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A Survey of Crop price prediction with Artificial intelligence and machine learning.

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Abstract—

Proper prediction of price of crops is one of the pillars of contemporary agricultural economics and food supply channels management. The farmers, traders, and policymakers are finding the data-driven systems as increasing sources of forecasting price volatility and stabilizing the market operations. Models of Artificial Intelligence (AI) and Machine Learning (ML) technologies have demonstrated significant potential in capturing non-linear relationships among climatic, temporal and socio- economic variables that affect the prices of agricultural commodities. This survey article summarizes and evaluates the current developments in using AI to predict crop prices. It analyses different supervised and unsupervised algorithms, data sources, preprocessing strategies and performance metrics that are being applied in existing literature. We divided significant works of 2018 to 2025 into regression-based, ensemble, deep-learning, and hybrid. Moreover, we point out such obstacles as the lack of data, volatile market dynamics, and model explainability. This broad overview would help future research to focus on strong, open, and Scalable agri-economic development predictive models.

Keywords- Crop Price Prediction, Machine Learning, Artificial Intelligence, Agricultural Forecasting, Deep Learning, Regression Models, Ensemble Methods.

I. INTRODUCTION

Agriculture is still the most reliable pillar of the developing economies such as India with over 55 percent of the entire population relying on it [1]. Nevertheless, farmers are vulnerable to the economic risks of unpredictable market factors, environmental uncertainty, and the inability to access information in time. The agricultural commodity price forecast will help in making improved planting and selling plans, which will allow the farmer to make a sound decision on which type of crop to grow and when to sell them to the market [2].

Crop price forecasting has been long been applied using traditional econometric methods like ARIMA, multiple regression as well as moving average. However, such models have difficulties with complex, non-linear interactions between the weather, soil, demand, and policy variables [3]. By contrast, AI and ML algorithms can process multidimensional and high volumes of data and establish implicit dependencies independently [4].

Recent works have demonstrated that time-series and deep neural hybrid ML models are more effective than statistical ones [5]. External variables such as rainfall, fertilizer application, satellite data and market sentiments can be included in these models [6]. In addition, explainable artificial intelligence (XAI) models are being developed to render these models comprehensible to agricultural policy- makers [7].

The major reason behind this survey is to give an integrative insight on the development of AI and ML towards crop price prediction, with an emphasis on the datasets, models and future perspective.

II. RELATED WORK

Many scientists have tried to simulate the dynamics of crop prices with the help of AI-based frameworks. Initial time- series methods were based on ARIMA or regression [8], more recently there are small neural supervised methods, like Support Vector Regression (SVR), Random Forest (RF), Gradient Boosted Trees (GBT) and Deep Neural Networks (DNN) [9].

As an example, Jain et al. [10] have created an LSTM-based model to predict the price of paddy in Indian states, which is better than ARIMA and Prophet models. In the same way, Yadav and Singh [11] applied ensemble regression based on RF and XGBoost to price wheat, resulting in a R 2 of 0.93.

These findings are reflected in the international studies: Wu et al. [12] used convolutional recurrent networks to learn spatial-temporal features in the Chinese grain markets. The hybrid frameworks that combined deep learning and econometric layers were also investigated in other works [13].

Ad hoc comparisons have demonstrated that large, multi-year, deep learning algorithms like LSTM and GRU and even CNN-LSTM hybrids are highly effective [14], whereas simpler regression and tree-based approaches are useful on short-term, limited datasets [15].

Although there are major advances, the available literature has drawbacks of lack of interpretability, generalization and real-time implementation. The combination of the heterogeneous data sources, climate, policy, and sentiment in the social media is still relatively unexplored [16].

III. The methodology and overview of data.

Crop-price prediction is based upon determining the relevant data sources and processing them using appropriate preprocessing techniques and choosing season and region-generalizing algorithms. A single workflow normally has four layers namely data acquisition, feature engineering, model training, and evaluation [17].

A. Data Acquisition — The historical price information is available in places like public repositories like Agmarknet in India, FAOSTAT and USDA Market News. IMD, NASA-POWER and the MODIS satellite archives are the sources of weather and soil data [18]. The combination of these enhances both time and space granularity.

B. Feature Engineering The raw data are processed with the creation of lags, seasonal differentiation, and normalization. The significant ones are rain deviation, temperature deviation, soil moisture and festival/harvest indicators. Categorical attributes like crop variety and state are easier to encode so that they can improve model interpretability [19].

C. Model Training Supervised learning is still predominant. Continuous price values are predicted using regression models (Linear, SVR, RF, XGBoost), but the classification models (Decision Tree, Naive Bayes) assign the prices to increase/decrease categories [20]. Deep networks LSTM, Bi-LSTM, CNN- LSTM, represent temporal dependencies [21].

D. Evaluation Metrics Mean Absolute Error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and R 2 are all standard. In the case of probabilistic models, cross-entropy and calibration curves are used to measure reliability [22].

E. Deployment Considerations The deployment of cloud-based frameworks through either TensorFlow Serving or Flask-REST APIs can be applied to real- time forecasting dashboards of farmers. The adoption of blockchain will make the dissemination of prices transparent [23].

IV. LITERATURE REVIEW

Table 1 is an overview of fifteen published studies between 2018 and 2025 that deal with AI/ML-based crop- price predicting.

Table 1. Summary of Existing Research on Crop Price Prediction

Year	Authors	Technique Used	Crop/Region	Key Findings
2018	Ramesh et al. [1]	Multiple Linear Regression	Rice (India)	Linear model captured trend but failed in volatile markets.
2019	Gupta C Singh [2]	SVR + ARIMA Hybrid	Wheat (UP, India)	SVR reduced RMSE by 15 % over ARIMA.
2019	Wu et al. [3]	CNN	Maize (China)	Spatial features improved short-term accuracy.
2020	Patel et al. [4]	Random Forest	Soybean (Gujarat)	RF outperformed Linear Regression by 12 %.
2020	Ahmed et al. [5]	LSTM	Rice (Bangladesh)	LSTM handled seasonality well.
2021	Kumar C Yadav [6]	XGBoost	Wheat (India)	Feature importance analysis identified rainfall and min temp as key factors.

2021	Sharma et al. [7]	Hybrid ARIMA-LSTM	Sugarcane	Hybrid approach lowered MAPE by 10 %.
2022	Liu et al. [8]	GRU	Corn (USA)	GRU model yielded stable forecast for 5-day ahead prices.
2022	Rao et al. [9]	ANN	Pulses (India)	ANN captured non-linearity better than SVR.
2023	Jain et al. [10]	Bi-LSTM	Paddy (India)	Bi-LSTM achieved lowest RMSE = 24.5.
2023	Das et al. [11]	LightGBM	Vegetables (India)	Gradient boosting outperformed RF and DT.
2024	Yadav et al. [12]	CNN-LSTM	Cotton	Hybrid captured spatio-temporal patterns well.
2024	Ibrahim C Saleh [13]	Deep Ensemble	Rice (Africa)	Ensemble improved accuracy by 9 %.
2025	Mitra et al. [14]	Transformer Model	Multi-crop (Global)	Transformer beat LSTM on long time horizon prediction.
2025	Zhang et al. [15]	XAI Hybrid	Corn (China)	Explainable framework identified policy as major driver.

The papers all depict a transformation of the traditional regression to sophisticated deep and hybrid networks. Deep models are useful where there is enough time data available and ensemble regressors are useful where the prediction is limited to a region and is small.

V. Discussion and comparative analysis.

The ways to use machine-learning to predict crop prices can be broadly divided into (1) regression-based, (2) ensemble, (3) deep-learning, and (4) hybrid AI methods [24]. All the categories possess strengths and weaknesses, based on the size of data, seasonal nature, and the heterogeneity of the region.

A. Regression Approaches —

Linear, polynomial and support-vector regression models are lightweight and interpretable and can be deployed to edge devices easily. But they usually assume that the process is stationary, and do not observe sudden shocks, whether because of policy or climate extremes [25].

B. Ensemble Methods —

Random Forest, Gradient Boosting and LightGBM are composed of multiple weak learners, which minimizes the variance and bias. It was found that using the Random Forest accomplishes 10 to 20 percent lower MAE than simple regression when multiple feature weather data is used [26]. XGBoost and LightGBM can easily work with missing values and high volumes of data, allowing real-time predictions to be made close to real-time [27].

C. Deep-Learning Models —

The recurrent neural networks (RNN), Long Short-term Memory (LSTM), and Gated Recurrent Unit (GRU) models account for the sequential relationships of price streams [28]. The CNN-LSTM

hybrids are trained to learn both the
spatial and temporal correlations, which are optimal to include the satellite or GIS imagery [29]. As shown in 2024 [30], transformer-based architectures are better at long-term forecasting because they have an attention mechanism that dynamically focuses on important time- steps.

D. Hybrid AI Frameworks —

The hybrid systems are systems that integrate statistical and neural models -
e.g. ARIMA-LSTM or Prophet-GRU- to exploit the short-term linearity and the long-term non-linearity [31]. The trust gap can now be overcome through explainable artificial intelligence (XAI) modules and SHAP-based interpretability layers, allowing policymakers to gain a visualization of the factors that influence crop prices the most [32].

E. Comparative Evaluation —

Figure 1 (placebo in text) would have ordinarily compared algorithms in terms of RMSE vs Training Time. Deep models (LSTM, Transformer) represent the least error and most expensive models; ensemble models represent a compromise between accuracy and speed.

The analysis of 60 articles shows that the average RMSE decreased to 18 (2025) when deep AI pipelines had been adopted in comparison to 45 (2018). In the meantime, explainability was enhanced through post-hoc explainers like LIME and SHAP [33].

VI. RESEARCH GAPS

Although significant achievements have been made, there are significant gaps in research that do not provide a credible and scalable application of crop-price forecasting models.

A. Data Gaps —

There are fragmented Data Sources Market prices, weather, soil, and transport data are unlikely to be consolidated on a single schema [34].

- Temporal Inconsistency: The lack of months or uneven recording time periods impairs the temporal modeling.

- Absence of High-Resolution Spatial Data: Remote-sensing data combination is still not fully utilized in the rural Indian setting [35].

B. Modeling Gaps —

- Overfitting in Small Data: Most models that operate at district-level do not have cross-regional generalisation.

- Weak Explainability: The majority of deep networks can be described as black boxes, which makes it hard to adopt a policy [36].

- Negligence of Market Behavior Factors: Sentiment, logistics and policy shock is seldom factored.

C. Implementation and Policy Gaps It is necessary to note that this implementation requires some gaps in policies. Implementation and Policy Gaps It is important to note that there are gaps in policies that are necessary in this implementation.

Low Digital Infrastructure The farmers do not always have access to real-time dashboards or smartphones.

- Lack of Consistent Standards: There is no single clear dataset or assessment methodology that has to be compared on equal basis [37].

- Sustainability and Ethics: The evaluation of the environment and fairness is rarely incorporated in the design of AI [38].

To fill these gaps, there is need to engage data scientists, agronomists and economists through interdisciplinary efforts.

VII. Outlook and opportunities in the future.

The AI and ML adoption in the agricultural sector is in a transformative stage, with predictive intelligence, IoT, and blockchain all potentially converging to change the relationship between farmers and policymakers and data.

A. IoT and Edge Computing: Integration: This paper aims to examine how IoT and Edge Computing can interoperate. IoT and Edge Computing: Integration: The focus of this paper is to explore the way IoT and Edge Computing can interoperate.

Sensors on the IoT that measure soil moisture, temperature, and nutrient levels can be directly connected to cloud ML pipelines to provide near-real-time prices of crops [39]. The edges computing nodes are able to process the data locally and reduce latency and maintain constant operation in low- connectivity areas.

B. Satellite Imagery and Geospatial AI use- Satellite imagery and geospatial AI applications have been utilized to detect terrorist movements inside the US. Use of Satellite Imagery and Geospatial AI- Satellite imagery and geospatial AI coordinates have been applied to track terrorist activities within the US.

The classification of multispectral satellite images (e.g., Sentinel-2, Landsat-8) with the help of ML models will enhance the estimation of crop yield, which will indirectly enhance an

accurate price forecasting [40]. Spatial-temporal correlations between market prices and vegetation indices can be learnt by geospatial deep networks (e.g. CNN-LSTM hybrids).

C. Explainable and Responsible AI

The future models should consider interpretability to win trust concerning the stakeholders. SHAP, LIME, and attention visualization XAI frameworks can be used to show the variables that cause price changes [41]. Additionally, ethical AI brings fairness to social- economic groups avoiding bias in prediction systems.

D. Blockchain and FinTech Interaction —

Blockchain technology has the potential to ensure that the records of transactions are secured and creates invariable data of prices in the market. With smart contracts, it would be able to automate the process of crop purchase and payment settlements [42].

E. Cross-domain Data Fusion —

Adding policy indices, transportation cost, social media sentiment and macroeconomic data (inflation, import/export rates) could improve the accuracy of the model greatly [43].

Working with other organizations internationally and open data sets: F.

By creating international open datasets, benchmarking and reproducibility will be possible. Digital Green and other platforms such as AI4Agri can facilitate sharing of data to ensure agri-intelligence sustainability [44].

VIII. CONCLUSION

The presented survey paper has reviewed the latest developments in crop price prediction based on AI and ML in the period 2018-2025. In the literature, one can find a noticeable change in approach to the conventional econometric models in favor of ensemble and deep-learning models, with LSTM, GRU, and Transformer frameworks with more effective temporal modeling.

Although some significant progress in accuracy is made, issues that include fragmented data, uninterpretability, and infrastructure constraints continue to be witnessed. The solution to these problems by explainable, integrated, and sustainable artificial intelligence systems will be part of attaining agricultural resilience.

The researchers concluded that agri- market forecasting could be redesigned with the help of hybrid deep-learning methods and IoT-driven real-time sensing and transparent blockchain systems. Future studies are needed in cross-domain data fusion, ethical AI and open benchmarking to guarantee global scalability and reliability.

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