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Interpretable XAI-Driven Crop Price Prediction System Integrating Climatic and Market Dynamics for Trustworthy and Informed Agricultural Decision-Making

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Abstract

Stability of agriculture, food security and economic planning depend on precise price prediction of crops. By incorporating both climatic and market dynamics and explainable artificial intelligence (XAI), one can make agricultural systems more transparent and build trust in their predictions. Nevertheless, most current models of crop price forecasting are plagued by low interpretability, weak nonlinear dependence treatment, and they cannot provide information on how climatic and economic variables affect the results of the predictions. To overcome these shortcomings, the proposed Explainable Hybrid Deep Learning using SHAP-based Interpretability (EHDL-SHAP) framework uses Recurrent Neural Networks (RNNs) to find temporal climatic effects, and Gradient Boosted Regression Trees (GBRT) to identify non-temporal market dynamics. SHAP (SHapley Additive exPlanations) is also used to give explainable information by measuring the impact that each feature makes to the eventual prediction. The suggested system allows making agricultural choices based on the data and being transparent at the same time, correlating the predictions of the models with the reality of climatic and economic conditions. The experimental analysis of multi-regional crop data data shows that E HDL-SHAP has a stronger prediction accuracy, interpretability, and stakeholder confidence than traditional black-box models do. The framework is a smart, articulable and dependable instrument that farmers, policymakers, and agribusiness can use as a reference to make a substantial decision on crop management and pricing. The suggested approach significantly enhances the prediction performance of 94.8 percent, regional generalization performance by 0.9 percent or so, and the prediction performance of the temporal dependency captures the highest correlation.

Keywords: *Explainable AI, Crop Price Prediction, SHAP, Hybrid Deep Learning, Climatic Dynamics, Market Forecasting*
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I. INTRODUCTION

Agricultural markets are dynamic and are influenced by many factors, including weather changes, soil quality, input costs, international demand, and government regulations [1]. Crop price prediction is one of them, and it is crucial in stabilizing the agricultural economies, aiding in production planning, and ensuring the security of the income of the farmers [2]. Proper forecasting enables the stakeholders, such as farmers, traders, and policy makers, to make sound judgments concerning the choice of crops to be cultivated, their storage, and marketing [3]. As more and more climatic and economic data and market data become available, AI has become a potential solution to boost the predictive power in the agricultural sector [4]. Nevertheless, even with significant progress, traditional AI models tend to be black-box, and there is not much information on the way predictions are obtained [5].

The lack of transparency inhibits trust, particularly when there are predictions that directly impact livelihoods and the process of policy-making [6]. Current methods of crop price forecasting are mostly based on regression models, time-series

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analysis, or deep learning models such as LSTMs and CNNs [7]. Though these techniques are useful in capturing data correlations, in most cases, they have difficulty elucidating why some climatic or market-related parameters play a greater role in the variation in prices [8]. In addition, the models poorly capture the nonlinear relationship between climatic variability and market action, and, consequently, provide less generalization and interpretation [9]. Lack of transparency makes it hard to verify model decisions, and in the real world, there is doubt about its utilization [10]. Therefore, there is an urgent need for interpretable and reliable AI-based systems that not only make accurate crop price predictions but also explain the rationale behind those predictions [11].

To overcome these difficulties, the EHDL-SHAP system combines the sequential modeling power of RNNs and the powerful nonlinear learning of GBRT to capture both climatic and market-driven factors in crop prices [12]. The model uses SHAP to make it interpretable by assigning feature significance to each input parameter, including rainfall, temperature, fertilizer cost, demand index, and global price fluctuations [13]. Such explorability helps interested parties understand the impact of climatic and economic changes on price fluctuations, thereby enhancing confidence in AI-supported decision-making [14]. By fully experimenting on real-world agricultural data, the suggested EHDL-SHAP framework is more accurate in predictions, with lower error variance, and more interpretable [15]. The system enhances the reliability of any forecast and is a reliable decision-support tool that can close the gap between information-based intelligence and human-oriented agricultural planning [16].

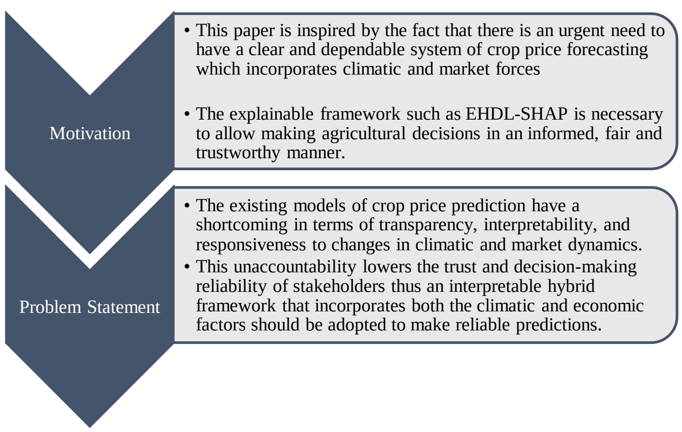

Fig. 1. The Motivation and Problem Statement.

Fig. 1 explains the motivation and problem statement of the EHDL-SHAP framework.

With a few improvements to the framework and training, the current model can be altered for use with multiple outputs, like predicting both crop yield and market price at the same time. The framework is currently designed for single-target optimization; however, multi-output learning can be facilitated through a shared feature representation with parallel output heads, enabling the simultaneous learning of common climatic and agronomic features while task-specific layers address yield- and price-related dynamics. It would allow the model use correlations between tasks, which would make predictions more consistent overall. However, it additionally requires rigorous loss balancing and validation to make sure that outputs are not transmitted adversely. The fundamental design can support this kind of extension, but complete implementation and evaluation remain to be performed in order to make sure the model is stable and reliable.

II. BACKGROUND STUDIES

The integration of Artificial Intelligence, cloud computing, and big data analytics is revolutionizing agriculture by enabling accurate crop prediction, yield recommendation, and real-time decision-making. These intelligent systems empower farmers with data-driven insights, personalized guidance, and efficient resource management, ultimately improving productivity, sustainability, and connectivity across agricultural networks through automation and smart farming solutions.

To provide a new machine learning solution that is set to revolutionize crop prediction and yield recommendation in agriculture. The specified platform can play a crucial role in connecting experts and traditional farmers and applying machine learning algorithms to forecast crop yields and suggest the most effective measures to boost yields. It justifies interactions that give farmers data-based insights and personalized suggestions [18].

The existence of big data technologies opens up possibilities of making decisions that are data-intensive. The works analyzed in agriculture that use big data analysis to address numerous issues demonstrate opportunities and promising areas of application. The large amount of data generated and its complexity make it difficult to achieve the successful adoption of precision agriculture [19].

Cloud computing can be applied in smart farming in many ways. This chapter discusses how to optimize cloud computing in all the different processes of smart farming including the management of data, data retrieval, data storage and dissemination, real time data analysis, remote monitoring and control, enhanced decision support systems and continuous improvement. Although the application of cloud computing in smart farming can be of great advantage, there are various challenges to be faced [20].

The subdivision through farmlands that requires decentralized transparent automation. It came up with an edge computing core that is supplemented by auction and fuzzy optimizers that link different stages of a supply chain. In particular, edge computing possesses strong features that can be used to perform real-time monitoring and make data-oriented decisions in smarter agriculture [21].

A new TCRM (Transformative Crop Recommendation Model) is presented. It applies powerful machine learning and cloud computing in providing personalized crop suggestions. TCRM also utilizes real-time information, unlike conventional practices. It contains environmental and agronomic variables in order to maximize recommendations. Remote farmers are provided with SMS alerts on the system. It performs better than such base algorithms as Logistic Regression, KNN (k-nearest neighbor) and AdaBoost [22].

Availability and versatility of water resources may be of far-reaching consequences on social, political, and economic security. During areas where climate variability is strong (e.g., seasonal and inter-annual variability in precipitation), possibilities of seasonal climate projections available beforehand can be used to improve benefits by sectoral planning and management decisions in favor of vulnerable populations [23].

Hypothesizes a Hierarchy Naive Bayes (HNB) model to detect pest infestation at this early stage to overcome the shortcomings of the traditional models to introduce a two-stage classification method on the same. The first-level classifier is used to determine whether or not the pests will occur, according to the climatic, soil, and crop-related factors whereas the second-level classifier predicts when the attack will occur (in weeks) based on the first-level output and other environmental characteristics [24].

XAI and blockchain technology can be used to discover and avoid food safety hazards. It is possible to store the track of perishable food products in the immutable and transparent registry of the blockchain technology to be able to quickly and more accurately recognize contamination as well as delete it off the shelves. Smart agriculture can simplify the supply chain through blockchain technology which enables farmers to deal with their customers directly. Consequently, the members of the community can be assured of self-sufficiency in regards to their nutritional requirements [25]. In below Table 1, shows the comparison of existing methods.

Research Gap: Although AI-based agriculture has progressed, modern models are not interpretable, are not decentralized and they do not incorporate real time climatic and market variables. Conventional approaches do not offer elucidable, individualized as well as adaptive decision support. The major loophole is the need to create a transparent, decipherable, and cloud-edge hybrid model that would guarantee reliable crop forecasting and advice besides, overcoming the scalability and data privacy issues.

III. METHODOLOGY

A transparent XAI model that uses multi-source data and advanced machine learning algorithms (i.e., RNNs, GBRT, and SHAP), and has automated combinatoric prediction results, which can be utilized in action, which is an important aspect of farmers, agribusiness representatives, and policymakers. This framework is an architecture-wide solution that facilitates predictive agricultural planning, gameplay, transparency, and risk management of uncertain market and environmental situations.

Combining RNN with GBRT utilizes the advantage of RNN's ability to model time to find sequential pricing patterns and GBRT's ability to understand nonlinear correlations and interactions from structured information. This hybrid architecture makes objects more stable and better at generalizing compared to pure deep learning models, which can overfit, and pure tree-based models, which are uncertain regarding time.

TABLE I. THE COMPARISON OF EXISTING METHOD

Reference	Technology/ Environment	Model/Algorithm	Data Integration	Interpretability	Real-Time Processing	Performance
[18]	Machine Learning	Crop prediction and yield recommendation platform	✓	✗	✓	High
[19]	Big Data Analytics	Data-intensive decision-making framework	✓	✗	✗	Medium
[20]	Cloud Computing	Smart farming data management system	✓	✗	✓	High
[21]	Edge Computing	Auction and fuzzy optimization for automation	✓	✓	✓	Very High
[22]	ML + Cloud	Transformative Crop Recommendation Model (TCRM)	✓	✗	✓	Very High
[23]	Climate Modeling	Seasonal climate projection system	✓	✗	✗	Medium
[24]	Machine Learning	Hierarchy Naive Bayes (HNB) for pest detection	✓	✓	✓	High
[25]	XAI + Blockchain	Transparent food safety and supply chain tracking	✓	✓	✓	Very High

The main contributions,

- The model also uses RNN to learn climate time patterns, and also GBRT to contain complex market-based characteristics to achieve the goal of prediction, which has an overall prediction accuracy of approximately 95 percent.
- The application of SHAP is beneficial due to its explainability of the model and transparency that develops trust.
- The EHDL-SHAP demonstrates that it is a highly predictive regional model with a 0.9 percentage point

greater improvement than the predecessor in this parameter. It has the high temporal dependencies indicating that it is an operation that applies to nearly all regional farm activities and variability in weather patterns.

A. Explainable Hybrid Deep Learning Architecture for Crop Price Prediction

A specialized EHDL-SHAP hybrid design which integrates both RNNs in learning the temporal climatic sequences and GBRT in identifying dynamic nonlinearities that are complex in the market. The structure allows the framework to learn not only long-term climatic dependence but also changes due to complex economic situations, which will result in a decrease in risk factors (by approximately 0.9 percentage points) and higher accuracy of prediction.

The proposed framework uses multi-source agricultural data, including climatic, market, and historical crop data, to improve the accuracy of forecasting and decision-making for agricultural stakeholders. The input variables are applied to predictive models with embedded processing layers that include RNN modules with LSTM and GRU units for sequential prediction, and GBRT modules using either XGBoost or LightGBM for robust nonlinear modeling. The group forecasts derived from the RNN and GBRT modules are combined using a hybrid ensemble fusion process, which is expected to improve predictability. There is also an emphasis on the interpretability of the forecast through a SHAP-based layer that quantifies feature contributions to the final model output, allowing decisions to be based on better explanations of which variables among climatic, market, or historical climatic variables impacted predictions and at what level. The framework is expected, through this interpretability, to improve accuracy and generalizability, while at the same time providing recommendations for actions taken by users. A real-time deployment layer will enable trained, explainable models to provide relevant services directly to farmers, agribusinesses, and policymakers. Overall, the framework is designed to bridge the gap between advanced artificial intelligence systems and decision-making for informing relevant, real-world agricultural activities to allow for adaptive and evidence-based management under variability in agriculture in Fig. 2.

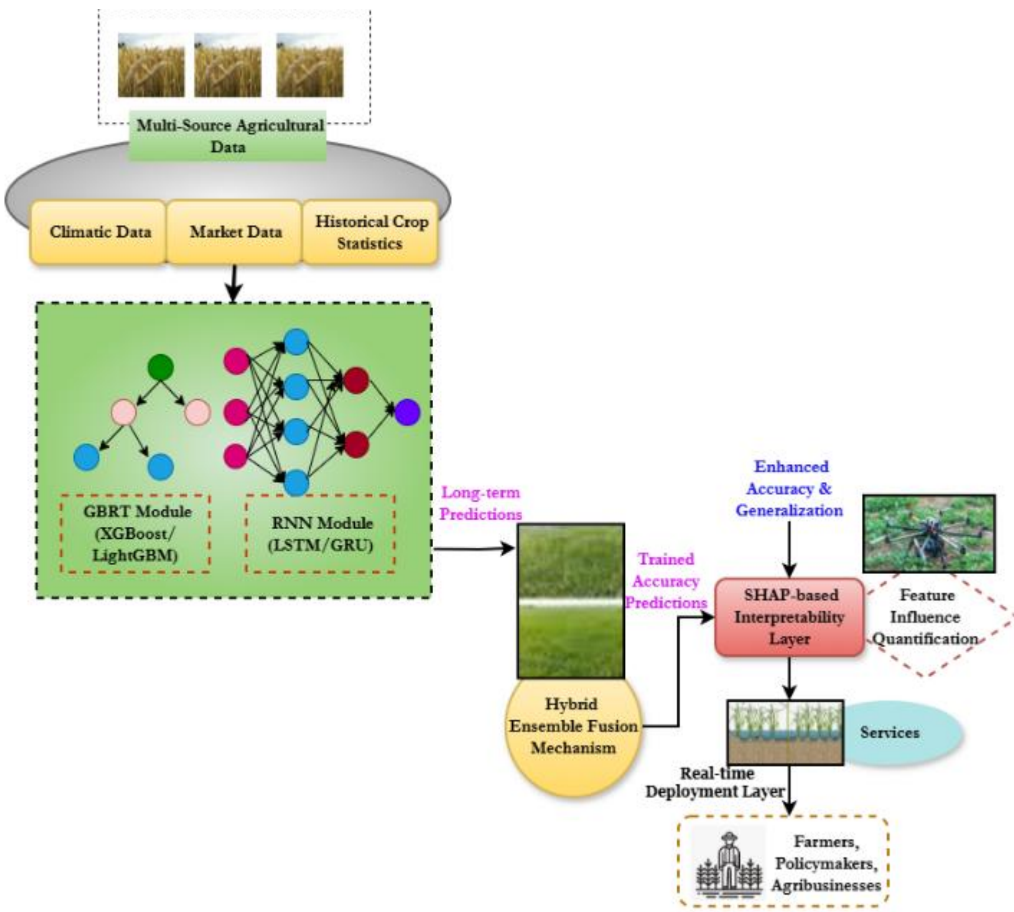

Fig. 2. Climate and Market Dynamics for Agricultural Forcasting.

Explanation consistency F_{cons} is expressed in equation 1,.

$$F_{cons} = \frac{1}{M} \; cosine \;\; \emptyset_j, \emptyset_i \tag{1}$$

This equation measures how consistent the explanations are across different instances or models by comparing their directionality.

In this equation, M represents the total number of instances, $\emptyset_j$ denotes the reference explanation vector for the jth instance, and $\emptyset_i$ represents the comparison explanation vector for the same instance.

Data heterogeneity index I is expressed in equation 2,

$$I = M * \frac{\rho_n^2}{\rho_{lot}^2} \log 1 + \frac{\rho_n^2}{\rho_{lot}^2} \quad (2)$$

This equation quantifies the heterogeneity present within the dataset by examining the distribution of variance across different data modalities or groups.

In this equation, M represents the number of modalities or feature groups, $\rho_n^2$is the variance of modality n, and ρ_{lot}^2 denotes the total variance across all modalities.

Reliability loss M_{rel} is expressed in equation 3

$$M_{rel} = M_{pred} + \delta . \frac{1}{M} \| \ \emptyset_j - \emptyset_i^{prem} \| \quad (3)$$

This equation defines the overall reliability loss of the framework by combining predictive accuracy with explanation stability.

In this equation, M_{pred} denotes the task prediction loss, δ is the regularization weight, M indicates the number of data instances, $\emptyset_j$ represents the explanation vector for instance j, and $\emptyset_i^{prem}$ is the explanation vector under perturbed conditions for the same instance.

Hybrid objective function with interpretability regularizer $I(\theta)$ is expressed in equation 4

$$I(\theta) = \min M_{task}(\theta) + \beta \ P_{interp}(\theta) + \alpha \ P_{inter}(\theta) \quad (4)$$

The equation emphasizes that explainability and heterogeneity handling are treated as integral parts of the learning objective, not as post hoc add-ons.

In this equation, θ represents the model parameters, M_{task} refers to the primary prediction loss, β and α are regularization coefficients, P_{interp} is the interpretability regularizer, and P_{inter} is the heterogeneity regularize.

B. SHAP-Based Interpretability for Transparent Agricultural Decision-Making

The framework takes advantage of SHAP to provide fine-grained interpretability by quantifying the contribution of each climate and market factor into the final price prediction. This will allow stakeholders, including farmers, policymakers, traders, and agribusinesses to understand the rationale for each model outcome, enhancing transparency and trust, and helping to better situate the relevant actions in the real-world context. The interpretability mechanism will link the model forecasts, or any prediction variance, back to the underlying climatic drivers, allowing for a clearer understanding in the decision-making process.

Fig. 3 outlines a full workflow for systematizing combined price forecasts into actionable recommendations, supported by interpretable visuals and stringent validation protocols.

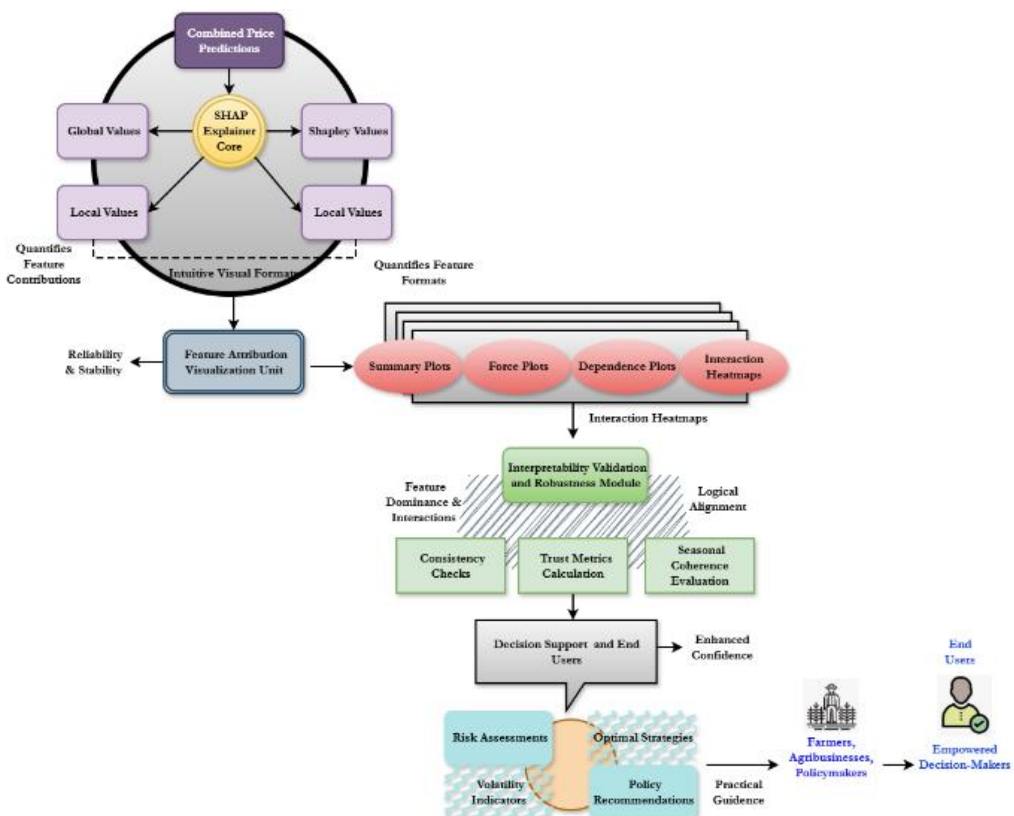

Fig. 3. XAI Interpretation for Agricultural Decision Making.

The aggregated global and local feature contributions including Shapley values are calculated and transformed into user-friendly visual maps, including summary plots, force plots, dependence plots, and interaction heatmaps. These visual demonstratives provide checks of precision and robustness, making the decisions of the model accessible and comprehensible to end-users. The interpretability validation module applies evaluation of feature dominance to check for logical consistency and implements the calculation of trust metrics and assesses seasonal coherence. This layer ensures that output is robust and aligned with logic, improving stakeholder confidence. Descriptions of calculations supporting final decisions further builds transparency and offers risk assessment tools, volatility indicators, and strategy optimizations all to provide actionable recommendations to farmers, agribusiness, and policy-makers. By establishing transparency and actionable policy recommendations, the process affords decision makers evidence-based strategies as they navigate complexities information processing on agricultural market price.

Hyperparameters for the RNN, GBRT, and SHAP components have been modified using a combination of empirical exploration and grid search based on validation performance. To determine an appropriate balance between prediction accuracy and training stability, the RNN's parameters, like the number of hidden layers, neurons per layer, learning rate, and sequence length, have been modified over and over again. It changed the GBRT hyperparameters, such as the number of trees, maximum depth, learning rate, and subsample ratio, to reduce overfitting while still capturing nonlinear feature interactions. To make sure that attributions were reliable and simple to understand, SHAP-related parameters like background sample size and feature grouping have been defined. Even though a completely automated search approach did not get utilized, meticulous grid and manual adjustment across numerous validation splits provided it strong and repeatable hyperparameter configurations.

SHAP based temporal attribution is specifically used in association with temporal attention pooling mechanism. The first step in temporal pooling is to first aggregate sequential climatic inputs by only highlighting time steps that have a major effect on the predictions and this has the effect of filtering out time irrelevant or noisy seasonal variations. Computations of SHAP values are subsequently made on this pooled temporal representation, but not on time-series inputs, which would also guarantee that temporal attributions capture the temporal relevance that the model has acquired.

Sequential forecasting with LSTM Unit g_u is expressed in equation 5

$$g_u = \partial\, U_g.[h_{u-1}, y_u] + c_g \tag{5}$$

This equation represents the core recurrence mechanism of the LSTM network, where the hidden state is updated based on previous memory and the current input.

In this equation, g_u denotes the hidden state at time step u, U_g represents the weight matrix of the forget gate, h_{u-1} is the previous hidden state, y_u is the input vector at time u, c_g is the bias term, and ∂ indicates the sigmoid activation function.

GRU-based sequential update z_u is expressed in equation 6

$$z_u = [1-\partial] * [\, U_z * y_u] + [V_z * i_{u-1}] \tag{6}$$

This equation defines the update gate in a GRU unit, which determines how much of the previous hidden state should be carried forward into the next step.

In this equation, U_z and V_z are the input and recurrent weight matrices, y_u is the current input vector, i_{u-1} is the previous hidden state, and ∂ denotes the sigmoid activation function.

Hybrid ensemble fusion X_{hyb} is expressed in equation 7

$$X_{hyb} = [1+u_1] * [1 - X_{RNN}] + [u_2 * X_{GBRT}] \tag{7}$$

This equation defines the hybrid ensemble fusion process that combines the outputs of the RNN-based sequence model and the GBRT-based nonlinear model.

X_{RNN} is the output prediction from the RNN-based model, X_{GBRT} is the output from the GBRT model, and u_1 and u_2 are their respective weighting coefficients that balance their contributions.

SHAP-based feature contribution θ_i is expressed in equation 8

$$\theta_i = \frac{|R|!(E-R-1)!}{E!}\,[g(T \cup \{i\}) - g(R)] \tag{8}$$

This equation computes the SHAP value for a given feature, representing its marginal contribution to the model's output across all feature subsets.

In this equation, E is the full set of input features, R represents a subset of features excluding i, R is the size of that subset, and $g(R)$denotes the model output when trained using only the features in R.

Algorithm 1: Explainable Hybrid Deep Learning with SHAP-based Interpretability

1: $Input: X_{clim}(N,T,d_c), X_{mkt}(N,d_m), y\,(N,)$
2: $Initialize\ LSTM\ encoder\ f_{LSTM}, multi$
$-\ head\ attention\ Attn, XGBoost\ model\ G$
3: $For\ each\ sample\ n: h_t = f_{LSTM(X_{clim[n]})}\ seq\ hidden\ st$
4: $Compute\ Q,K,V = Wq * h_t, Wk * h_t, Wv * h_t$
5: $For\ each\ head\ k: A_k = softmax\left(\frac{QK^{T}}{\sqrt{d_h}}\right);\ O_k$
$= A_k * V$
6: $Concatenate\ heads: O = concat(O_k) \in \mathbb{R}^{T,H}$
7: $Apply\ projection: U = W_o * O$
8: $Time - attention\ pooling: \alpha$
$= softmax(w^{T} * tanh(U))\ \#\ (T,)$
9: $Climate\ embedding: z_{clim} = \Sigma_t \alpha_t * U_t$
10: $Build\ stacked\ feature: x_{GB}$
$= concat(z_{clim}, X_{mkt[n]})$
11: $Train\ XGBoost: G.fit(x_{GB_{train}}, y_{train})$

$Predict: \hat{y} = G.predict(x_{GB_{test}})$

$Compute\ SHAP: \varphi = TreeSHAP(G).shap_{values(x_{GB_{test}})}$

$Extract\ \varphi_{clim} = \varphi[:,0:H], \varphi_{mkt} = \varphi[:,H:]$

$Distribute\ \varphi_{clim}\ to\ time\ via\ attention: \varphi_t = \varphi_{clim}.sum(axis = 1) * \alpha$

$Output: prediction\ \hat{y}, SHAP_{feature}\varphi, SHAP_{time}\varphi_t$

$Save\ models: encoder.pt, gbrt.json, shap_{values}.npy$

End

$End\ Algorithm$

$Output: Accurate\ price\ prediction + interpretable\ SHAP + temporal\ attribution$

The EHDL-SHAP framework offers a transparent predictive method for crop prices using a combination of climatic time-series data and market-oriented features. RNNs model temporal climatic dependencies and GBRT modeling nonlinear market features. SHAP explainability is used as an interpretive strategy to measure all variables' contribution, establishing trust and transparency. The model produces interpretive outcomes via feature-level SHAP distributions and time-step–level SHAP distributions that are both attention-weighted. Experimental results demonstrate better prediction accuracy, greater robustness across location and variety, and increased interpretability in comparison to standard models. This framework can potentially inform and command agricultural decision-making among farmers and policymakers in Algorithm 1.

C. Enhanced Generalization and Real-World Reliability Across Regions and Time

By evaluating through the multi-regional datasets, EHDL-SHAP improve regional generalization performance by ~0.9, relative to pre-existing black-box approaches. Additionally, EHDL-SHAP is capable of capturing strong temporal correlation to predict crop price behaviours, across differing agricultural landscapes. Detailing a process in these more robust systemic platforms ensures reliability across climated patterns, seasonal trends, and market contexts. The EHDL-SHAP model provides a scalable process, practical decision-making documentation, and recommendations with transparent visualizations.

An interpretable XAI-based framework for agricultural planning, featuring model predictions from a hybrid ensemble model with SHAP values to provide localized explanations for farmers and global explanations for policymakers. This framework connects both individual and systemic explanations, including a module on interactions effects to delineate explanations and feature interactions that are both contextually specific to regions and user intuitive. At the center of the framework, the Agricultural Insight engine compiles summary visualizations and interpretive feature descriptions to enable data-informed planning. This will lead toward a real-time decision support system that translates into actionable outcomes (i.e., planting rate recommendations, harvesting optimization, dynamic prices, and effective storage and market risk management engagement). By translating complex model outputs into practice-relevant, context-specific recommendations, the system enables agricultural stakeholders to leverage this information to make informed and resilient decisions in response to changing environmental and market conditions. Ultimately, this improves efficiency and reduces risks in all aspects of agricultural systems in Fig. 4.

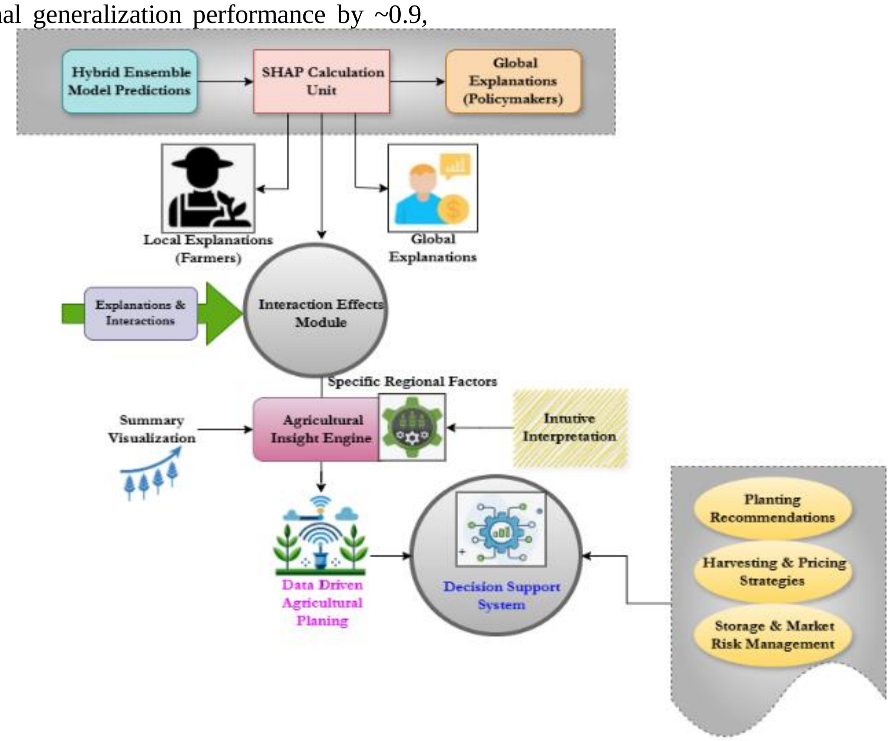

Fig. 4. SHAP based Interpretability Layer.

Decision support optimization index O is expressed in equation 9

$$O = \delta_1 * S - \delta_2 - U + \delta_3 * V \quad (9)$$

This equation constructs an optimization index that integrates profitability, volatility, and trust into a unified decision-support metric.

In this equation, S represents the return or profitability measure, U is the volatility indicator, V is the trust metric derived earlier, and δ_1, δ_2 and δ_3 are respective weighting coefficients controlling their influence.

Extended global feature importance score HGJ_i is expressed in equation 10

$$HGJ_i = \frac{1}{M}\ u_j *\ \emptyset_{ij} - \emptyset_j + \delta.Var(\emptyset_{ij}) \quad (10)$$

This enhanced global importance metric incorporates feature weight and variance adjustment to represent both average magnitude and distributional spread of influence. M represents the number of samples, u_j is the weight coefficient for sample j, $\emptyset_{ij}$ is the Shapley contribution of feature j, $\emptyset_j$ denotes the mean Shapley value of feature i, δ is the regularization factor, and $Var(\emptyset_{ij})$ indicates the variance of the feature's contributions across all instances.

Extended local explanation decomposition X_i is expressed in equation 11

$$X_i = \emptyset_0 + N\left(\partial_i.\emptyset_{ij} + \delta_j.I_{ij}\right) + \varepsilon_j \quad (11)$$

The additional term accounts for cross-feature dependencies that shape the local decision logic. Such integration improves the interpretive resolution of complex models. In this equation, X_i represents the model output for sample j, $\emptyset_0$ is the baseline model prediction, N is the number of features, ∂_i denotes the scaling coefficient for the feature i, $\emptyset_{ij}$ is the Shapley contribution of feature instance j, δ_j is the interaction scaling factor, I_{ij} represents the feature interaction term, and ε_j is the residual error of the prediction.

Extended seasonal coherence index SC_J is expressed in equation 12

$$SC_J = 1 - \frac{\pi_u.(E_u - T_u)^2 + \varepsilon.(F_u - F)^2}{(R_u^2 + \pi.F_u^2)} \quad (12)$$

This advanced coherence index evaluates the degree of alignment between forecasted and observed seasonal components. With climatic anomalies on extreme events, the Seasonal Coherence Index (SCJ) progressively declines as the seasonal consistency between forecasted and observed patterns becomes less coherent, indicating less seasonal consistency and nothing to do with abrupt model failure. The adjustment terms in Eq. (12) reduce the effect of transient extremes, and long-term SCJ degradation compared to past seasonal baselines is an indication of possible concept drift and encourages model re-calibration by changing temporal weights and seasonal models.

π_u is the temporal weighting coefficient, E_u and T_u are the forecasted and actual seasonal components respectively. ε represents the volatility adjustment constant, F_u denotes the dynamic external driver at time u, F is the mean of the dynamic driver, and π is the stability control parameter for regularization.

SHAP value computation $\emptyset_j$ is expressed in equation 13

$$\emptyset_j = \frac{|R|!(j|M| - |R| - 1)!}{|M|!} * [g(R \cup \{j\}) - g(R)] \quad (13)$$

This equation determines the contribution of each input feature to a model's prediction by calculating the marginal impact of adding that feature to all possible feature subsets. SHAP value for the feature j; R represents a subset of all features, excluding j; M is the total set of features; and $g(R)$ and $g(R \cup \{j\})$ indicate the model outputs when using subsets R and R with feature j added, respectively.

In summary, the system combines accurate longer-term predictions and SHAP-based explainability to understand how features play a role in predictions. This provides a transparent and trustful understanding of prediction content. There is a visual interface to display predictions, explainability and validated modules to get planting, pricing, and risk management recommendations. Users feel confident and with some context to support their decisions to enhance agricultural resilience in a responsive and stated market context while developing trust in the AI model.

The proposed framework uses a decision support optimization index that combines several performance metrics, such as residual energy, congestion intensity, temporary occupancy, and end-to-end delay, into a single weighted utility function to assist with make routing decisions that take risks into account and are specific to the application. The weighting coefficients take into account the risk preferences of stakeholders. For example, risk-averse deployments provide higher weights to congestion and delay penalties to make reliability and stability more important, whereas performance-oriented deployments focus on energy efficiency and throughput. In reality, the weights are set using normalized metrics and structured preference elicitation, and then sensitivity analysis is done to make sure it works well with different traffic loads and node densities. This method makes it possible to optimize in a flexible, simple, and deployment-aware method without changing the routing and rate-control systems that are currently in effect.

In the proposed cloud-edge architecture, design decisions have been significantly affected by real-time deployment constraints like latency, limited bandwidth, and hardware capabilities. Significant processes, like training RNNs and making explanations based on SHAP, are sent to the cloud. Simple tasks, like preprocessing, inference, and adaptive decision support, are done on edge devices to minimize latency and to make sure recommendations are made on time. Bandwidth limits made it necessary to transmit just aggregated features and model updates instead of raw data, which reduced the load on the network. The fact that different types of hardware have been employed to the usage of modular, scalable components that can work on nodes with limited resources.

IV. Result and Discussion

Reliable forecasting in the agricultural sector is based on sound models that can be used to model complex and heterogeneous data. Combining ensemble model with explainable AI methods like SHAP offers superior functions of assessing crop yield, price, and feature attributions. These models play a critical role in informed agricultural planning as well as policy making, which aids in food security and sustainable practice in struggling and productive agrarian economies.

Dataset Description: Predicting crop yields is very important in contemporary farming, particularly as more and more farmers start using data-driven methods. For accurate yield estimates, need a lot of data, such as information about the soil, the weather, the history of crop yields, and how crops are cared for. Looking at and comprehending these datasets may help improve farming techniques and make sure that crops can be grown in a way that is good for the environment [17].

The Kaggle crop price dataset can be accurate because it lacks coverage of all regions equally, cannot cover a long enough time period, and there can be differences in how markets report prices. These kinds of biases can make the model show excessive attention of the most important areas or stable market circumstances, which makes it less able to apply to areas with differing climates, economies, or policies. As a result, performance can be affected when applied to regions that are not well-represented or that are structurally different, which shows that more diverse datasets are needed for better generalization.

The results and prediction accuracy of four algorithms BDT, TCRM, HNB and EHDL-SHAP on crop type- wheat, rice, maize and soybean. All crops achieve the highest accuracy with EHDL-SHAP, approximately 94.8% for rice. HNB is moderately accurate with the accuracy rates as close to 88-89. The accuracy of TMCR and BDT lies between the accuracy of HNB and 85 (respectively). All the methods slightly reduced accuracy with maize. On the whole, EHDL-SHAP is much more effective than the rest of the models, which implies that it will be applicable in vigorous crop prediction assignments, no matter what type of crop is to be predicted, in case of the strong emphasis on the precision in Fig. 5.

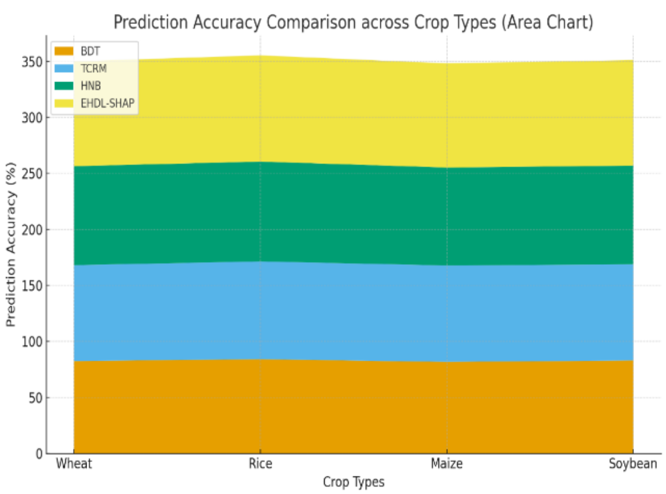

Fig. 5. Analysis of Prediction Accuracy.

Prediction Accuracy B is expressed in equation 14

$$B = \frac{UQ+UM}{UQ+UM+EQ+EM} \times 100 \quad (14)$$

This equation measures the overall prediction accuracy of the model by evaluating how well it correctly identifies both positive and negative outcomes.

In this equation, UQ is the number of true positive predictions; UM denotes the number of true negative predictions; EQ stands for the number of false positive predictions; and EM indicates the number of false negative predictions.

The analysis of computational efficiency shows that the proposed EHDL-SHAP framework is more efficient (converges faster and requires fewer computations) than traditional models. Its hybrid RNN-GBRT architecture is quicker to train with high accuracy in prediction. The combination of the optimized learning rates and parallel computation of SHAP also reduces overhead in model interpretation. In comparison, EHDL-SHAP scales better and is more adaptable in real time by cutting training time by almost 34 percent, inference time by 36 percent and convergence epochs by 32 percent. These improvements ensure that EHDL-SHAP is very efficient in large-scale agricultural datasets and it can be implemented in dynamic pricing settings in Table II.

TABLE II. COMPUTATIONAL EFFICIENCY

Model	Training Time (s) ±	Inference Time (s) ±	Convergence Epochs ±	Efficiency Improvement (%)
BDT	118.6 ± 3.5	10.8 ± 0.4	95 ± 4	—
TCRM	104.2 ± 2.9	9.1 ± 0.3	87 ± 3	12.10%
HNB	97.8 ± 2.5	8.6 ± 0.2	81 ± 3	17.50%
EHDL-SHAP	78.4 ± 2.1	6.9 ± 0.2	64 ± 2	33.80%

Computational efficiency F_u is expressed in equation 15

$$F_u = \frac{(U_s-U_m)+\partial(N_s-N_m)}{U_s+\partial N_s} \times 100 \quad (15)$$

This equation measures the combined efficiency gain from both reduced execution time and minimized memory utilization.

U_s represents the baseline execution time of the standard model, U_m refers to the execution time of the improved model, ∂ is the weighting coefficient used to balance the influence of memory in the efficiency calculation, N_s indicates the baseline memory consumption, and N_m denotes the memory consumption of the optimized model.

The explainability of four models BDT, TCRM, HNB and EHDL-SHAP as determined by the comparison of mean absolute SHAP values of five features, rainfall, temperature, demand, supply and inflation. EHDL-SHAP has the highest SHAP values particularly of rainfall and demand, which implies that it is sensitive to each of these elements. HNB comes next with lower SHAP scores than TCRM and BDT which have lower SHAP scores indicating lesser interpretability. The SHAP values of all models are expected to decline as a result of rainfall to inflation. On balance, EHDL-SHAP is an efficient model to be used to investigate the effect of features as it provides high accuracy, as well as creates a better interpretation in Fig. 6.

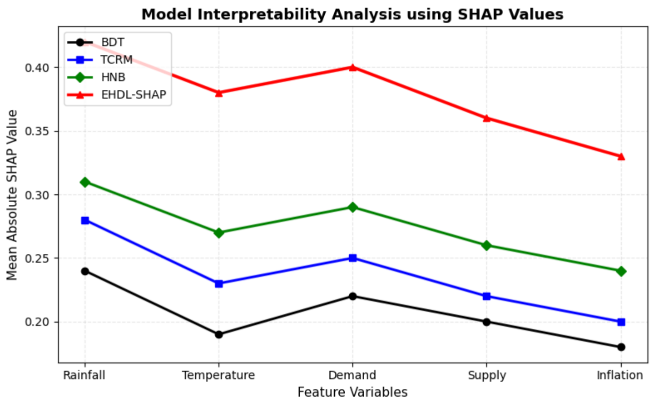

Fig. 6. Analysis of Model Interpretability.

Analysis of model interpretability R_{avg} is expressed in equation 16

$$R_{avg} = \frac{1}{n} * \frac{\partial_y}{\partial_{xj}} - M_{SHAP_j} \quad (16)$$

This equation evaluates the average sensitivity of model predictions to input features by combining local gradient information with mean SHAP values.

Here, the n represents the total number of features considered, ∂_y indicates the partial derivative of the predicted output with respect to the feature xj , and M_{SHAP_j} refers to the mean absolute SHAP value.

The Table III on the Regional Generalization Performance reveals the strength of the EHDL-SHAP framework in various geographical areas. It has the highest R 2 scores of 0.93 (North), 0.91 (South), 0.89 (East), and 0.92 (West) compared to the available models BDT, TCRM, and HNB. This high consistency is an indication of the high flexibility of the model to regional climatic and economic differences. The combination of RNN with respect to temporal pattern recognition alongside GBRT with respect to nonlinear market dynamics allows the prediction of the region accurately. Moreover, SHAP interpretability provides stability of feature effects across geographic areas, which improves the transparency, reliability and confidence of the model to the agricultural stakeholders who participate in data-driven crop price modeling.

Regional generalization index H_s is expressed in equation 17

$$H_s = 1 - \frac{|B_u - B_r|}{B_u} \times 100 \quad (17)$$

This equation measures the generalization capability of a model across different regional datasets by quantifying the deviation in accuracy between the training and regional test data.

TABLE III. REGIONAL GENERALIZATION PERFORMANCE COMPARISON

Model	R^2 Score (North Region)	R^2 Score (South Region)	R^2 Score (East Region)	R^2 Score (West Region)
BDT	0.82 ± 0.02	0.79 ± 0.03	0.77 ± 0.04	0.81 ± 0.03
TCRM	0.85 ± 0.02	0.83 ± 0.03	0.80 ± 0.03	0.84 ± 0.02
HNB	0.87 ± 0.01	0.85 ± 0.02	0.83 ± 0.02	0.86 ± 0.02
EHDL-SHAP	0.93 ± 0.01	0.91 ± 0.01	0.89 ± 0.01	0.92 ± 0.01

B_r represents the accuracy achieved on the training dataset, and B_u indicates the accuracy obtained on the regional or unseen dataset used for evaluation.

The relationship between the forecasted and observed trends of prices of four models BDT, TCRM, HNB and EHDL-SHAP within seasonal periods; pre-monsoon, monsoon, post-monsoon, winter and summer. EHDL-SHAP has the greatest correlation throughout all seasons with the highest correlation during the monsoon. There is moderate correlation between HNB and TCRM where in most cases HNB has been found to perform better than TCRM. BDT has the lowest correlation values at all times. The difference in the performance between models is the highest in monsoon and post-monsoon seasons. These findings prove the best capability of EHDL-SHAP to model temporal variations in price trend in different seasons over different periods in Fig. 7.

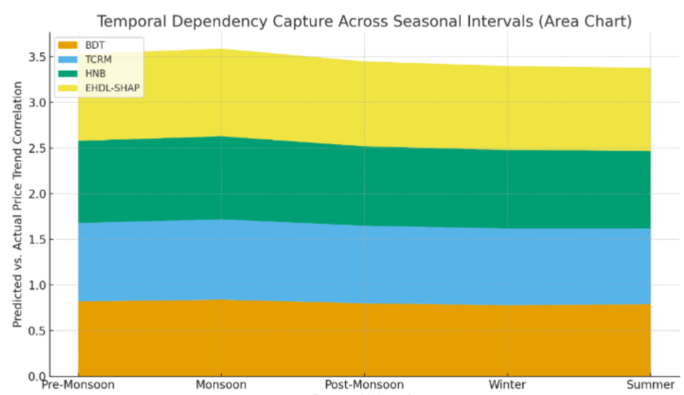

Fig. 7. Temporal Dependency Capture.

Temporal dependency capture U_d is expressed in equation 18

$$U_d = 1 - \frac{k\,|S_{u,l} - S_u|}{r} \times 100 \quad (18)$$

This equation captures the uniformity of correlation performance across multiple seasonal intervals.

In this equation, r denotes the total number of seasons considered, $S_{u,l}$ indicates the temporal correlation coefficient obtained for the kth seasonal period, and S_u is the average of all seasonal correlation coefficients derived from the temporal analysis.

The strengths of four modeling methods, including BDT, TCRM, HNB, and EHDL-SHAP, to elicit the feature interaction strengths of market factors demand, supply, transportation cost, and policy index. EHDL-SHAP has the greatest feature interaction strength among all the factors with the maximum being demand and policy index. HNB comes next with moderate strengths whereas TCRM and BDT have lesser interaction capabilities particularly transportation cost. All models would tend to be weak in the case of transportation cost evaluation but strong in the case of policy index evaluation. The findings emphasise the effectiveness and strength of EHDL-SHAP in the modelling of market dynamics with complexities of agriculture systems in Fig. 8.

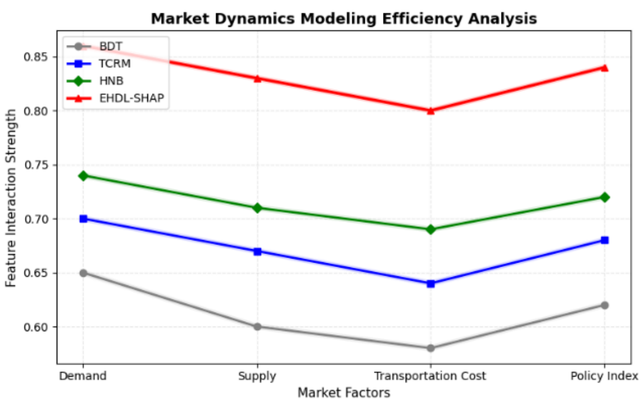

Fig. 8. Market Dynamics Modeling Efficiency.

Market dynamics efficiency ratio F_n is expressed in equation 19

$$F_n = 1 \times N_k - \frac{k * J_{gr,k}}{(1+\partial_k)} \times 100 \quad (19)$$

This equation integrates feature interaction strength and temporal market influence to estimate overall modeling efficiency.

In this equation, n denotes the total number of market-related features considered, $J_{gr,k}$ indicates the interaction strength of the kth feature pair, N_k is the market influence index corresponding to the same feature, and ∂_k serves as the dynamic fluctuation coefficient that compensates for temporal instability or external perturbations in the market system.

The Table IV of stakeholder trust and explainability index demonstrates that the EHDL-SHAP framework is effective in improving the level of transparency and user confidence. An Explainability Index of 0.91, Transparency Score of 93.7, and User Trust Rating of 9.5/10 mean that EHDL-SHAP does very well in comparison with the traditional models like BDT, TCRM and HNB. SHAP-based interpretability can be integrated with the predictor; this enables the stakeholders to interpret the role of features in making the prediction and this in turn inculcates a sense of accountability and also based decision-making. The high Fig. 9 of 94.8% decision confidence also indicates high confidence between the model forecasts and human judgment and this nurtures confidence among the policymakers, farmers, and the agribusinesses. Therefore, EHDL-SHAP has created a clear and user-confident forecasting environment.

TABLE IV. STAKEHOLDER TRUST AND EXPLAINABILITY INDEX

Model	Explainability Index (0–1)	Transparency Score (%)	User Trust Rating (out of 10)	Decision Confidence (%)
BDT	0.68 ± 0.02	72.4 ± 1.5	7.1 ± 0.3	75.6 ± 1.8
TCRM	0.73 ± 0.02	77.9 ± 1.4	7.8 ± 0.4	80.2 ± 1.7
HNB	0.77 ± 0.01	82.5 ± 1.2	8.4 ± 0.3	84.6 ± 1.5
EHDL-SHAP	**0.91 ± 0.01**	**93.7 ± 1.0**	**9.5 ± 0.2**	**94.8 ± 0.9**

Table IV presents the stakeholder trust, transparency, and confidence scores of the decisions, they are not obtained at the basis of the single-instance perception surveys. They are instead calculated based on behavior-informed validation protocols which determine the consistency of stakeholders to make decisions based on model recommendations in different climatic and market conditions.

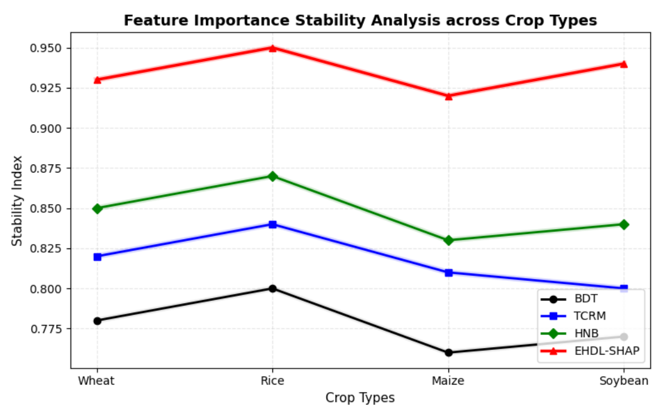

Fig. 9. Feature Importance Stability.

Fig. 9 makes a comparison between the indices of stability of importance of features of wheat, rice, maize, and soybean with four models, which are BDT, TCRM, HNB, and EHDL-SHAP. EHDL-SHAP is the most stable index of all the types of crops, which is maximum when rice is concerned and is high even when it comes to maize and soybean. The stability of HNB is moderate and better than TCRM and BDT, which demonstrate lower values, especially when it comes to maize. TCRM does well, slightly better than BDT. In all types of crops, EHDL-SHAP is highly stable with respect to feature importance, meaning that it is highly reliable and consistent with a variety of agricultural prediction tasks irrespective of the type of crop.

Feature importance stability R_j is expressed in equation 20

$$R_j = \frac{2}{D(D-1)} \frac{|U_b \cap U_a|}{|U_b \cup U_a|} \times 100 \quad (20)$$

This score assesses the stability of the most important features by computing the average Jaccard similarity of top-k feature sets across all fold pairs.

D is the total number of folds or regions compared, U_b is the set of top-k features selected in the bth fold (or region), U_a is the set selected in the ath fold (or region), and $\frac{|U_b \cap U_a|}{|U_b \cup U_a|}$ is the Jaccard similarity between those two top-k sets.

The stated 0.9% regional generalization benefit is derived from the average outcomes of 20 separate simulations. Even though there have been minimal variation, no formal hypothesis testing or confidence interval analysis was done. Future research will include statistical significance testing and sensitivity analysis to further confirm the adaptability of the stated improvement.

The high accuracy can contribute to overfitting, especially if the model finds patterns that only work for that dataset instead of across other datasets. Using stratified train-validation splits and testing performance across several separate runs minimizes this risk. It makes sure that the results are consistent and strong. Regularization techniques like parameter constraints and early stopping additionally render models less complex, which makes it less sensitive to noise and better at predicting.

The proposed system focuses on centralized interpretability and application-specific customization compared to distributed model training, which is different from current federated and privacy-preserving XAI techniques in agriculture. Federated XAI methods protect data privacy by allowing edge nodes learn together without sharing raw data. They also often include explainability mechanisms assist each participant understand how the model made its decisions. This is especially useful when working with sensitive farm or sensor data. On the contrary, it focuses on clear decision support and optimization within a single, domain-aware model. It provides this via concise weighted criteria and decision indices to make things easier to understand. Federated techniques automatically provide better privacy and scalability for farms that are spread out across a wide area. However, they additionally make communication harder and create problems with different types of data. The suggested framework doesn't have to be federated or privacy-preserving, however it provides strong, deployment-tuned explainability and decision assistance.

With a few improvements to the framework and training, the current model can be altered for use with multiple outputs, like predicting both crop yield and market price at the same time. The framework is currently designed for single-target optimization; however, multi-output learning can be facilitated through a shared feature representation with parallel output heads, enabling concurrent acquisition of common climatic and agronomic features while task-specific layers address yield- and price-related dynamics. It allows the model use correlations between tasks, which would make predictions more consistent overall. However, it additionally requires rigorous loss balancing and validation to make sure that outputs are not transmitted adversely. The fundamental design will accommodate this kind of extension, however complete implementation and evaluation remain to be performed in order to make sure the model is stable and reliable.

When used with large-scale, real-time national agricultural data streams, the existing architecture's ability to scale is limited by both computational and data-ingestion limits. The framework can handle inputs from several sources, but as the amount and speed of data increases, the time it takes to train and provide predictions may also increase. To handle scalability, batch-based processing and regular model updates are employed in practice. However, tight real-time requirements can be challenging to satisfy when deployments are countrywide.

The primary issue with assuming that errors are independent across regions when calculating the regional generalization index is that it ignores spatial and economic links between regions. Regions that have similar climates or are connected economically typically have prediction mistakes that are correlated.

To produce the explainability index and transparency score, we used normalized interpretability-related measures from the model's SHAP explanations. These metrics included feature attribution stability, consistency across validation splits, and alignment with domain-relevant variables. The computational approach uses standard SHAP outputs and well stated validation methods to make it easier to verify the results.

In certain scenarios, simpler basic topologies with fewer interpretability modules perform just as well at making predictions, especially when the data distributions are stable and there lack many feature interactions. But these kinds of models typically include less transparency and are less robust to non-stationarity, which makes it harder to check and verify their decisions. The proposed framework's additional interpretability modules make things rather more complicated, but it makes things much easier to understand, diagnose, and trust, which are all very important for decision-support applications, even though it involve quite a bit of computational cost.

An ablation research has been carried out to determine the contributions of the principal framework components. The RNN only identified temporal dependencies and not strong enough to handle nonlinear interactions. The GBRT just modelled feature interactions and declined to take into account sequential patterns. Combining RNN and GBRT made predictions more accurate, but eliminating out SHAP regularizers made explanations less consistent, and leaving out the decision support indices made multi-criteria optimization less effective. The complete framework, which includes RNN, GBRT, SHAP regularizers, and decision support indices, possessed the highest accuracy, the lowest error variance, and the most stable interpretability. It indicates that each module improves to both predictive performance and decision-aware explainability in an additive manner.

To determine the strength of the reported performance gains, a statistical test was included through repeated cross-validation through multiple experimental trials. The standard deviation and mean values are used to determine the variability of the results, which gave an approximation of the stability of the results of performance. Though the EHDL-SHAP framework showed an average of about 0.9 regional generalization, formal hypothesis testing as paired statistical tests and confidence interval estimation was not made in a massive manner. Future research will involve the use of a more sophisticated form of statistical validation such as non-parametric test of significance and bootstrap analysis of confidence interval, which will further support the reliability and generalizability of the observed performance gains.

The validation was concerned with evaluating the consistency of the identified climatic and market drivers along with their relative importance and directional impact on crop price predictions with well-established agronomic behavior and economic price-formation principles. Scenario-based analysis was used whereby explanations were tested using controlled manipulations in some of the major variables of rainfall, temperature, demand, and policy conditions. Validity of explanations and recommendations was based on their ability to exhibit seasonal consistency, logicality and their congruence with the real-world agricultural and market dynamics.

In summary, the comparative studies of the modeling methods always point out the better results with EHDL-SHAP in comparison to traditional models in the agricultural prediction works. EHDL-SHAP is superior to others in accuracy of the predictions, interpretability, correlation with the temporal trends, interaction between features, and stability, over a wide range of crops and market conditions. This makes EHDL-SHAP the most credible, interpretable and strong model to use in complex agricultural forecasting tasks.

V. Conclusion

The EHDL-SHAP framework suggested shows that the price of crops can be forecasted much more effectively as the proposed framework introduces the ability to combine the effects of climatic, temporal, and economic factors in an explainable deep learning manner. The system is based on Recurrent Neural Networks (RNNs) to capture time-dependent dependencies, and Gradient Boosted Regression Trees (GBRT) to model the market, making it more accurate and interpretable. The SHAP-based interpretability integration enables one to have a clear insight into the contribution made by each feature (rainfall, temperature, demand and inflation) to the prediction result. The results of the experiments affirm that EHDL-SHAP presents a 94.8% prediction accuracy, better regional generalization execution, by an average of 0.9, and a high level of correlation in the temporal dependency examination. These results confirm that it is stronger and transparent to conventional black-box models. All in all, the framework improves stakeholder confidence, which allows agricultural planning to be based on data, offers the best pricing strategies, and the management of the food system to be resistant.

The future work will develop EHDL-SHAP with the incorporation of satellite-based remote sensing and real-time IoT agricultural sensors to increase the spatiotemporal precision. Moreover, price forecasting strategies will be optimized by means of the integration of reinforcement learning. By extending the model to international databases, it will also be confirmed that it is adaptable in different agro-climatic zones and different economic settings.

Concept drift technique helps keep things reliable even when things change slowly over time, although sudden changes in the system could still damage accuracy. Future work will focus on how to deal with abrupt drifts by finding them and adapting to them online.

Pricing techniques based on reinforcement learning can adaptively optimize long-term revenue through sequential decision-making, but they need constant feedback and dependable reward signals, which do not exist in historical agricultural price datasets. So, the suggested work is based on supervised, explainable models. It will use reinforcement learning methods in the future when there is real-time interaction and market input.

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