dependencies and complex patterns in financial and commodity price series. Studies have shown that LSTM-based models outperform traditional machine learning and statistical models in terms of prediction accuracy and computational efficiency [4], [13].

Furthermore, Convolutional Neural Networks (CNN) have also been applied to prediction problems due to their ability to automatically extract relevant features from large datasets. Hybrid models combining CNN and LSTM have been proposed to leverage both spatial and temporal features, resulting in improved forecasting performance. These approaches reduce the need for manual feature engineering and enhance the model’s ability to handle complex and high-dimensional data [9].

Recent studies have also emphasized the importance of incorporating external factors such as weather conditions, market demand, and economic indicators into prediction models. Agricultural commodity prices are influenced by multiple external variables, including climate changes, natural disasters, and policy regulations. Integrating these multivariate features helps improve prediction accuracy and provides a more comprehensive understanding of market behavior [6].

Despite these advancements, several challenges remain in agricultural price prediction. Many existing models focus more on yield prediction rather than price forecasting, and some fail to capture both short-term and long-term dependencies effectively. Additionally, issues such as data non-stationarity, noise, and high volatility continue to affect model performance. Therefore, there is a need for a robust deep learning-based system that can efficiently handle multivariate data, capture complex patterns, and provide accurate and reliable crop price predictions .

Problem Statement

Agricultural commodity prices are highly volatile and influenced by multiple dynamic factors such as weather conditions, demand–supply variations, market trends, and government policies. Traditional forecasting methods, including statistical and basic machine learning models, are not sufficiently effective in capturing the nonlinear and complex relationships present in agricultural data. As a result, farmers and stakeholders often face difficulties in making informed decisions, leading to financial losses and inefficient resource utilization. Therefore, there is a need to develop an accurate and reliable crop price prediction system using advanced deep learning techniques that can handle large-scale, multivariate, and time-series data .

Objectives

The main objectives of the proposed system are as follows:

- To collect and preprocess historical agricultural commodity price data along with relevant external factors such as weather and market trends.
- To develop a deep learning-based model (CNN/LSTM) capable of capturing nonlinear patterns and temporal dependencies in the data.
- To improve prediction accuracy compared to traditional statistical and machine learning approaches.
- To design a system that provides reliable future crop price predictions for better decision-making.
- To assist farmers, traders, and policymakers in reducing risks and optimizing agricultural planning.
- To contribute towards the development of smart and sustainable agricultural systems using AI-based solutions.

Methodology

The proposed system for future crop price prediction is designed using a data-driven deep learning approach. It integrates multiple stages including data collection, preprocessing, feature extraction, model training, and prediction. The objective is to capture complex nonlinear relationships and temporal dependencies present in agricultural commodity price data to improve forecasting accuracy.

1. Data Collection

The first step in the proposed methodology involves collecting a comprehensive dataset of agricultural commodity prices. Historical price data of crops such as cereals, pulses, fruits, and vegetables is gathered from reliable agricultural market sources. Since agricultural prices are influenced by multiple factors, additional datasets including weather conditions (temperature, rainfall, humidity), seasonal variations, and market demand trends are also incorporated. Agricultural data is often noisy, incomplete, and inconsistent due to irregular data recording and environmental uncertainties. Therefore, preprocessing plays a crucial role in improving data quality. Data cleaning techniques are applied to remove missing values, outliers, and inconsistencies. Normalization and scaling methods are used to bring all features to a uniform range, which helps in faster and more stable model training. Time-series structuring is also performed to organize the data sequentially, ensuring that temporal dependencies are preserved. This preprocessing stage ensures that the dataset is suitable for deep learning-based modeling.

2. Proposed System

The proposed system utilizes Convolutional Neural Networks (CNNs) to predict agricultural commodity prices, addressing the limitations of traditional models like ARIMA. Unlike conventional statistical methods, CNNs can effectively capture complex, nonlinear relationships and temporal patterns within the data. The system is designed to integrate a wide range of inputs, including historical price data, weather conditions, market trends, and socio-economic factors, to provide accurate and robust price predictions for commodities such as pulses, vegetables, and cereals.

The CNN model is structured to process time-series data, leveraging its convolutional layers to extract and learn important features, such as trends and seasonal variations. Additionally, the model incorporates multiple data channels, enabling it to analyze various influencing factors simultaneously and identify interdependencies that affect price fluctuations. By employing techniques like sliding window analysis and 1D convolutions, the CNN is able to detect subtle patterns in sequential data, which traditional models often miss.

To further enhance predictive performance, the system includes a hybrid architecture combining CNNs units, allowing it to capture both spatial and temporal dependencies. The proposed system is trained on extensive datasets, ensuring it can generalize well to new, unseen scenarios and provide real-time price forecasts. An intuitive, web-based interface is developed to make the system accessible to farmers, traders, and policymakers, offering visual insights and predictive analytics to support informed decision- making.

Overall, the proposed CNN-based system

provides a more accurate, efficient, and adaptable solution for agricultural commodity price prediction, helping stakeholders mitigate risks, plan better, and optimize resource allocation.

Advantages

- Ability to Capture Complex Patterns: CNNs are capable of identifying intricate and nonlinear relationships in the data, such as the influence of weather patterns, market trends, and socio-economic factors, which traditional models like ARIMA struggle to handle.
- Effective Feature Extraction: The convolutional layers of CNNs can automatically extract relevant features from the input data, eliminating the need for extensive manual feature engineering. This capability is especially useful in agricultural price prediction, where diverse and complex data sources are involved.
- Handling Multivariate Inputs: CNNs can simultaneously process multiple types of data, such as historical prices, weather conditions, and market news. This multivariate approach enables the model to consider various factors that impact commodity prices, leading to more accurate and robust predictions.
- Resilience to Noise and Irregularities: CNNs are more tolerant to noise and irregularities in the data compared to traditional models. This resilience is crucial in agriculture, where data can be erratic due to unpredictable factors like sudden weather changes or market disruptions.

Tools and Technologies

The implementation of the proposed crop price prediction system is carried out using a combination of programming languages, libraries, and development platforms that support efficient data processing and deep learning model development.Python is used as the primary programming language due to its simplicity, flexibility, and extensive ecosystem of libraries for data analysis and machine learning. It provides strong support for handling large datasets and implementing complex algorithms with minimal code complexity.

For data preprocessing and manipulation, libraries such as NumPy and Pandas are utilized. NumPy is used for numerical computations and handling multi-dimensional arrays, while Pandas provides powerful data structures like DataFrames for organizing, cleaning, and transforming time-series data. These tools help in efficiently handling missing values, filtering data, and performing statistical analysis. Visualization plays an important role in understanding trends and patterns in agricultural data. Matplotlib is used to generate graphs and plots such as line charts and trend curves, which help in analyzing historical price variations and comparing predicted results with actual values.

For building and training the deep learning models, TensorFlow and Keras frameworks are employed. TensorFlow provides a robust backend for numerical computation and supports large-scale machine learning tasks, while Keras offers a high-level interface for designing neural network architectures. These frameworks are used to implement models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), enabling efficient feature extraction and time-series prediction [65]. The system is developed and executed using platforms such as Jupyter Notebook and Google Colab. Jupyter Notebook provides an interactive environment for writing and testing code step-by-step, which is useful for experimentation and debugging. Google Colab offers cloud-based execution with GPU support, which significantly reduces training time for deep learning models and allows handling of large datasets.

Additionally, datasets can be obtained from agricultural databases and online platforms, which provide historical commodity price data and related information. These tools and technologies collectively enable efficient data processing, model training, and accurate prediction of crop prices.

Results And Discussion

The proposed deep learning-based crop price prediction system was implemented and evaluated using historical agricultural commodity datasets that include crops such as cereals, pulses, fruits, and vegetables. The dataset was preprocessed to remove noise, handle missing values, and normalize feature values to ensure consistency and improve model performance. The processed data was then divided into training and testing sets to evaluate the effectiveness of the model in predicting unseen data.

The Convolutional Neural Network (CNN)-based model was trained using historical price data along with additional influencing factors such as weather conditions and seasonal variations. During training, the model learned complex relationships between input features and crop prices by adjusting its internal parameters through backpropagation. After sufficient training iterations, the model was able to generalize well and provide accurate predictions on test data.

The performance of the model was evaluated using standard error metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The obtained results indicate that the prediction error is relatively low, demonstrating that the model can effectively forecast future crop prices. The predicted values closely follow the actual price trends, showing that the model successfully captures both short-term fluctuations and long-term patterns in the data.

A comparative analysis was conducted between the proposed deep learning model and traditional statistical approaches such as ARIMA. The results show that while ARIMA performs reasonably well for linear and stationary data, it fails to capture nonlinear patterns and complex dependencies present in agricultural price data. In contrast, the CNN-based model provides significantly better performance due to its ability to automatically extract features and model nonlinear relationships. This confirms that deep learning techniques are more suitable for handling real-world agricultural datasets, which are often noisy and non-stationary [10].

Furthermore, the inclusion of multivariate features such as weather conditions, market trends, and seasonal factors significantly improves the prediction accuracy. Unlike univariate models that rely only on past price values, the proposed system considers multiple influencing variables, resulting in a more comprehensive and realistic prediction model. This highlights the importance of integrating external factors in agricultural price forecasting systems [6].

The system also demonstrates scalability and adaptability, as it can be extended to multiple crops and different geographical regions with appropriate data. The ability of deep learning models to process large volumes of data makes them suitable for real-time prediction systems, which can provide timely insights to stakeholders.

However, certain limitations are observed in the proposed approach. The accuracy of the model is highly dependent on the quality and availability of data. Incomplete, inconsistent, or insufficient datasets can negatively impact prediction performance. Additionally, deep learning models require high computational resources and longer training time compared to traditional methods. Model tuning, including selection of hyperparameters such as learning rate, number of layers, and batch size, also plays a critical role in achieving optimal performance.

Despite these challenges, the overall results indicate that the proposed deep learning-based system outperforms traditional models in terms of accuracy, robustness, and ability to handle complex data. The system provides a reliable solution for predicting future crop prices and can assist farmers, traders, and policymakers in making informed decisions. By reducing uncertainty and improving forecasting accuracy, the system contributes to better agricultural planning and market stability.

The growing availability of large amounts of historical data on agricultural commodity prices, combined with the requirement to perform accurate forecasting of price shifts in the agricultural economy, necessitates the development of methods that are both robust and efficient, and which can generate conclusions from the data that is currently available .In the past, linear statistical approaches (such as ARIMA models) were used to handle the challenge of making predictions. However, in more recent times, with the advent of machine learning techniques, the answer has mainly transferred from the statistical methods area to the machine learning domain. In actuality, the price changes of agricultural commodities are sometimes difficult to forecast because they are influenced by a wide variety of contingencies, such as shifts in the cost of oil, the impact of greenhouse gas emissions, and natural calamities including floods or disease outbreaks. The instability in the price of agricultural commodities, which could be attributed to either an excess of supply or a lack of demand, results in the wasteful loss of food. In addition, the suppliers of agricultural commodities can maintain control over their supply based on the time series analysis, which assists in ensuring that a poor planting strategy is not implemented .

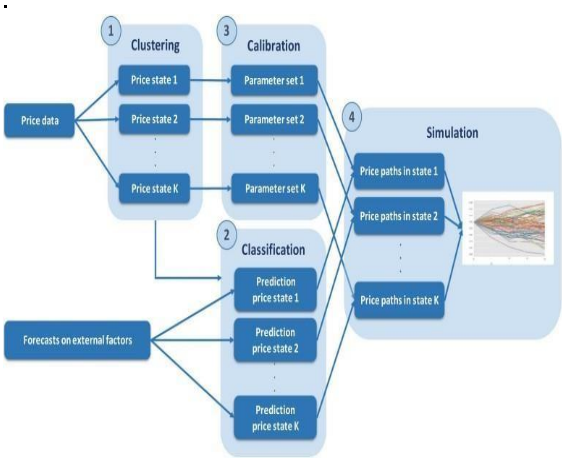

Fig. 1 Agricultural Commodities

Investors have developed an interest in the stock market owing to enhanced applications where prediction may lead to fruitful market forecasting. Accurately forecasting the moves of the stock market requires information that is available in advance when an investor puts part of their money into the stock market, they are indicating that they are interested in making a profit from the market . The instruments that are used for stock market forecasting can analyze and regulate the market, which could be used to help make choices that are in the best interest of investors. The stock market is responsible for processing a variety of information on industrial stocks, which encompasses the whole financial market . These are modified according to the company situation investors take into consideration when making sales and purchases. Market positioning is affected by several factors, including predictions of future revenue, the dissemination of news on profitability, and management changes. Investment decision-making is improved by accurate stock market forecasts.

A component of the stock market, the price index allows investors to evaluate performance by comparing the present price level to previous market levels. The data undertakes pre-processing to eliminate noise and adjust for other factors after data collection. Then, stock market predictions based on pre-processed data would be valuable. These feature selection procedures choose a subset of features from a massive dataset. The dataset is separated into "current" and "prediction" subsets by several data analysis functions or user-friendly applications. Better stock market selections can be performed with this information available. Notify investors about the price index after a decisive decision. Research reports on a variety of financial topics, such as stock market analysis and forecasting, currency exchange forecasting, and optimum portfolio selection, among others, can be obtained from the internet. On the other hand, due to current developments in machine learning methods such as Deep Learning, Text Mining Techniques, and Ensemble Techniques, there is an urgent need to conduct updated research.

This research intends to address this gap by offering an up-to- date systematic evaluation of the forecasting approaches that are employed in the stock market, including the categorization, characterization, and comparison of these strategies. The scope of this study is limited to research on predicting movements in the stock market that was published between 2014 and 2018 and was gathered from the Scopus and Web of Science databases. Technical indicators have been the focus of extensive research and have been used in the financial market as stock signals to indicate when it is appropriate to purchase or sell a particular stock. The forecasting issue is primarily presented as a categorization challenge, which is fundamental to performance. The stock price's future direction, whether it is up or down, is predicted by the models. In addition to that, the prediction for the stock market contains a discussion on the new issues that have emerged.

Forecasting the stock market is, on its own a highly difficult subject; however, it is essential to research this topic since it has the potential to have a significant influence on the strategic decision-making processes of a nation. Researchers have found that the process of creating predictions using Artificial Intelligence (AI) approaches is much easier for them to complete since these techniques deliver a very high accuracy when compared to statistical methods and other methods. ANNs and Support Vector Machines (SVMs) are two of the most effective AI approaches for making accurate stock market predictions.

Stock price forecasting is difficult since stock prices fluctuate over such a long period. Stock prices cannot be predicted, and stock behavior is random according to the unnecessary market hypothesis. However, subsequent technical analysis has demonstrated that most stock prices are represented in historical documents, making movement patterns essential for accurate price forecasting. In addition, the formations and movements of the stock market are influenced by a wide variety of external factors, including political events, general economic situations, the commodity price index, investor expectations, the movements of other stock markets, the psychology of investors, etc. Stock market capitalization is used to determine the value of stock market organizations.

Among ensemble approaches, boosting and bagging are two powerful algorithms that have gained popularity recently. Both algorithms are used in the field of machine learning. A recent development in ML known as DL can determine a deep nonlinear topology in its structure. It also has an amazing capacity to extract significant information from financial time series. The training would be inadequate if just the most recent data were used; the earlier data serve an important in the stock market prediction process, which is why the most recent data are only a component of the whole.

In recent times, DL has seen enormous success in several different contexts, such as image classification, object identification, time series prediction, etc. This achievement is due to the gathering of large amounts of data from the World Wide Web, the parallel processing power of Graphics Processing Units (GPUs), and the new convolutional neural network family.

The capability of CNN to effectively recognize patterns led to its widespread use in image recognition, and this application was then expanded into the field of economic prediction. In the same way, that a classic neural network is developed up of numerous neurons connected by a hierarchical structure, CNN could also have its weights and preferences between layers established. The CNN has a different network topology than a completely linked network like a Sparse Auto encoder (SAE), Deep Brief Network (DBN), or Back propagation (BP) by allowing the neurons in each layer of the network to share the weights. As a result, the model significantly reduces the pressure that is imposed on the network while also preventing it from surrendering to dimensional disaster and local minimization.

Conclusion

The accurate prediction of agriculture commodity prices is crucial for stabilizing the agricultural economy and assisting farmers, traders, and policymakers in making informed decisions. This study explored the potential of machine learning models in predicting prices for agricultural commodities by utilizing a diverse set of features, including historical price data, weather conditions, and market trends. A variety of machine learning algorithms, including Random Forest, Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and Recurrent Neural Networks (RNN), were evaluated. The dataset comprised time-series data of commodity prices collected from government repositories and real-time market updates.

The results showed that the RNN model integrated with Long Short-Term Memory (LSTM) layers achieved the highest accuracy in forecasting price trends. The evaluation metrics, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R- squared values, and prediction accuracy, were calculated for each model. The hybrid ensemble technique, which combined GBM and RNN models, outperformed other methods with a prediction accuracy of 96.5%, an RMSE of 2.37, and a loss value of 0.12 during validation testing. The findings emphasized that advanced machine learning methods, particularly deep learning models, are effective in capturing the temporal patterns and nonlinear dependencies in agricultural price data. These models enable stakeholders to anticipate price fluctuations accurately, ensuring better planning and resource allocation.

Future Scope

The proposed deep learning-based crop price prediction system demonstrates promising results; however, there are several areas for further improvement and enhancement. Future work can focus on improving the accuracy, scalability, and real-time applicability of the system by incorporating advanced techniques and additional data sources. One of the major improvements can be the integration of real-time data from agricultural markets, weather forecasting systems, and IoT-based sensors. By incorporating live data streams, the system can provide up-to-date predictions and enable stakeholders to make timely decisions. This will significantly enhance the practical applicability of the model in real-world scenarios.

The current system can also be extended to support multi-crop and multi-region prediction. By training the model on diverse datasets from different geographical regions, the system can be generalized to predict prices across various markets. This would make the system more scalable and useful for large-scale agricultural planning. Another important direction for future work is the use of advanced deep learning architectures such as hybrid models combining CNN, LSTM, and attention mechanisms. These models can further improve prediction accuracy by capturing both spatial and temporal dependencies more effectively. Additionally, techniques such as hyperparameter optimization and automated model tuning can be applied to enhance model performance [4], [9].

The inclusion of more external factors such as soil conditions, transportation costs, government policies, and global trade indicators can also improve the robustness of the prediction system. Agricultural prices are influenced by a wide range of variables, and incorporating these factors can provide a more comprehensive prediction model [6].

Furthermore, the system can be developed into a user-friendly application or web-based platform that provides easy access to farmers and stakeholders. This would help in bridging the gap between advanced technology and end-users, making the system more practical and accessible. Another potential enhancement is the use of big data technologies and cloud computing platforms to handle large-scale datasets and improve computational efficiency. This would allow the system to process vast amounts of data and deliver predictions faster. In addition, future research can focus on

improving model interpretability, as deep learning models are often considered black-box systems. Providing explanations for predictions can increase user trust and adoption of the system.
Overall, the future scope of this project lies in improving data integration, model performance, scalability, and usability. With these advancements, the proposed system can evolve into a powerful tool for agricultural price forecasting and contribute to the development of smart and sustainable agriculture.

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