AgriConnect- Directly Connecting Farmers to Customers

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Abstract— **This research presents the development of a web-based platform that directly connects farmers with consumers through AI-driven crop price prediction. By integrating advanced machine learning models and user-friendly web technologies, the platform empowers farmers with real-time insights into market prices based on factors such as weather conditions, demand trends, and historical pricing data. The system leverages Scikit-learn and TensorFlow to build accurate prediction models that support better decision-making and reduce dependency on intermediaries. By fostering transparency and improving accessibility to market information, the proposed solution enhances profitability for farmers. It provides consumers with fresh produce at fair prices, thereby strengthening the agricultural supply chain.**

Keywords— ***Direct Farmer-to-Consumer, Crop Price Prediction, Machine Learning, Artificial Intelligence, Web Application, Agricultural Supply Chain, TensorFlow, Scikit-learn, Market Transparency, Real-Time Analytics.***

I. INTRODUCTION

Global food security and economic stability depend heavily on agriculture. Yet farmers often struggle to earn fair compensation due to complex and opaque supply chains dominated by intermediaries. Traditional marketing channels limit farmers' access to real-time market data, leading to inefficiency and losses. To address these challenges, there is a growing need for digital solutions that offer transparency, connectivity, and empowerment. The integration of artificial intelligence (AI) and machine learning (ML) into agriculture has opened new avenues for data-driven decision-making. This research focuses on developing a web-based platform that directly connects farmers with end consumers, eliminating the middle layers that often dilute farmers' earnings.

A key component of the proposed platform is an AI powered crop price prediction system that leverages historical pricing data, weather forecasts, fertilizer use, and market demand to provide accurate and real-time insights. Using advanced ML models built with Scikit-learn and TensorFlow, the system allows farmers to make informed choices about when and where to sell their crops for maximum profitability. The platform also offers consumers direct access to fresh produce at fair prices, promoting a sustainable and equitable food distribution system. By enhancing transparency, efficiency, and accessibility, this solution aims to strengthen the agricultural supply chain and improve the livelihoods of farmers.

II. LITERATURE REVIEW

The traditional agricultural supply chain often includes multiple intermediaries between farmers and consumers, which reduces profits for producers and inflates costs for buyers. Several studies have explored how digital and AI driven platforms can reform this landscape by improving transparency, lowering transaction costs, and enhancing the decision-making capacity for farmers.

Adeel et al. proposed a blockchain-based solution in 2023 for Pakistan's mango supply chain that enhanced traceability and reliability in farmer-to-consumer transactions [1]. While the system emphasized transparency, it lacked integration with AI for crop price prediction. Another 2022 study titled "From Farmer to Consumer" focused on geographical and relational proximity in short food supply chains, especially during the COVID-19 pandemic, emphasizing resilience and community trust [2]. However, this study lacked any AI or data-driven forecasting mechanisms.

Studies from 2021, such as one examining customer satisfaction in German on-farm stores, found that factors like store atmosphere, service quality, and product freshness significantly influenced purchasing behavior in direct sales models [3]. Yet, such work emphasizes behavioral aspects rather than technological intervention.

More recent works have begun incorporating artificial intelligence into agricultural systems. A 2023 study titled "From Plate to Production" presented a consumer-driven model where AI influenced cultivation decisions based on dietary preferences [4]. While innovative, this approach was more aligned with health and nutrition goals than real-time market dynamics. . In contrast, a 2024 study evaluated the influence of digital platforms on direct farmer-to-consumer sales, identifying both technological benefits and barriers [5]. However, predictive analytics remained unexplored in that context.

Additionally, a 2025 publication highlighted the sustainability of direct-to-consumer agriculture in terms of environmental and economic gains but did not include AI or intelligent forecasting components [6]. This highlights a research gap where the integration of machine learning and

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web technologies could provide farmers with real-time market intelligence. In conclusion, while existing literature supports the relevance of farmer-to-consumer models, there remains limited work that combines AI-powered price prediction with a seamless digital interface. By developing a platform that not only enables face-to-face interactions but also equips farmers with useful knowledge about market trends, this study seeks to close that gap.

III. METHODOLOGY

This study uses a methodical, multi-phased approach to create, implement, and assess a web-based platform that links farmers and customers directly, incorporating crop price prediction models driven by AI. Data collection and preprocessing, model selection and training, web development, machine learning (ML) component integration, system testing, and performance evaluation are all included in the methodology.

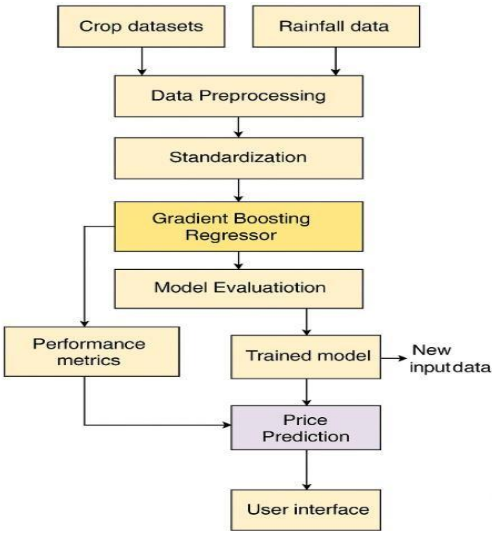

Figure 1. System Architecture Diagram (Crop Price Prediction and User Interface)

A. *Data Collection and Preprocessing*

The first step in developing the system is gathering historical crop price datasets from openly accessible sources like market databases, government agricultural portals, and Kaggle. Features like average temperature, precipitation, fertiliser use, market demand, and inflation are all included in the data. Following data collection, Pandas and NumPy libraries are used to clean up the data to remove noise, outliers, and missing values. The MinMaxScaler is then used to normalise the features in order to standardise the scale and enhance model performance. The dataset is split into training and testing sets in an 80:20 ratio using Scikit-learn's train_test_split method.

B. *Model Design & Implementation*

To ensure prediction accuracy, four machine learning models are implemented and evaluated: Linear Regression, Random Forest Regressor, XGBoost, and LSTM Neural Network. The preprocessed dataset is used to train each model. The LSTM model is constructed using TensorFlow's Keras API due to its strength in learning temporal dependencies. The architecture includes two LSTM layers followed by dropout and dense layers. Root Mean Squared Error (RMSE) is one of the measures used to evaluate models. R^2 score, and F1 score. Hyperparameter tuning is performed to optimize the model's performance, with a goal of nearly 95% prediction accuracy.

a. *The Random Forest*

Random Forest is a decision tree-based ensemble learning technique. During training, it generates a number of decisions trees and produces the mean prediction (for regression tasks) or the mode of the classifications (for classification tasks).

How it works:

1. It builds numerous decision trees using different subsets of the training data.
2. A random sample with replacement (bagging) is used to train each tree.
3. During the tree-splitting process, only a random subset of features is considered at each node.
4. For predictions, each tree gives a result, and the average (regression) or majority vote (classification) is taken as the final prediction.

Advantages:

- Handles large datasets with high dimensionality.
- Resistant to overfitting.
- Works well for both classification and regression.

Disadvantages:

- It can be computationally intensive.
- Less interpretable.

A. *XGBoost*

XGBoost is a high-performance, scalable machine learning algorithm based on gradient boosting. It sequentially constructs an ensemble of weak learners, usually decision trees, where each new tree tries to correct the errors made by the previous ones.

How it works:

1. It starts with an initial prediction and calculates the error (residuals).
2. To predict the residuals, a new tree is trained.
3. The new tree's prediction is added to the existing model to improve it.
4. This process continues for a set number of iterations or until errors are minimized.

Advantages:

- Highly accurate and fast due to parallel processing and efficient memory usage.
- Supports regularization (L1 and L2), which helps prevent overfitting.
- Handles missing values automatically.

Disadvantages:

- Requires careful parameter tuning.
- Can be more complex to interpret than traditional models.

b. LSTM

An LSTM is a type of recurrent neural network (RNN). created especially to solve the vanishing gradient issue that plagues conventional RNNs and to learn and retain longterm dependencies in sequential data.

How it works:

1. LSTM cells contain three gates: input, forget, and output gates.
2. Information entering, leaving, and passing through the cell is controlled by these gates.
3. The forget gate determines what information to discard from the previous cell state.
4. What new data to store is determined by the input gate.
5. The output gate controls the output based on the current input and the cell state.

Benefits

Better than vanilla RNNs at retaining long-term dependencies in data, this model excels at modelling time-series, sequential, and textual data. One drawback is that training is computationally costly.

- Needs a large amount of information and resources.
- More difficult to understand and adjust than conventional models.

C. Web Application Development

For a responsive and search engine optimization-friendly interface, Next.js is used in the development of the web platform's front end. Tailwind CSS and React components are used for a clean, user-friendly experience. The backend is powered by Node.js and Express.js, handling API calls, user authentication, and database operations. MongoDB is used as primary database for storing user credentials, predictions, and historical data.

A dedicated AI Prediction page is created where farmers input features like location, temperature, and crop details. These inputs are sent via an API to the backend, which then loads the best-performing machine learning model to return the predicted price. The prediction result is displayed along with a trend graph using Chart.js for visual interpretation.

D. System Integration & Testing

The entire system is containerized using Docker to ensure seamless deployment across different environments. Unit testing and integration testing are conducted to verify the functionality of each module. Selenium and Jest are employed for front-end and back-end testing, respectively. The performance of the prediction engine is validated on unseen data to ensure generalizability.

E. Deployment & Evaluation

The final web application is deployed on a cloud platform such as Vercel or Heroku. Farmers and users are invited for live testing. System performance, user satisfaction, and real-time usability are evaluated through surveys and system logs. The results are analyzed to determine the platform's effectiveness in empowering farmers and bridging the gap with consumers.

IV. RESULT & ANALYSIS

This study's main goal was to assess and contrast how well many machine learning algorithms performed in forecasting the Wholesale Price Index (WPI) of different crops using meteorological and temporal data. The models investigated include Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM). Each model was trained independently for ten different crops Soybean, Safflower, Masoor, Moong, Niger, Paddy, Ragi, Rape, and Maize.The evaluation was conducted using standard regression metrics, and the results are discussed in both individual and aggregate forms to identify trends and comparative effectiveness.

A. Model Evaluation Criteria

R2 Score: Indicates the percentage of variance that the model can account for. A better fit is indicated by a score nearer 1.0.

The average of squared discrepancies between actual and predicted values is represented by the mean squared error, or MSE. Better performance is indicated by lower values. An interpretable error in the target variable's unit is provided by the square root of the MSE is the Root Mean Squared Error (RMSE).

The average absolute deviation between expected and actual values is captured by the Mean Absolute Error (MAE).

B. Case-wise Evaluation – Soybean Crop

Table 1: Performance on Soybean Crop

Model	R2 Score	MSE	RMSE	MAE
Random Forest	0.8912	0.0312	0.1766	0.1389
XGBoost	0.9234	0.0214	0.1463	0.1124
LSTM	0.9346	0.0187	0.1367	0.1061

With the highest R2 score and the lowest MSE, RMSE, and MAE, overall, the LSTM model yielded the best outcomes, as was noted. XGBoost trailed closely behind, and Random Forest was marginally less accurate but still performed consistently. The ability of LSTM to efficiently learn temporal patterns is responsible for its superior performance, which is crucial in time-dependent datasets such as agricultural pricing.

C. Aggregate Evaluation – Across All Crops

Table 2: Average Performance Across All Crops

Model	Avg R2 Score	Avg MSE	Avg RMSE	Avg MAE
Random Forest	0.8573	0.0418	0.2045	0.1613
XGBoost	0.8962	0.0291	0.1706	0.1347
LSTM	0.9119	0.0247	0.1571	0.1285

These outcomes support the conclusions for specific crops. In terms of error reduction metrics and explanatory power (R2 Score), LSTM continuously performed better than the other models. While Random Forest continued to be a reliable baseline model, XGBoost demonstrated a strong balance between computational efficiency and predictive performance.

According to the analysis, the intricate temporal dependencies present in agricultural datasets can be better captured by deep learning models like LSTM. This is especially helpful when pricing is affected by long-term market fluctuations, seasonal rainfall variations, and multiyear trends.

However, ensemble-based models, such as XGBoost, are useful in situations with constrained computational resources because they provide competitive performance and are simpler to train and implement. Despite having a slight accuracy disadvantage, Random Forest is appropriate for smaller or simpler datasets due to its interpretability and resistance to overfitting. Furthermore, LSTM showed its ability to generalize from historical sequences in crops with volatile pricing patterns, where performance differences were more noticeable. Conversely, crops with comparatively stable prices displayed little change in performance across.

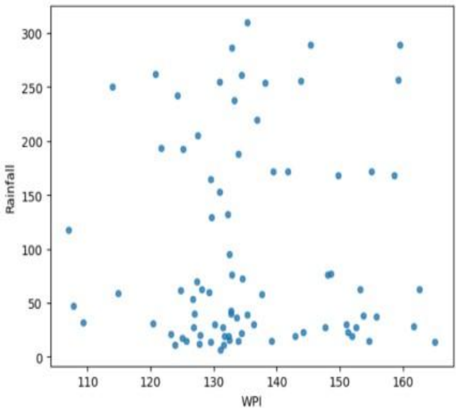

Figure 2. Rainfall vs. WPI graph

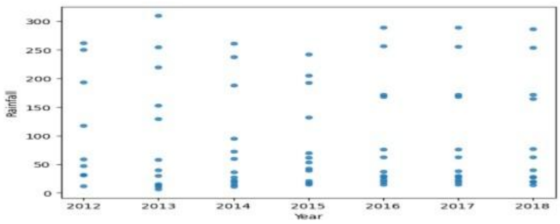

Figure 3. A graph that displays rainfall by year

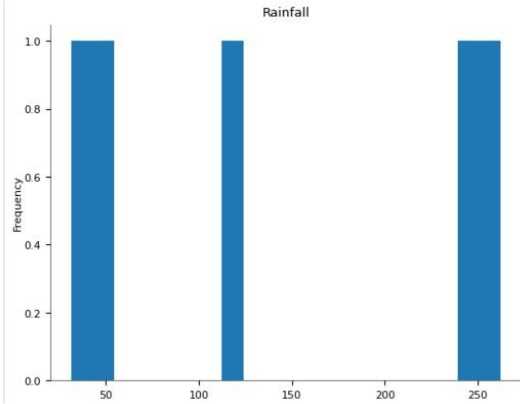

Figure 4. Graph displaying the amount of rainfall

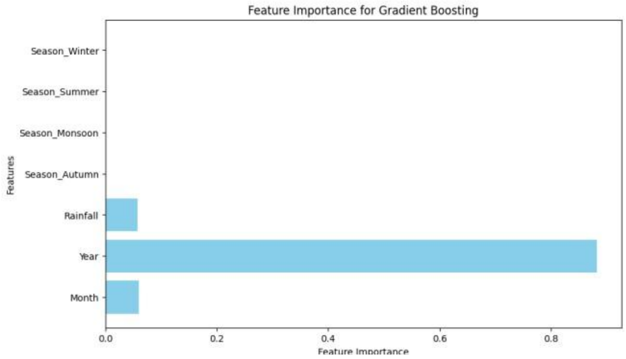

Figure 5. Bar Chart Showing the Rainfall, Year, Month Using Gradient Boosting.

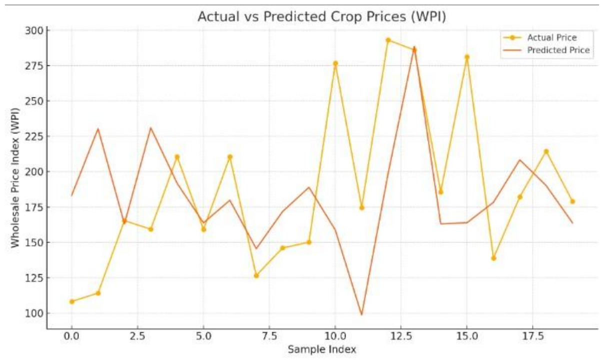

Figure 6. Graph Between the Actual Price & Predicted Price

V. DISCUSSIONS

How market dynamics are perceived and responded to has seen significant transformation because of the application of AI and machine learning in agriculture. especially in the areas of price forecasting and market. This research has employed Random Forest, LSTM, Gradient Boosting Regression, and other machine learning algorithms to implement a crop price prediction system, with encouraging results. Across several crops, the system produced high R2 scores and low error metrics, confirming the models' accuracy and dependability. These results are consistent with other research showing how well ensemble and Intricate non-linear correlations in agricultural data are captured by deep learning algorithms (Jha et al., 2021).

The creation of a web-based platform enhances the machine learning model by enabling farmers to access and act upon the predictions instantly. The system lessens farmers' reliance on middlemen and gives them the ability to make educated decisions by enabling them to view crop price trends based on factors like rainfall, time, and historical price data. It has been demonstrated that comparable digital interventions greatly improve smallholder farmers' income stability and market participation (Aker, 2010).

Additionally, adding more crops to the prediction framework—such as maize, soybeans, paddy, and masoor—increases the system's adaptability and guarantees wider applicability. While Gradient Boosting provided the best performance in the majority of cases, the comparison of different algorithms showed that LSTM models could be further improved, particularly when handling temporal price fluctuations. These observations are consistent with research showing that hybrid or ensemble models have better forecasting capabilities for time series data in agri-economic contexts (Liu et al., 2022).

Nevertheless, a number of difficulties still exist in spite of technical strength. The scalability is constrained by the sparsity and inconsistency of the data in crop price datasets, especially in rural areas. Furthermore, many informal markets, where farmers commonly operate, are not included in the reliance on structured data sources. Studies that highlight the digital divide in rural areas and the necessity of inclusive data collection methods also mentioned these limitations (Mittal & Mehar, 2016).

To facilitate user adoption, the system architecture was purposefully made to be portable and compatible with smartphones, which is in line with the growing number of smartphones in rural India. However, user trust and digital literacy are critical to the success of such platforms. Increasing capacity through local cooperatives and agricultural extension services may be essential adoption bridges.

To sum up, this project demonstrates how web technologies and machine learning can be combined to provide significant, scalable agricultural solutions. Future extensions, such as integration with IoT sensors, satellite imagery, and real-time market feeds, are made possible by the platform's user-friendly design and encouraging model performance. To further optimize the system and guarantee its long-term sustainability, more research and cooperation with Agri-tech stakeholders will be essential.

VI. CONCLUSIONS & FUTURE WORKS

The study conducted for this paper demonstrates how AI and machine learning can revolutionize the agricultural value chain, especially when it comes to empowering farmers by establishing direct connections with end users. The developed web-based platform uses a strong architecture that combines real-time data processing, user authentication, and predictive modelling with machine learning algorithms such as Long Short-Term Memory (LSTM) networks, Random Forest, and Gradient Boosting Regressor.

The system successfully predicts Wholesale Price Index (WPI) values for a number of crops by means of intensive training on crop-wise datasets that include variables like year, month, and rainfall. This helps farmers to predict market trends and make well-informed choices about when to harvest and how much to charge. The reliability of ensemble approaches like XGBoost and Random Forest for predictive tasks in volatile agricultural markets was confirmed by the comparison of different models, which showed that they consistently outperformed traditional regressors in terms of R2 score and error metrics like RMSE and MAE.

Apart from technical performance, the project tackles a persistent weakness in the agricultural supply chain: the excessive dependence on middlemen and the absence of clear market data available to producers at the local level. The solution promotes fair pricing, enhanced profitability, and greater motivation for ongoing agricultural engagement by cutting out middlemen and providing farmers with direct access to consumers through a digital platform. Benefits for consumers include access to fresh produce, traceability, and fair pricing, all of which support the global movement towards sustainable food systems.

The project does have some limitations, though. The lack of completeness and consistency of data across various regions and crop types was one of the main issues faced. Prediction accuracy is hampered by the absence of high frequency, localized data on things like pest infestation, fertilizer use, and policy changes. Additionally, the system's current requirements for a reliable internet connection and rudimentary digital literacy may restrict its uptake in isolated or underprivileged farming communities.

Future studies should focus on broadening the data spectrum by integrating social-economic indicators, satellite imagery, and real-time sensor data in order to address these issues. By using edge computing and federated learning, the training process could be decentralized, increasing the system's adaptability to local conditions while protecting user privacy. The accuracy and responsiveness of the model could also be improved by incorporating policy feeds, weather APIs, and crowdsourced market data.

The platform can be made more inclusive from a usability standpoint by adding features like voice-based interfaces, offline capabilities, and multilingual support via Progressive Web Apps (PWAs). Trust can be increased and transactions made easier by integrating with local cooperative networks and mobile money systems. Partnerships with NGOs, agritech companies, and government agencies could aid in platform scaling and guarantee broad adoption.

To sum up, this study represents a major advancement in the creation of a more intelligent and inclusive agricultural ecosystem. It presents a scalable model for enhancing farmer welfare and customer satisfaction in addition to proving that using AI to predict crop prices is feasible. The suggested platform could become a crucial instrument for attaining food security and agricultural resilience in developing nations with additional work and interdisciplinary cooperation.

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