

# Explainable and Drift-Aware Machine Learning Framework for Crop Price Prediction Using Visual and Temporal Data

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**Abstract** - One of the greatest difficulties for farmers in many (developing) countries is income volatility due to crop price fluctuation. Traditional statistical forecasting models often are not capable of modeling the changing, nonlinear characteristic of an agricultural market. In this research we present a drift-aware and interpretable AI system for crop price prediction from heterogeneous sources: weather data, market prices, seasonal effects and crop quality features computed from images of the crop. Our approach is based on a combination of Convolutional Neural Networks (CNN) for computation of crop quality and a Long Short-Term Memory (LSTM) for the time series price prediction. The model is able to deal with concept drift occurring in the market via Adaptive Windowing (ADWIN) at the time of prediction, and we are able to understand its predictions with Shapley Additive exPlanations (SHAP). Our system offers a prediction accuracy of 96.59%, and we make a prediction on a weekly basis to support farmers' sales decisions.

**Key Words:** Agricultural Decision Support Systems, Concept Drift Detection, Crop Price Prediction, Explainable AI (XAI), Multimodal Deep Learning

## 1. INTRODUCTION

Agriculture, as the basic source of food and global food security, is playing an important part in the global economy. However, farmers are frequently faced with tremendous financial risk due to the unpredictable market price and restricted access to accurate, real-time information about the market conditions. The price of crops depends on various parameters, such as climatic condition, season and demand-supply equilibrium, and the quality of crops. In reality, farmers often make decisions based on historical price trends or local market estimates, which may be outdated compared to real-time prices, leading to inaccurate predictions [1].

Recent research utilizing the progress of machine learning and deep learning has shown capability to build the prediction models to analyze agricultural market trends. These machine learning techniques can effectively capture nonlinear and complicated time-series data, and have been used successfully in various prediction applications [2]. In addition, many research works have investigated on application of these models for agricultural price forecasting and decision support [3].

Despite that, most of current research are focusing on utilizing the numerical historical data while neglecting influential factors such as crop quality and climate conditions. Moreover,

most machine learning models are considered as a 'black box' and are difficult to interpret, thus decreasing the level of user confidence, and lack of transparency is a great limitation in the practical agricultural applications [4].

In order to overcome those limitations, in this study, a drift-aware and explainable artificial intelligence framework is developed for crop price prediction. In the proposed framework, multiple sources of information including crop images, climate, market price and seasonal factors are integrated together to better capture agricultural information. By combining visual analysis of crop quality, temporal prediction and explainable AI, the goal is to provide accurate predictions and better decisions.

The main contributions of this study are as follows:

- The CNN-based estimation of crop quality and its integration with the LSTM-based price prediction model.
- The use of ADWIN to detect concept drift for adapting the model to the dynamic environment.
- Application of SHAP to improve the interpretability of the developed models.
- Building of the multimodal agricultural decision support system.

## 2. LITERATURE REVIEW

### 2.1 Agricultural Market Dynamics

The agricultural markets are driven by seasonability and volatility. A close observation of prices can identify the relationships between demand and supply cycles that dominate their price fluctuations. Specifically, prices fall as supply increases in season and rise in out season when supply is scarce [1]. Environmental influences such as climatic uncertainty, transport constraints and political situation also affect agricultural market stability and thus bring uncertainty to the agricultural pricing system. The above difficulties show the importance of developing more sophisticated prediction techniques that account for the market dynamics.

## 2.2 AI in Agriculture

AI is another key technology in present day agriculture which provides more optimized and data based decisions, and increases efficiency. Several AI applications in agriculture are Crop monitoring, yield prediction, disease detection and market forecast. It has been proven that deep learning methods (such as Neural Networks) have achieved excellent results while dealing with agricultural data [5].

Precision agriculture makes use of sensors and IoT (Internet of Things) along with machine learning models to efficiently utilize resources and protect the environment, helping farmers to make better decisions using the information provided by real-time and past data [6].

## 2.3 Research Gap

Despite, all these methods could not suggest a combined framework capable of simultaneously considering the visual input, the time prediction, the adaptability to drift, and the explainability. The applications of such methods can thus not be as wide as those for agriculture. Additionally, most predictive models are not interpretable, thus challenging for end users to trust or integrate them into practical application [4]. Traditional models also do not take into account concept drift that is likely to occur due to the change in data distribution with time.

To address these gaps, in this work, the proposed model is a unified framework that combine visual crop quality, temporal forecasting, drift detection, and explainable AI into a decision support system for agriculture.

## 3.METHODOLOGY

### 3.1 Data Sources

The present study exploits diverse heterogeneous data sources to consider the multifaceted driving forces of crop price. The data sources that will be considered are the mandi price data on past values, meteorological inputs (temperature, rainfall, humidity, etc.) and seasonality values and image data of the crops.

The time series based historical prices can provide with the market trends and seasonal patterns. Weather influences agriculture as a primary factor affecting the yield. The factors like seasonal impacts would affect agriculture production and demand which in turn affects the market price of the crop. Crop images, in addition, help us to understand the quality of the crop which determines the value of the crop in the market. This combined information with varied features is better representation for agriculture and increases reliability of the predictive models [6].

## 3.2 Methodology Framework

The Proposed System is a multimodal framework which is comprised of the following 5 components:

- CNNs to predict the quality of crop
- Combining market and environmental data to engineer the features
- LSTM to predict the price of crop
- ADWIN to detect concept drift
- SHAP to interpret the model

This multimodal framework integrates both spatial (image based) and time-series data to improve the predictive power of the model. By considering multiple modalities, the framework is capable of capturing more intricate relationships between the environmental conditions and market price which are generally neglected in the conventional systems [7].

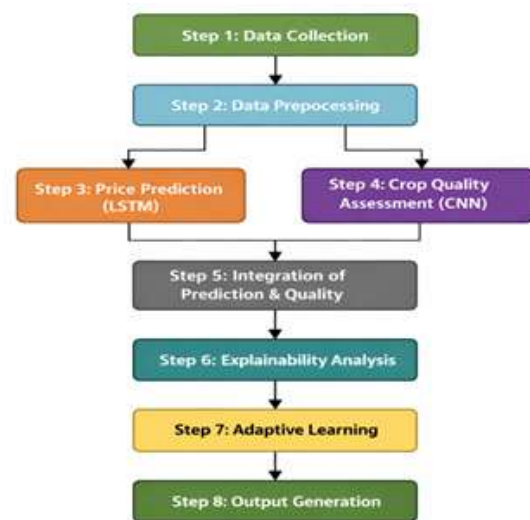


**Figure 1: Proposed Multimodal Framework for Crop Price Prediction**

Combining CNN and LSTM makes the model effectively learn both spatial and temporal relationships in agriculture related data. The former extracts useful features from crop images while the latter processes time series of prices. ADWIN ensures adaptability to ever changing market environment and SHAP provides interpretability to make the framework suitable for practical decision support system.

## 3.3 Model Description

### 3.3.1 Crop Quality Analysis (CNN)

A CNN has been used for the extraction of visual features from crop images, and the classification of these into crop quality types, i.e. ripe, unripe, and damaged. There is extensive research indicating the suitability of the CNN architectures to the tasks of image recognition and crop [3]. These quality features extracted are translated into numerical features for usage within the prediction model.

$$y = \sum(w * x) + b$$

### 3.3.2 Price Prediction (LSTM)

To determine the time series trend of crops prices, an LSTM (Long Short-Term Memory) model is employed here. An LSTM model is a kind of recurrent neural network that is especially suited to learn long-range dependencies from sequential data [2]. Because of its efficiency in detecting non-linear dynamics, LSTM models have proved successful in the time-series forecasting for agricultural prices prediction [8].

$$\text{LSTM: } (h_t = f(W_h h_{t-1} + W_x x_t + b))$$

- $(h_t)$ : Hidden state at time (t) (output)
- $(f)$ : Activation function (e.g., tanh or ReLU)
- $(W_h)$ : Weight matrix for hidden state
- $(h_{t-1})$ : Hidden state at time (t-1) (previous input)
- $(W_x)$ : Weight matrix for input
- $(x_t)$ : Input at time (t)
- $(b)$ : Bias vector

### 3.3.3 Drift Detection (ADWIN)

Concept drift is the phenomenon where the distribution of data changes over time. The ADWIN (Adaptive Windowing) algorithm is implemented to detect concept drift. The ADWIN dynamically sets a size of the sliding window over incoming data, and it statistically determines that the changes in data stream is significant [9]. This will ensure that the accuracy of the prediction is always maintained even in the rapidly changing environment of the markets.

### 3.3.4 Explainability (SHAP)

SHapley Additive exPlanations (SHAP) are also employed to measure the impact each feature has on the prediction output of the model in order to increase transparency and interpretability. SHAP is the first theoretically sound method for explaining both local and global predictions with a great potential for understanding machine learning models for final users [4].

$$f(x) = \phi_0 + \sum_{i=1}^M \phi_i$$

### 3.3.5 Feature Engineering

Feature engineering can aggregate many input factors that combine temporal information such as month, year, market factors, such as trends of price, as well as climate data, crop quality data, which improve model accuracy by extracting useful features from inputs and lowering the noises [10].

## 4.RESULTS AND DISCUSSION

### 4.1 Model Performance

The metrics used for performance evaluation of the proposed model were traditional regression metrics, i.e. RMSE (Root Mean Squared Error), MAE (Mean Absolute Error) and

prediction accuracy. From the table, it can be seen that CNN-LSTM achieved an accuracy of 96.59% with RMSE of 25.5 and MAE of 24.6 which is better than previous machine learning models namely LR, RF and SVR (The baseline models such as ARIMA and XGBoost achieved lower prediction accuracies compared to the proposed mode). This increase in performance is due to the capability of LSTM network to effectively model long-term dependencies of price in time series, whereas the ability of CNN models to capture crop quality features. Hence use of multimodal inputs allow capture of interrelations between environmental, visual and market data, which results in higher prediction performance. Overall, the developed model shows lower error and increased accuracy compared to other models. With the integration of the drift detection mechanism, it also keeps the prediction stable over time-varying market scenarios common in agriculture markets.

$$\text{MAE} = (1/n) \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$\text{RMSE} = \sqrt{(1/n) \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

- $(n)$ : Total number of observations.
- $(\Sigma)$ : Summation symbol (sum of all samples).
- $(y_i)$ : Actual value.
- $(\hat{y}_i)$ : Predicted value.

**Table -1: Comparison of Different Models**

| Model               | MAE  | RMSE | Accuracy |
|---------------------|------|------|----------|
| ARIMA               | 45.2 | 52.8 | 82%      |
| XGBoost             | 32.4 | 38.6 | 88%      |
| CNN-LSTM (Proposed) | 24.6 | 25.5 | 96.59%   |

## 4.2 Market Insight Analysis

Experimental analysis showed some key information on features influencing crop price. Of all input features, price trend was found to be the most important predictor which indicates the strong dependency of price over the time series. This insight validates the importance of temporal dependencies captured by the LSTM model. Also seasonal variations played a significant role in crop price, for example agricultural output follows a cyclic nature, price fall during its peak season when the output is at its maximum and vice versa at lean season due to insufficient availability. Beside time related factors, crop quality that we obtained from the images is also one of the most important features that affect crop price; Higher the quality of crop, the higher will be the market price of crop and this indicates the necessity of including visual features to predict the market price. It again confirmed the contribution of image analysis with time series forecast.

## 4.3 Explainability Results

SHAP was used to identify the impact of each feature on the prediction results to enhance model transparency. From the explanation, the factors that have major impacts on the prediction are market price, seasonal index and crop quality.

SHAP offers both global and local interpretability to users to provide explanation about the factors that contribute to prediction. It is significant in agricultural domain since farmers and stakeholders can be provided a trust and understandable system which can gain confidence of farmers.

The interpretation mechanism mentioned helps in overcoming the limitation of traditional machine learning methods since traditional machine learning methods are always seen as black box.

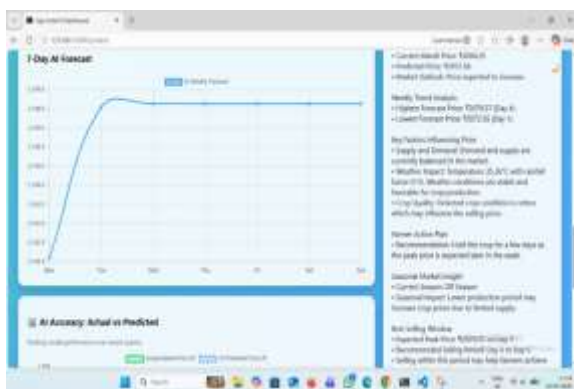


**Figure 2: Visualization of Price Forecast and Model Explainability Interface**

## 4.4 Practical Implications

The presented framework offers tremendous practical applications for the stakeholders in the agricultural domain. Based on the accurate and interpretable price predictions given by the system, farmers can gain substantial insights to determine the appropriate selling time of their crops. The predictive capabilities in terms of forecasting short-term price

dynamics empower farmers to recognize opportune times for selling to optimize profit. Combining drift detection ensures the model is always reliable in the event of changes in market conditions, thus lowering the risks associated with price fluctuations. Therefore, the presented system leads to:

- better decision-making through the application of decision-support systems on relevant data
- lower financial risk associated with the vagaries of market prices
- higher profit through effective selling time:

These applications show the potentiality of AI-based decision-support systems for revolutionizing farmer involvement in the agricultural market. This serves as an example where the combination of modalities, through multimodal learning, leads to better predictive accuracy compared to the performance of each modality alone.

## 5. CONCLUSION & RECOMMENDATIONS

In this paper, the proposed model is a drift-aware, explainable AI framework to predict crop prices by fusing heterogeneous data sources: crop images, weather, market price, and seasonal factors. The proposed framework uses Convolutional Neural Networks (CNNs) to perform image-based crop quality recognition and Long Short-Term Memory (LSTM) networks to forecast market prices as a time-series data. Additionally, Adaptive Windowing (ADWIN) to adapt to concept drift in market environment and SHAP (SHapley Additive exPlanations) for model explainability.

Experimental results show that our framework offers superior prediction accuracy and lower prediction error compared to conventional machine learning models. The fusion of visual quality information and market information represents the agricultural systems with richness and completeness, while the drift detection helps the framework adapt to dynamic market fluctuations. Also, the use of explainable AI helps to understand and trace the cause of prediction in the model.

From the application viewpoint, the proposed framework is able to provide efficient decision support to farmers to plan selling strategies according to market price prediction. The system could increase the profits of farmers by diminishing market uncertainties and increasing access to efficient market participation information.

However, there still are some limitations to our proposed system. Firstly, the quality and availability of data can greatly affect the performance of the model, especially in areas with limited digital access. Secondly, the generalization capability across various crops and geographical regions of the model needs further study. In addition, the complexity of the deep learning models may lead to increased deployment difficulty in resource-constrained environments.

## Recommendations and Future Work

There are several directions for future research to extend the above framework:

- Multi-region deployment: The model can be extended for deployment across multiple regions to improve its generalizability.
- Real-time implementation: Real-time data streams and prediction methods should be developed and integrated to implement the real-time monitoring.
- Mobile based application development: Design mobile friendly applications for easy access to farmers.
- IoT integration: Integrate sensors- based data in the model for environmental monitoring.
- Continuous model updating: Implement continuous learning methods to keep the model updated for the dynamic market conditions.

The potential to build an intelligent and robust agriculture decision support system is highlighted by the framework of deep learning, explainability and adaptiveness.

## REFERENCES

- [1] Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice* (2nd ed.). OTexts, <https://otexts.com/fpp2/>.
- [2] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735–1780, <https://doi.org/10.1162/neco.1997.9.8.1735>.
- [3] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90, <https://doi.org/10.1016/j.compag.2018.02.016>.
- [4] Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems (NeurIPS)*, <https://papers.nips.cc/paper/7062-a-unified-approach-to-interpreting-model-predictions>.
- [5] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press, <https://www.deeplearningbook.org>.
- [6] Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming: A review. *Agricultural Systems*, 153, 69–80, <https://doi.org/10.1016/j.agry.2017.01.023>.
- [7] You, J., Li, X., Low, M., Lobell, D., & Ermon, S. (2017). Deep Gaussian process for crop yield prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, <https://ojs.aaai.org/index.php/AAAI/article/view/10644>.
- [8] Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50, 159–175, [https://doi.org/10.1016/S0925-2312\(01\)00702-0](https://doi.org/10.1016/S0925-2312(01)00702-0).
- [9] Bifet, A., & Gavaldà, R. (2007). Learning from time-changing data with adaptive windowing. In *Proceedings of the*
- SIAM International Conference on Data Mining*, <https://doi.org/10.1038/nature14539>.
- [10] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674, <https://doi.org/10.3390/s18082674>.
- [11] Russell, S. J., & Norvig, P. (2010). *Artificial intelligence: A modern approach* (3rd ed.). Pearson, <https://www.pearson.com/en-us/subject-catalog/p/artificial-intelligence-a-modern-approach/P200000003500>.
- Agricultural Systems*, 153, 69–80, <https://doi.org/10.1016/j.agry.2017.01.023>.
- [12] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521, 436–444, <https://otexts.com/fpp2/>.
- [13] Benidis, K., Rangapuram, S. S., Flunkert, V., et al. (2020). Neural forecasting: Introduction and literature overview. *arXiv preprint arXiv:2004.10240*, <https://arxiv.org/abs/2004.10240>.
- [14] Samek, W., Wiegand, T., & Müller, K. R. (2017). Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. *arXiv preprint arXiv:1708.08296*, <https://arxiv.org/abs/1708.08296>.
- [15] Graves, A. (2012). *Supervised sequence labelling with recurrent neural networks*. Springer, <https://link.springer.com/book/10.1007/978-3-642-24797-2>.