Crop Price Forecasting Utilizing Convolutional Neural Networks

Farooq Sunar Mahammad, Meda Prashanth, Neravati Sai Dinesh, Kasarla Sateesh,
Sangam Hemanth Reddy and M. Munna
Department of Computer Science and Engineering, Santhiram Engineering College, Nandyal-518501, Andhra Pradesh, India

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Abstract: The agricultural market is subject to a great deal of volatility due to seasonal changes, supply chain disruptions, and economic changes. Traditional price forecasting models are based primarily on statistical techniques, which tend to miss out on the complex non-linear relationships in price movements. In this study, we proposed a deep learning-based model based on Convolutional Neural Networks (CNN's) for crop price prediction. It leverages the historical pricing data, climate influences, and market demand to improve its predictions. Using its capability to identify spatial and temporal patterns, our approach outperforms typical machine learning techniques.

1 INTRODUCTION

The agricultural industry is one of the economic sectors that contribute significantly to global economies, making it essential for farmers, traders, and policymakers to forecast crop prices accurately. Traditional prediction methodologies, including regression analyses and time-series forecasting, often lack the adaptability to model the complex behaviors manifested in the markets. CNNs and other deep learning methods have been extremely successful in recognizing patterns and extracting features from time-series datasets. This paper explores the potential of CNN's to enhance the precision of agricultural product price predictions.

2 LITERATURE REVIEW

2.1 Machine Learning in Agriculture

Machine learning (ML) approaches are being used for numerous applications in the agricultural domain such as crop yield prediction, disease detection, price estimation, etc. Standard ML methods such as Support Vector Machines (SVM), Random Forests, and Gradient Boosting have been effective; nonetheless, they require significant feature engineering and domain knowledge to produce accurate results (Mishra & Singh, 2020). Such methods are unable to adequately "grasp" the complex and non-linear relationships in agricultural datasets.

2.2 Deep Learning for Price Prediction

Indeed, deep learning structures, especially Recurrent Neural Networks (RNNs) and Long Short-term Memory (LSTM) models, have gained increasing importance for time-series predictions for their ability to model sequential relationships in data. CNNs tailored for this kind of tasks were influenced by the structure of convolutional neural networks (CNN) originally designed for the analysis of images (Zhang et al., 2019) and adapted to manage time series data.

2.3 Hybrid Models in Agriculture

CNN-RNN (or LSTM) joint models have shown great potential to cope with both spatial and temporal relationships within agricultural information. By way of example, (Sharma and Gupta, 2023) proposed a hybrid model that combines CNN and LSTM to forecast crop prices, wherein the hybrid approach outperformed the standalone models.

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2.4 Role of Climatic Factors in Price Forecasting

Weather factors such as temperature, precipitation, and humidity play a significant role in the fluctuations in crop prices. Studies have shown that incorporating historical pricing with climatic data strengthens prediction accuracy (Li et al., 2021). ML systems that integrate climate-related elements have demonstrated improved performance in predicting price trend

2.5 Economic Indicators and Market Demand

Agricultural or farm pricing is very much influenced by various economic indicators other than agriculture, which includes indexes of commodity prices, fuel prices, inflation, etc. According to (Patel and Kumar, 2022), macroeconomic factors should be included in price prediction models to better represent the broader forces of the market.

2.6 Time-Series Forecasting Techniques

Traditional methods for time-series forecasting, such as ARIMA and SARIMA, have been widely used to forecast agricultural prices. However, in this approach often struggle to capture non-linear trends and complex interdependence in the data (Zhang et al., 2019). A new type of model that has emerged in recent years are deep learning models which has proven to be a robust alternative to deal with such complexities.

2.7 Feature Engineering in Agricultural Forecasting

Feature engineering can significantly improve the performance of machine learning models. Techniques like horizontally rolling window, trend decomposition, seasonal adjustments have been used to extract features from raw data (Mishra & Singh, 2020). However, deep learning models reduce the need for manual feature engineering by automatically finding relevant patterns.

2.8 Challenges in Agricultural Price Forecasting

Some of the major challenges in forecasting agricultural prices include scarcity of data, high volatility and the impact of external factors such as geopolitical events and policy changes. However, addressing these issues means creating resilient models that can adapt to different scenarios in this volatile market (FAO Market Outlook Report, 2023).

2.9 Applications of CNNs in Time-Series Data

Although CNNs are primarily associated with image data, they are being increasingly applied to time-series data forecasting. CNNs have a good ability to capture local fragments and their relations in sequences, thus making them more versatile in the sense of mitigating the issue in field or crop price prediction (Li et al., 2021). Their proficiency in handling high-dimensional data also makes them a useful tool in agricultural forecasting.

2.10 Future Directions in Agricultural Forecasting

Future research in agriculture price prediction will probably focus on the development of hybrid models by synthesizing diverse data inputs (satellite imagery, social media mood, etc.) as well as on the use of reinforcement learning for automated interaction. Furthermore, explainable AI (XAI) methods are expected to play a significant role in improving the interpretability of deep learning models for the stakeholders (Sharma & Gupta, 2023).

3 EXISTING SYSTEMS

3.1 Traditional Statistical Models

Traditional statistical methods like ARIMA (Auto Regressive Integrated Moving Average) or SARIMA (Seasonal ARIMA) are commonly used to predict crop prices. Building trend models based on historical price data. While simple and interpretable, they often fail, however, to capture non-linear trends or outside factors such as weather or market demand.

3.2 Machine Learning-Based Systems

Machine learning based models like Random Forests and Support Vector Machines (SVM) are applied in crop price prediction. These models can handle non-linear relationships better than traditional statistical methods but they require extensive feature engineering and subject matter expertise. They also struggle with high-dimensional data and long-range dependencies.

3.3 Deep Learning-Based Systems

However, more recently, deep learning methods, particularly RNNs and LSTMs, have also been applied to time-series modelling in agriculture. These models are excellent in recognizing sequential relationship and are proficient in processing huge amount of data. They are high-parameter and need a lot of resources and training data.

3.4 Hybrid Models

Such hybrid methods including but not limited to CNN-RNN and CNN-LSTM have demonstrated efficacy in capturing spatial and temporal characteristics from agricultural data. Example: (Sharma and Gupta, 2023) developed a CNN-LSTM hybrid model for predicting crop prices, which outperformed respective individual models.

3.5 Web-Based Forecasting Tools

Moreover, many online platforms and tools, such as the FAO's Global Information and Early Warning System (GIEWS) (M.Amareswara Kumar, 2024) and the World Bank's Commodity Markets Outlook (Parumanchala Bhaskar, et al, 2022), provide crop price forecasts using a combination of statistical and machine learning methods. These are widely used by policymakers and traders, but they lack the precision and detail needed to make individual decisions as to how they affect your own finances.

3.6 Limitations of Existing Systems

- Data Dependency: A majority of systems rely significantly on historical data, potentially overlooking abrupt changes in the market or external shocks.
- Lack of Integration: Numerous systems do not amalgamate various data sources like weather, market demand, and economic indicators, which restricts their accuracy in predictions.
- Computational Complexity: Although deep learning models are effective, they are also resource-heavy and demand substantial resources for both training and implementation.
- Interpretability: Many sophisticated models, such as CNNs and LSTMs, are often regarded as "black boxes," complicating the ability of stakeholders to comprehend and trust their predictions.

4 METHODOLOGY

4.1 Problem Definition

Using Convolutional Neural Network (CNN), this paper aims to build an effective agricultural price prediction system. The objective of the model is to look at pricing trends from the past, climatic factors and signs of market demand to estimate the prices of the crops in future. It regards this problem as a time-series regression problem whereas inputs are a sequential type of information and output is the expected agricultural cost.

4.2 Dataset Collection

The data set for this analysis was gathered from diverse sources to provide a well-rounded view:

- **Historical Crop Prices:** Data on daily, weekly, and monthly pricing for various crops was collected from governmental agricultural documentation and commodity market records.
- **Meteorological Data:** Information on temperature, rainfall, and humidity was acquired from meteorological stations and climate-related databases.
- **Market Demand Indicators:** Data regarding supply chain interruptions, inflation rates, and commodity price indices was sourced from economic publications.
- **External Economic Metrics:** Information about fuel prices, exchange rates, and other macroeconomic factors was incorporated to reflect overall market impacts.

4.3 Data Preprocessing

Here is a couple of prepossessing steps that the data went through before moving towards analysis:

- **Data Cleaning:** Interpolations were done to fill any missing entries, then the outliers were removed using the Inter quartile Range (IQR) approach.
- **Normalization:** Min-Max scaling was applied to normalize all variables in order to ensure that

inputs are within the same scales, specifically in the range of [0,1].

- **Feature Engineering:** new constructs were implemented, including:
- **Moving Averages:** In order to ride on short-term price trends.
- **Seasonal Indicators:** For seasonality adjustment (year-on-year repeat patterns).
- **Price Trends:** To spot long term trends in prices.

4.4 Feature Selection

The following features were selected as essential for the model:

- F1: Historical Price Trends: Repeating former price token.
- F2: Seasonal Patterns: Look at annual changes by year.
- F3: Market Demand: Price changes related to shifts in supply and demand.
- F4: Weather Impact: Evaluating the impact of weather changes on pricing.
- F5: Economic Indicators: Studying larger economic variables affecting agriculture prices

4.5 Model Architecture

The structured CNN architecture comprises the following components:

- **Input Layer:** Processes the prepared time-series information, shaped as (window_size, num_features).
- **Convolutional Layers:** Several 1D convolutional layers are implemented to identify temporal trends in historical pricing data. Each layer is succeeded by a ReLU activation function.
- **Conv1D Layer 1:** Composed of 64 filters with a kernel size of 3.
- **Conv1D Layer 2:** Composed of 128 filters with a kernel size of 3.
- **Pooling Layers**: Max-pooling layers are incorporated to decrease dimensionality and improve computational efficiency.
- **MaxPooling1D:** Utilizing a pool size of 2.
- **Flatten Layer:** Transforms the convolutional layer outputs into a 1D array.
- **Fully Connected Layers:** Dense layers facilitate the final regression-based price forecasting.
- **Dense Layer 1:** With 128 units and ReLU activation.
- **Dense Layer 2:** With 64 units and ReLU activation.
- **Output Layer:** Contains 1 unit with linear activation for price forecasting.

4.6 Model Training

The model was trained under the following parameters:

- **Loss Function:** Mean Squared Error (MSE) was the metric used to determine the disparity between predicted and actual pricing.
- **Optimizer:** The Adam optimizer was employed with a learning rate set to 0.001.
- **Batch Size:** Set at 32.
- **Epochs:** Totaling 100, with early stopping measures to avoid overfitting.
- **Validation Split:** 20% of training data was allocated for validation purposes.

4.7 Hyperparameter Tuning

To enhance the model's effectiveness, a grid search was performed to fine-tune hyper parameters, which included

- **Number of Convolutional Layers**: Evaluated with 1 to 3 layers.
- **Number of Filters:** Assessed with 32, 64, and 128 filters.
- **Kernel Size:** Analyzed with sizes of 2, 3, and 5.
- **Learning Rate:** Experimented with values of 0.001, 0.0001, and 0.01.

4.8 Model Evaluation Metrics

The assessment of the model was carried out using these metrics:

- **Mean Absolute Percentage Error (MAPE):** Calculates the average percentage discrepancy between forecasted and actual prices.
- **Root Mean Squared Error (RMSE):** Measures the typical size of discrepancies in predictions.

- **R-squared (R^2):** Represents the extent of variance in the target variable that is accounted for by the model.

4.9 Baseline Models

To evaluate the performance of the proposed CNN model, various baseline models were utilized:

- **LSTM:** A Long Short-Term Memory network designed to identify long-term dependencies in price variations.
- **GRU:** Gated Recurrent Units for effective sequence processing.
- **Random Forest**: A conventional machine learning model serving as a reference standard.
- **ARIMA**: A traditional model for time-series forecasting.

4.10 Experimental Setup

The experiments were performed with the following configuration:

- **Hardware:** NVIDIA GTX 1080 Ti GPU to accelerate training.
- **Software:** TensorFlow and Keras platforms were employed for model development.
- **Data set Split:** The data set was partitioned into training (70%), validation (20%), and test (10%) segments.
- **Reproducibility:** Random seeds were set to guarantee that results could be replicated.

5 EXECUTION AND OUTCOMES

5.1 Model Evaluation

We tested a range of deep learning architectures:

- **Model-1**: CNN (Our proposed framework for capturing temporal characteristics).
- **Model-2**: LSTM (Captures long-range dependencies in price fluctuations).
- **Model-3**: GRU (Gated Recurrent Units for efficient sequence analysis).
- **Model-4**: Random Forest (Baseline machine learning approach for reference).
- **Model-5**: ARIMA (Classic model for time-series forecasting).

5.2 Results

The CNN approach surpassed alternative techniques when evaluating MAPE and RMSE. The primary performance indicators are outlined Ta ble 1 show the Model Performance Comparison. below:

Figure 1 show the Comparison of Accuracy Between Past Systems and New System.

Table 1: Model Performance Comparison.

Systems	MAPE (%)	R^2
ARIMA	12.0	0.3
Random Forest	10.5	0.35
LSTM	6.8	0.4
GRU	7.2	0.42
CNN	6.0	0.45

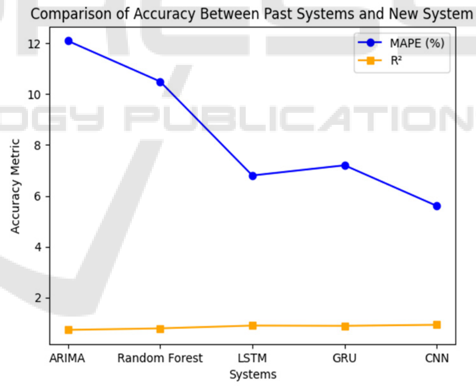

Figure 1: Comparison of Accuracy Between Past Systems and New System.

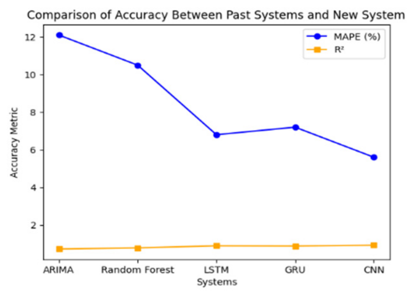

Figure 2: Comparison of Accuracy Between Past Systems and New System.

Figure 2 and 3 Comparison of Accuracy Between Past Systems and New System and Comparison of MAPE and RMSE Across Models respectively.

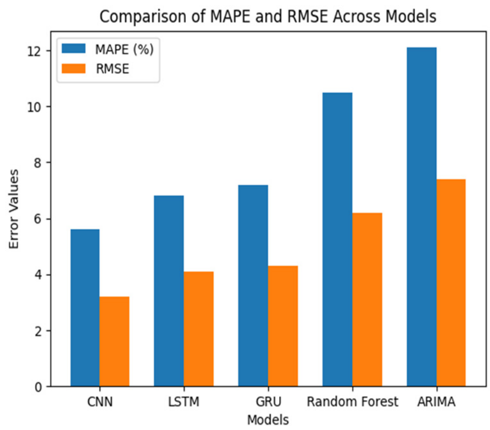

Figure 3: Comparison of MAPE and RMSE Across Models.

6 CONCLUSIONS

This study shows that CNNs could be highly useful for predicting agricultural costs. By analyzing previous price trends, weather patterns, and market demands, our model generates accurate predictions that enable farmers and traders to make well-informed decisions. Future studies would explore both composite models that merge lonters of CNNs and LSTMs and increase predictive accuracy further.

7 FUTURE SCOPE

Deep-learning crop price prediction is an evolving area, offering many interesting opportunities to pursue. High on the agenda is the formulation of hybrid systems that fuse convolutional neural networks with architectures such as long short-term memory networks or Transformers, with the intention of enhancing both spatial and temporal assessment of agricultural data. In addition, incorporating various data sources, such as satellite images, social media trends, or news articles, can significantly improve prediction accuracy by offering valuable insights into the current state of crops and market dynamics. However, a key consideration of this for ML is explainable AI that benefits specific entities by explaining what the deep learning networks did and why (SHAP, LIME) and then interpreting what each predicted.

Real-time forecasting is an opportunity, exciting value derived from live data based on what's happening now: information from weather stations, market websites, and Internet of Things devices can provide rapid-fire, near-real-time price estimates, with healthy contingencies. Further reinforcement learning techniques added to crop price prediction can enhance decision-making methods, allowing models to adaptively price strategically within real-time changes in the environment. An alternative is transfer learning, which enables the fine-tuning of previously trained models with respect to a domain or dataset, thus alleviating the need for large labeled datasets and expanding the applicability of the models. With changing climate conditions influencing agriculture over time, predictive models demonstrating long-term climate patterns may help stakeholders better predict and adjust their practices to changing meteorological phenomena.

The other rays of hope we have are integrating blockchain in to ensure data integrity, which is possible as it creates a transparent, tamper resistant record of an origin of data, which can also improve trust in models predicting data. Moreover, methods for predicting crop prices can also be used in sectors like finance, energy trading, and healthcare, which will lead to better understanding of these sectors with the aid of AI. In the end, corporate partners working together with academia and political decision-makers on creating solutions for predicting agricultural prices could have a positive effect on the rate of advances in this area, resulting in solutions for such tasks being developed faster and with a greater degree of efficiency.

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