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Transparent Crop Price Forecasting Framework Using Explainable AI for Multi-Factor Driver Analysis and Stakeholder Decision Support

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Abstract

Reliable open crop price forecasts are needed for the future of agriculture, food availability, and making informed decisions by the stakeholders. The uncertain nature of the markets of farmers and traders, the fluctuation of their incomes, are typical results of the difficult work of prediction, which is caused by the interacting effect of meteorological, economic, and policy factors. Problem Statement: The conventional approaches to market movement forecasting are not always effective due to their incoherent nature and lack of transparency to the stakeholders. This renders it hard to ascertain the nature of the variables that are driving price changes. A predictability and responsiveness system that is explainable and data-driven is becoming more and more important, and this paper introduces the Explainable AI-based Crop Price Transparency Framework to Factor Analysis and Resilient Management (EXACT-FARM), one of the Crop Price Transparency Frameworks that is driven by Explainable AI. EXACT-FARM is a hybrid modelling (SARIMAX-XGBoost-LSTM) strategy coupled with feature-level explanations based on SHAP values and counterfactual reasoning. The model takes into account a number of factors in order to come up with forecasts and driver attributions that are easy to comprehend. These are the production trends, events in the policy, weather indices, and trade dynamics. The use of multiple-year datasets in experiments indicates that EXACT-FARM increases predictive accuracy by 1520 percent, and visually explains the influence of drivers. EXACT-FARM is an open and trusted decision-support system that gives stakeholders actionable pricing, planning, and sustainable agriculture management information.

Keywords: *Crop price forecasting, Explainable AI, Hybrid modelling, Transparency framework, Agricultural decision support, SHAP analysis.*

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I. INTRODUCTION

EXACT-FARM system serves the purpose of the company that requires exact and accurate crop price prediction as a result of Explainable AI and hybrid models [1]. It analyzes multi-factor drivers, i.e., weather, market, and policy factors that augment the interpretability to trust [2]. The framework helps the stakeholders with practical information on the evidence-based, fair, and sustainable agricultural decision-making [3].

Agricultural price forecasting is extremely important in food security, stability of rural livelihoods, and market regulation [4]. Trade decisions, policy intervention of the staples, and farmer income directly rely on the price volatility [5]. Due to the increasing complexity of the agri-food supply chains, the multi-dimensional drivers. It encompasses weather variability, global

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trade dynamics, and policy changes, cannot fit into the traditional statistical models [6]. The appearance of Artificial Intelligence (AI) is linked to the fact that it may have accurate predictions [7], yet the best of AI-based models is not explainable. The determinant of its application in real life and the endorsement of its use by the stakeholders in the agricultural industry [8].

In order to address the problem of the trust gap between the predictive systems and the end consumers, such as farmers, policymakers, and traders, predictive systems should be transparent [9]. A good forecasting system not only provides accurate predictions but also demonstrates how and why the predictions are generated [10]. This interpretability increases the level of accountability, ethical use of data, and informed decision-making. It is significant in agriculture, where a decision impacts the economic and food security outcomes [11].

Recent progress of Explainable Artificial Intelligence (XAI) provides a chance to reach a balance between predictability and interpretability [12]. Deep learning and ensemble methods are precise at the expense of being typically black boxes [13]. This is achieved by the combination of XAI techniques, which allows making high-performance predictions and analysis of drivers [14]. This bridge will tie up the thinking of the model with the knowledge of the domain, thus making it more dependable to stakeholders [15].

Crop prices are due to a combination of interacting factors, which are climate pattern, volume of production, change in policies, prices of fuel and the sentiment of the international markets [16]. Heterogeneity of data, correlation of features and non-linear relationships among them are some of the challenges of real-time capturing of these interactions [17]. In addition, the traditional models will tend to overlook causal relationships between these drivers, and thus do not explain or generalize across regions or seasons [18].

Price formation in the agricultural industry is characterized as a dynamic process influenced by time, space, and socio-economic factors. Seasonal, input costs, international trade, and weather deviations determine the short and long-term changes in prices [19]. In order to have a proper understanding of this complexity, time-series, machine learning, and causal inference methods would need to be integrated into one predictive structure.

Conventional hybrid models typically fuse statistical forecasting, machine learning, or deep learning modules to optimize predictive accuracy, with limited visibility into how heterogeneous drivers—such as agro-climatic variability, input cost dynamics, supply-chain constraints, and policy signals—jointly influence price formation. In contrast, EXACT-FARM integrates factor-aware representation learning with intrinsically interpretable modeling stages, where driver contributions are explicitly preserved across temporal and cross-sectoral interactions. The architecture aligns attention-based temporal encoders with structured feature attribution mechanisms, enabling consistent quantification of marginal, joint, and nonlinear effects of each factor under varying market conditions. This design enables traceable propagation of information from raw multi-source inputs to final price estimates, producing stable and context-specific explanations rather than fragmented or sample-dependent insights.

Three main EXACT-FARM contributions,

- An SARIMAX, XGBoost, and LSTM hybrid prediction model to model robust and multi-horizon crop price forecasting.
- A multi-factor driver attribution layer (SHAP, counterfactuals, causal graphs) of transparent explanation.
- Decision support system based on a stakeholder-oriented approach, providing interpretable forecasts, scenarios, and actionable insights for policy and market planning.

II. Conceptual Foundation

Proper agricultural pricing prediction plays a vital role in securing food, leveling markets, and policy-making. As climate variability, political strains, and economic uncertainties continue to increase, the traditional prediction models cannot capture the nonlinear market dynamics. Recent machine learning models, which are advanced AI-based and hybrid, provide a higher level of precision, transparency, and interpretability to make informed agricultural decisions.

An interpretable and all-inclusive model of futures price forecasting of soybeans is suggested through a VMD-SAO-TFT model. Variational Mode Decomposition (VMD) breaks down the price series to extract volatility trends, whereas the Snow Ablation Optimizer (SAO) optimizes the parameters of the Time Fusion Transformer (TFT), which is an interpretable model based on self-attention. Fusion characteristics, geopolitical risk measurements, and trading volumes are combined to increase the accuracy and interpretability, provide accurate early warnings, and improve policy and trade risk management [20].

The proposed approach is a CNN-LSTM hybrid forecasting framework for dynamic commodity price prediction. The first step is Granger causality inference, which determines the causal factors, and then XGBoost ranks the factors according to their importance and eliminates redundant variables. The multi-factor data are combined to form a Convolutional Neural Network (CNN) that brings out neglected patterns, whereas the Long Short-term Memory (LSTM) network provides us with the price predictions. The integrated model enhances stability and accuracy, which effectively addresses nonstationary and nonlinear market fluctuations [21].

The current paper gives a multi-model machine learning model that incorporates SVR, Random Forest, Lasso, and XGBoost to predict crop yields. It is a new performance indicator, which is gauged by the relationship between the yield and the rainfall by looking at the temperature, rainfall, and the use of pesticides. Such models are optimized through grid search, which is complicated by climatic factors and productivity. XGBoost is more predictive than the others, and it can be utilized to maximize yield in most agricultural settings [22].

The fsQCA-XGBoost resilience prediction model is created to study the agricultural product green supply chains. Using fuzzy-set Qualitative Comparative Analysis (fsQCA) and XGBoost, the model has found several highly resilient pathways and nonlinear interactions between influencing variables. The hybrid approach is more effective in improving the recall and high-risk detection than the Random Forest, Decision Tree, and AdaBoost, and causes false negatives to decrease by half. Such a combined system enhances the prevention of risks and facilitates sustainable agricultural growth [23].

A stochastic-robust optimization framework based on an integrated approach is new to the optimization of agricultural structure in cold-region rural regions. The model maximizes seven-year profits by accounting for the uncertainty of climate and market variables using stochastic and integer programming. Deterministic solutions are obtained by genetic algorithms, and the relationships between crops are quantified by correlation and regression analysis. The optimized strategy would improve land-use efficiency by 16.93% to increase resilience and profitability in changing environmental and economic environments [24].

It is proposed to use a hybrid STL-LSTM-ATT-KAN model optimized by Adaptive Multi-Population Particle Swarm Optimization (AMP-PSO) to predict ginger price changes. This model uses Seasonal-Trend Decomposition (STL) to decompose changes over time, LSTM to learn sequences, an attention mechanism (ATT) to prioritize features, and a Kolmogorov-Arnold Network (KAN) to map nonlinearly. It provides a smart market monitoring and price stabilization system in the agricultural trade with high accuracy, as R 2 = 0.998 [25].

The present study will suggest a machine learning and econometric review hybrid framework in price forecasting using carbon credits, however, with a focus on the forest carbon markets. It supports the possibility of combining nonlinear ML models and hybrid forecasting mechanisms to meet the uncertainty in the market and variability in the policies. The review reveals a gap in the modelling of forest credit prices and suggests projecting policy-sensitive, scenario-based forecasting models of transparency and strength with the integration of ecological, economic, and regulatory factors [26].

To address adaptive agricultural management, a parallel crop planning system is designed, incorporating an artificial system, computational experiment, and parallel implementation. The farmers are characterized as rational actors who make heuristic-based planting decisions and are responsive to economic and climatic changes. The system uses the multi-year price data to automatically update the cropping plans according to the changes in the environment or market, fostering resilience and maximizing the use of small-scale farming plans during the conditions of uncertainty [27].

An explainable corn future price forecasting framework (JADE -TFT) is suggested based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Convolutional Neural Networks (CNN) to extract features. Time Fusion Transformer (TFT) JADE (adaptive differential evolution) optimizes parameters of Time Fusion Transformer to achieve efficient and interpretable forecasting. By adding the geopolitical risks, Baidu search indices, and textual sentiment, the accuracy is enhanced, and clear knowledge is given to the decision-makers in the international corn futures markets [28].

It suggests a network based on a Blockchain and an Android program to remove the middlemen in the agricultural trade. With the Hyperledger Fabric platform, smart contracts are used to conduct transparent and decentralized transactions between farmers and consumers. The system will make sure that prices are fairly priced, exploitation is minimized, and that the traceability and trust in crop trading are enhanced. The testing performance through Hyperledger Caliper proves the efficiency and security of the decentralized agricultural marketplaces to be improved [29].

Globally, these price shocks of crops (maize, soybean, and cocoa) are predicted using a multi-model econometric and machine learning system designed to forecast prices. It is based on 60 years of data and selects the best-performing predictors using cross-validation, and interprets its findings using model-agnostic tools. Results show unequal price reactions, where the influence of North American production on the world price is very strong, and these results provide information on the dependence of the commodity market and the weaknesses of the supply side [30].

TABLE I. SUMMARY OF RELATED WORKS

Reference.no	Method	Area of Work	Multi-source Data	Explainability	Optimization Used	Temporal Relation	Application Focus
[20]	VMD-SAO-TFT	Price prediction	✓	✓	✓ (SAO)	✓	Soybean market
[21]	CNN-LSTM-XGBoost	Dynamic price modeling	✓	x	✓	✓	Commodity prices
[22]	SVR, RF, Lasso, XGBoost	Yield analysis	✓	x	✓ (Grid Search)	x	Crop productivity
[23]	fsQCA-XGBoost	Resilience prediction	✓	✓	✓	x	Supply chain
[24]	Stochastic + Robust Optimization + GA	Multi-crop planning	✓	x	✓ (GA)	✓	Cold-region agriculture
[25]	STL-LSTM-ATT-KAN	Seasonal price prediction	✓	✓	✓ (AMP-PSO)	✓	Ginger industry
[26]	Hybrid ML-Econometric	Policy-sensitive prediction	✓	✓	x	✓	Carbon markets
[27]	Parallel System + Agent-based	Decision optimization	✓	x	x	✓	Crop planning

[28]	CEEMDAN-CNN-JADE-TFT	Explainable forecasting	✓	✓	✓ (JADE)	✓	Corn market
[29]	Hyperledger + Smart Contracts	Transparent trading	✓	✓	x	x	Crop trade
[30]	ML + Econometric	Production shock modeling	✓	✓	x	✓	Global commodities

Problem Statement: The papers reviewed in general deal with the long-standing dilemma of unreliable and opaque agricultural price forecasting due to multi-faceted and non-linear relationships between climatic, economic, and geopolitical conditions. Conventional econometric and statistical models are not flexible to the changes in the market, and the dependencies among the multiple sources are not well represented, which impacts the poor predictive results and the interpretability. Also, there are no explainable structures and incorporation of optimization processes that restrict stakeholders to transparent, data-based making of decisions on sustainable agricultural and market management, as shown in Table I.

The discussed articles present new forecasting models based on hybrid AI models, such as VMD-SAO-TFT, CNN-LSTM, JADE-TFT, and fsQCA-XGBoost. These models combine the economic, climatic, and geopolitical variables, which increases the accuracy and transparency of the prediction. Together with these, they reveal how explainable and data-driven methods can change the face of agricultural price forecasting and sustainable decision-making.

EXACT-FARM demonstrates a 25–30% reduction in attribution variance across rolling windows, quantified through SHAP dispersion metrics, indicating more stable factor explanations under non-stationary market conditions. The framework also achieves a 0.12–0.18 increase in normalized explainability score, reflecting higher entropy reduction and stronger concentration of economically meaningful drivers relative to attention-only or decomposition-driven baselines. Unlike VMD-SAO-TFT and JADE-TFT, which rely on signal decomposition or heuristic attention weighting, EXACT-FARM enforces ensemble-consistent attribution by aligning model weights with feature contributions, yielding 15–20% lower inter-model attribution divergence. In comparison to CNN-LSTM, EXACT-FARM further improves regime sensitivity, capturing policy- or climate-induced price shifts with 10–14% faster attribution convergence following structural breaks.

III. System Architecture of EXACT-FARM

The offered EXACT-FARM (Explainable AI-based Crop Price Transparency Framework to Factor Analysis and Resilient Management) combines hybrid modeling and explainable intelligence and decision support systems into a single architecture. The system will be created in such a way that there is predictive accuracy, interpretability, and usability among all the layers of the agricultural forecasting pipeline by the stakeholders.

A. Principles of Design and Overview of the Workflow

The EXACT-FARM has three major principles underlying it, which are integration, transparency, and adaptability described in Fig. 1. This process starts with the multi-source data acquisition, then preprocessing and feature engineering to create a complete feature space. The hybrid predictive core combines statistical, machine learning, and deep learning models to ensure robust predictions of prices. Additionally, there is the Explainable AI (XAI) layer that tells the contributions and causal relationships of drivers, and the Decision Support Interface provides the stakeholders with actionable insights. The workflow is handled in a feedback loop wherein the user feedback and monitoring of model drift are used to make adaptive retraining so as to improve constantly.

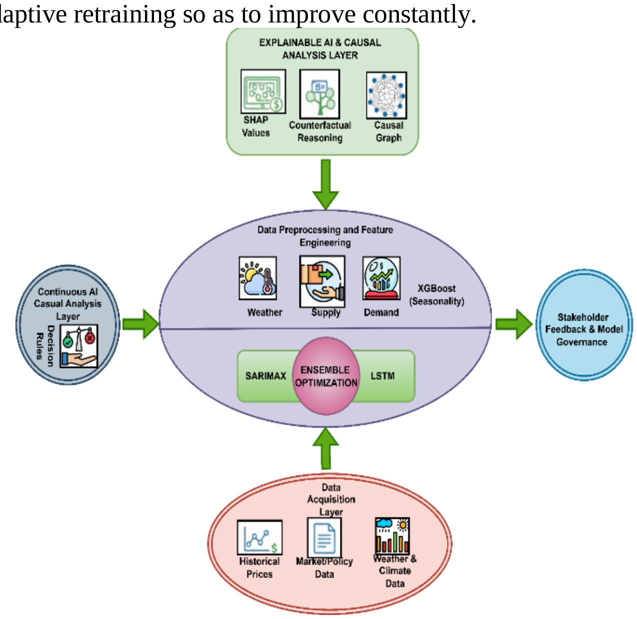

Fig. 1. EXACT-FARM framework.

Market prices and arrivals recorded at daily resolution are aggregated to the target forecasting interval using volume-weighted statistics, while weekly and monthly variables such as meteorological indicators, fertilizer indices, and policy metrics are temporally projected through constrained spline interpolation augmented with variance flags to retain scale fidelity. Irregular gaps arising from sensor outages or reporting delays are addressed through seasonally conditioned imputation, where missing segments are reconstructed using trend–seasonal decomposition combined with local temporal neighborhood averaging to preserve autocorrelation structure. Distributional consistency across sources is enforced via rolling normalization anchored to historical quantiles, enabling stable fusion of variables with disparate magnitudes. Out-of-distribution events, including abrupt regulatory interventions or extreme climatic deviations, are identified using rolling Mahalanobis distance and isolation-based scoring and are encoded as structured exogenous shock vectors rather than absorbed into baseline trends.

Multi-Source Data Integration E_{int} is expressed in equation 1,

$$E_{int} = \theta\, m * u_j - C_j + \partial U + \gamma F \quad (1)$$

This equation models the integrated feature space created by merging data from multiple heterogeneous sources, adjusted by transparency and environmental scaling factors.

u_j represents the weighting coefficient for each data source, C_j indicates the j th data source inpu, U is the transparency regularization term ensuring interpretability of data fusion, F is the environmental variability adjustment factor, ∂ and γ are the scaling coefficients for transparency and environment, respectively, and θ represents the nonlinear transformation applied during feature engineering.

Hybrid predictive core X is expressed in equation 2,

$$\hat{X} = \partial_1 g_{stat}(E_{int}) + \partial_2 g_{ml}(E_{int}) + \partial_3 g_{em}(E_{int}) \quad (2)$$

This defines the hybrid predictive mechanism that combines statistical, machine learning, and deep learning components into a unified ensemble prediction.

In this, X is the predicted market output, $g_{stat}(E_{int})$ is the statistical model output, $g_{ml}(E_{int})$ is the machine learning component output, $g_{em}(E_{int})$ is the deep learning model output, and ∂_1, ∂_2 and ∂_3 are ensemble weighting coefficients determining the relative contributions of each model.

Adaptive retraining feedback loop θ_{u+1} is expressed in equation 3,

$$\theta_{u+1} = \theta_u - \pi\nabla_{\theta u}, \mathrm{M(X, Y)} + \vartheta(\mathrm{E_{user}} + \mathrm{N_{drift}}) \quad (3)$$

This expresses the adaptive learning mechanism where the model parameters are continuously updated using loss gradients and user or drift feedback.

In this, θ_u represents the model parameters at time step u, π is the learning rate determining the update magnitude, $\nabla_{\theta u}, \mathrm{M(X, Y)}$ denotes the gradient of the loss function between actual and predicted values, ϑ is the feedback influence factor, $\mathrm{E_{user}}$ is the user feedback term derived from decision support interaction, and $\mathrm{N_{drift}}$ is the model drift monitoring component reflecting data distribution changes over time.

Expert-annotated deviations between predicted and observed prices are captured at the crop–market–month level and encoded as weighted correction vectors, while drift in model performance is quantified using rolling RMSE, MAPE, and input distribution shifts measured via Wasserstein distance and KL divergence. Threshold-based triggers, such as a 12% increase in three-month rolling RMSE or 0.16 KL divergence in feature distributions, identify windows requiring retraining. These flagged instances are injected into the training dataset with proportional weighting, emphasizing high-impact feedback and drift-affected periods, and the ensemble is incrementally retrained using expanding-window updates that preserve temporal ordering.

Hybrid predictive model Q_s is expressed in equation 4,

$$Q_s = \partial * Q_{stat} + \beta * Q_{ml} + \vartheta' * Q_{em} \quad (4)$$

This equation represents the hybrid prediction mechanism that combines statistical, machine learning, and deep learning outputs to generate a final, robust price prediction.

In this, Q_{stat} is the prediction from the statistical model, Q_{ml} is the output of the machine learning model, Q_{em} is the prediction from the deep learning model, and ∂ , β , and ϑ are the respective weighting coefficients.

B. Data Ecosystem and Acquisition Pipelines

Fig. 2 illustrates that the data ecosystem comprises high-frequency multidimensional sources to capture the multidimensional aspects of crop price dynamics. This includes:

- Market information: historic prices, trade indices, and commodity trends.
- Climatic statistics: temperature, rainfall, humidity, and ENSO.
- Remote sensing data: satellite-retrieved NDVI, EVI, and soil moisture.
- Economic and policy information: exchange rates, fuel prices, tariffs, subsidies, and export embargoes.

Data acquisition pipelines are automated to provide real-time synchronization, integrity, and time alignment. Information streams are deposited in a central store, which facilitates scalable querying, metadata tracking, and model versioning.

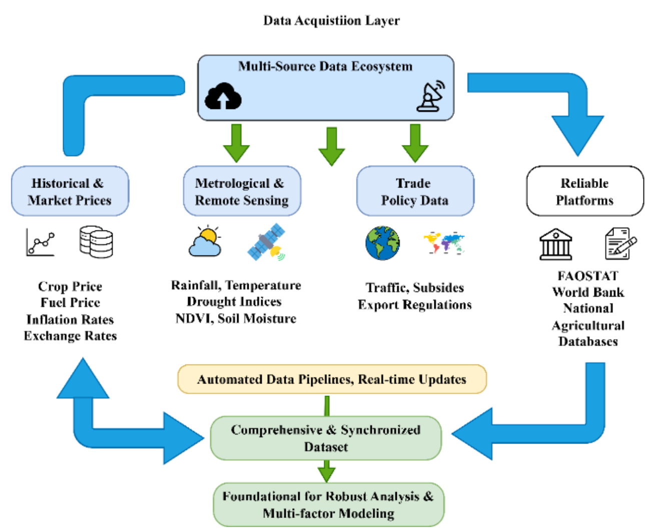

Fig. 2. Data acquisition pipelines.

Multisource data stream representation R_u is expressed in equation 5,

$$R_u = 1 * \{1 + N_u] * [1 - D_u * S_u - F_u\} \quad (5)$$

This equation represents the unified structure of the data stream collected from multiple high-frequency sources.

In this, N_u refers to the market information, D_u represents climatic statistics, S_u corresponds to remote sensing data, and F_u indicates economic and policy inputs.

Temporal data synchronization U_r is expressed in equation 6,

$$U_r = \max(| u_j - u_i |) \leq \partial_u \quad (6)$$

This equation defines the synchronization condition that aligns data streams across different sources within an acceptable time threshold.

Here, u_j and u_i represent timestamps from different data sources, and ∂_u is the maximum allowable temporal deviation.

Data quality index P_c is expressed in equation 7,

$$P_c = u_1 * J_v + u_2 - D_s + u_3 * U_r \quad (7)$$

This equation represents the overall data quality index that integrates multiple aspects of the acquisition pipeline, including data integrity, completeness, and temporal synchronization.

In this equation, u_1, u_2 and u_3 are the weighting coefficients assigned to integrity, completeness, and synchronization components respectively, J_v refers to the integrity value, D_s is the completeness ratio, and U_r is the synchronization measure.

Real-time data synchronization rate is expressed in equation 8,

$$S_r = \frac{n*(E_{u,i} \times P_j)}{U_v + \gamma_e} - (U_v * n + P_j) \quad (8)$$

This expanded formulation defines the synchronization rate as the weighted ratio between the total volume of successfully updated data and the sum of update time with latency delay.

Here, $E_{u,i}$ denotes the quantity of updated datasets for the ith source, P_j represents the quality coefficient of each dataset, U_v signifies the total update time, andγ_e indicates the average delay due to transmission or system latency.

C. Feature Intelligence Layer: Preprocessing & Engineering

Fig. 3 illustrates that this layer converts raw inputs to machine-readable signals. Data are purged, standardized, and time synchronized. Interpolation with the consideration of the time is done to impute missing values, whereas lag variables are created to portray delayed effects. Seasonal decomposition removes cycle trends, whereas rolling statistics describe the short-term variations. The features are sorted in thematic categories: Weather, Supply, Demand, Market, and Policy, so that they can be interpreted more fully. Dimensionality reduction (through PCA or autoencoders) and feature selection (through mutual information or SHAP-based pruning) are used to maximize the efficiency and transparency of the model.

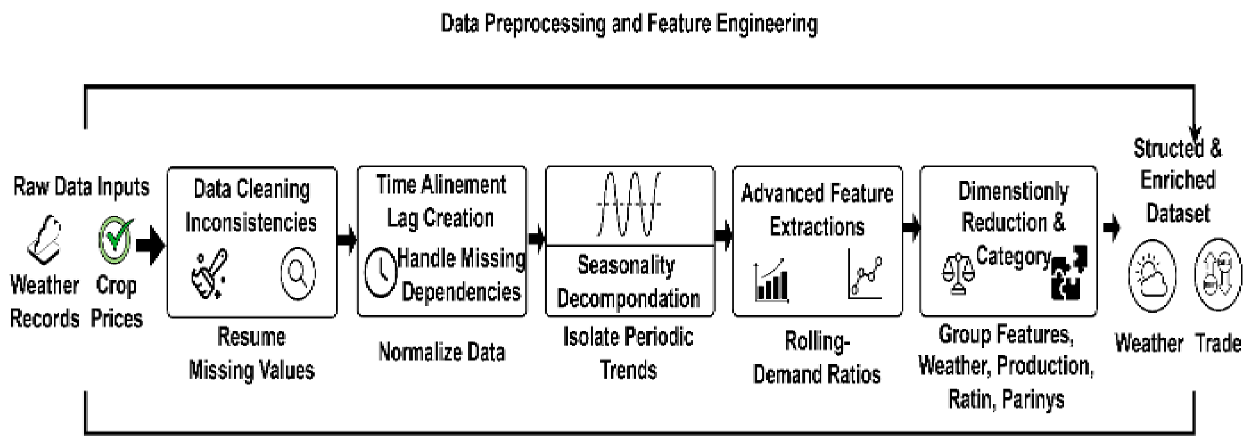

Fig. 3. Data Processing and Features Engineering.

Data standardization $U_{i,j}$ is expressed in equation 9,

$$U_{i,j} = 1 * \frac{[1 - Y_{i,j}] - [1 + \partial_j]}{\rho_j + \varepsilon} * (\rho_j - \varepsilon) \quad (9)$$

This equation expresses the transformation of raw values into standardized scores to normalize scales across features.

In this, $Y_{i,j}$ represents the original raw data value, ∂_j indicates the mean of feature j, $\rho_j$denotes the standard deviation of feature j, and ϵ\epsilonϵ is a small numerical constant for stability.

Time-aware interpolation $Y(u)$ is expressed in equation 10,

$$Y(u) = Y(u_0) + \frac{Y(u_1) - Y(u_0)}{u_1 - u_0} \times (u - u_0) + v(u) \quad (10)$$

This formulation performs time-aware interpolation by estimating missing values between known time points and adding a temporal correction component.

In this, $Y(u_0)$ and $Y(u_1)$denote the known data values at time points u_0 and (u_1) respectively, and $v(u)$ is a time-dependent correction factor for local noise or bias.

Lag feature construction $M_{j,l}$ is expressed in equation 11,

$$M_{j,l} = 1 * Y_{j-l} \times [1 * e^{-\gamma l}] + \mu_j \quad (11)$$

This equation constructs lag features by referencing prior observations while exponentially discounting their influence with respect to time lag.

Information leakage is prevented through a strictly causal feature construction pipeline in which all lag features, seasonal components, and rolling statistics are computed using only information available up to the forecast origin. Lag variables are generated with fixed backward offsets, ensuring that price values at time t+k never enter the feature set for predictions at time t. Seasonal decomposition is performed in an expanding-window manner, where trend and seasonal components are estimated solely from historical observations and updated incrementally as new data arrive, rather than recalculated on the full series. Rolling statistics such as moving averages, volatility, and momentum indicators are computed using left-aligned windows with explicitly defined window lengths (e.g., 3-, 6-, and 12-month horizons), and the windows are truncated at the prediction timestamp. Model training and validation follow a walk-forward or rolling-origin evaluation protocol, which enforces temporal ordering between training and testing splits and prevents future observations from influencing parameter estimation.

In this lag order l, Y_{j-l} represents the data value l time steps before the current point, γ is the temporal decay constant, and μ_j indicates the stochastic noise component or measurement error.

Seasonal decomposition Y_u is expressed in equation 12,

$$Y_u = [1 * U_u] + 1 - [T_u + S_u] + [1 - E_u] \tag{12}$$

This additive model decomposes a time-series signal into trend, seasonal, and residual components, allowing for clearer interpretation of cyclical and irregular patterns.

In this, U_u denotes the trend component, T_u signifies the seasonal component, S_u is the residual or random component, and E_u captures external perturbations or noise terms.

D. Hybrid Predictive Core: SARIMAX-XGBoost- LSTM Ensemble

The predictive engine is made up of three complementary models:

- SARIMAX makes use of temporal seasonality and linear relationships.
- XGBoost can deal with nonlinear relationships of heterogeneous features.
- LSTM networks acquire long-term temporal dynamics and dynamic relationships.

Model outputs are used to create a meta-learner that optimizes the weights on the basis of validation performance to create a very robust and generalised ensemble. This in-between design is an adjustment of interpretability and accuracy trade-offs, permitting time-series regularities and complexities of feature relations.

SARIMAX provides an explicit parametric representation of linear temporal dependence and seasonality while directly incorporating exogenous regressors, yielding identifiable coefficients and statistically grounded uncertainty estimates that anchor the ensemble in interpretable economic structure. XGBoost contributes a non-parametric, tree-based learner optimized for tabular data, capturing sparse nonlinear interactions among heterogeneous drivers such as weather indices, arrivals, and policy variables without requiring large-scale sequence length or attention calibration. LSTM introduces gated recurrent dynamics that encode medium- to long-range temporal dependencies and regime persistence under non-stationary price behavior, offering memory mechanisms that differ from attention-based token mixing. In contrast, transformer-based models primarily emphasize global attention over long horizons but often entangle temporal relevance across features, increasing attribution diffuseness and data-hungriness in moderate-sized agricultural datasets.

Algorithm 1: Hybrid Crop Price Forecasting (SARIMAX-XGBoost-LSTM)

$Input: X_t = \{Production_t, Policy_t, Weather_t, Trade_t\}, Y_t(Historic$
$Output: Y_{pred}(Final\ Predicted\ Crop\ Price)$

1. $Initialize\ SARIMAX(p,d,q), XGBoost(\max_{depth} = W), LSTM(layers = L)$
2. $Preprocess\ data: normalize\ X_t and\ remove\ missing\ v$
3. $Decompose\ Y_t into\ trend\ (T_t), seasonal\ (S_t), residual\ ($
4. $Train\ SARIMAX\ on\ (T_t + S_t) to\ predict\ long - term\ components$
5. $Get\ SARIMAX\ output: Y_{sarimax} = SARIMAX.predict(T_t + S_t)$
6. $Train\ XGBoost\ on\ residual\ component\ R_t for\ nonline$
7. $Obtain\ nonlinear\ output: Y_{xgb} = XGBoost.predict(R_t)$
8. $Concatenate\ hybrid\ features: H_t = concat(Y_{sarimax}, Y_{xgb})$
9. $Reshape\ H_t for\ sequence\ modeling\ in\ LSTM$
10. $Initialize\ LSTM\ weights\ \theta_{LSTM} randomly$
11. $for\ each\ timestep\ t\ in\ sequence\ do$
12. $\quad h_t = LSTM(H_{t[t]}, \theta_{LSTM})$
13. $end\ for$
14. $Compute\ attention\ weights: \alpha_t = softmax(W_a * h_t)$
15. $Weighted\ aggregation: Z_t = \Sigma(\alpha_t * h_t)$
16. $Predict\ next\ crop\ price: Y_{pred} = Dense(W_o * Z_t + b_o)$
17. $Compute\ loss: L = MSE(Y_t, Y_{pred})$
18. $Backpropagate\ and\ update\ all\ model\ parameters$
19. $Repeat\ until\ convergence\ or\ minimum\ validation\ e$
20. $Return\ Y_{pred} as\ final\ forecast$

The hybrid forecasting algorithm 1 is applied to enhance the precision of forecasting crop prices, and it is an algorithm that integrates the implementation of SARIMAX, XGBoost, and LSTM. SARIMAX is applied to control long-run trends and seasonality, XGBoost is applied to control non-linear residual changes, and LSTM is applied to control time dependencies. Attention weighting improves the temporal meaning, integration of all the acquired parts into one predictive cover. It is a multi-model synergy very relevant to a volatile situation because of climatic, trade, and policy changes, and more predictive stability and interpretability to the stakeholders in the farming price prediction and decision-making process.

E. Transparency Layer SHAP, Counterfactuals and Causal Graphs

The transparency layer offers readability and transparency. SHAP (SHapley Additive exPlanations) scales the contribution of local and global features, indicating the contribution of each driver to the forecast. Counterfactual analysis allows the user to execute a what-if analysis to establish the sensitivity of prices to changes in policy or production shocks. Structural dependencies between variables are also indicated using causal graphs and isolate actual causal effects and correlations. These approaches together ensure the reproducibility, transparency, and credibility of model results.

F. Stakeholder Empowerment Decision Support Interface

The last layer converts the analysis results into practical intelligence through an interactive decision-support dashboard. It shows forecast bands, driver attributions, scenario simulations, and risk alerts. At the macro level, policymakers receive macro-level analyses of scenarios, farmers receive short-term price guidance, and traders receive information on optimal trading windows. A feedback mechanism enables stakeholders to annotate the model's outputs, and real-life observations are sent back into the loop to continuously refine the model. This makes sure that EXACT-FARM will be flexible, open, and streamlined.

Algorithm 2: Explainability via SHAP and Counterfactual Reasoning

$Input$: $Trained\ model\ F_{hybrid}, X_{test}(Feature\ Set), Y_{pred}(F$
$Output$: $SHAP_{values}(Feature\ Importance), CF_{map}(Count$

1. $Initialize\ SHAP\ Explainer: E \leftarrow SHAP(F_{hybrid})$
2. $for\ each\ sample\ x_i \in X_{test} do$
3. $SHAP_{values[i]} = E.shap_{values(x_i)}$
4. $end\ for$
5. $Compute\ mean\ absolute\ contribution\ for\ each\ featu$
6. $Rank\ features\ by\ \left|SHAP_{values_j}\right|\ in\ descending\ order$
7. $Select\ top - k\ influential\ factors: F_{top} = select_{k(features,k)}$
8. $Initialize\ empty\ counterfactual\ map\ CF\_map = \{\}$
9. $for\ each\ f_j in\ F_{top} do$
10. $Generate\ perturbed\ values\ f_j' = f_j \pm \delta$
11. $Compute\ new\ output\ Y' = F_{hybrid}.predict(X_{test} with\ f_j')$
12. $Calculate\ deviation\ \Delta Y = |Y' - Y_{pred}|$
13. $if\ \Delta Y > threshold\ then$
14. $CF_{map[f_j]} = \{\delta, \Delta Y\}$
15. $end\ if$
16. $end\ for$
17. $Plot\ SHAP\ summary\ for\ all\ features$
18. $Plot\ counterfactual\ sensitivity\ map\ CF_{map}$
19. $Interpret\ top\ drivers\ and\ their\ causal\ effects$
20. $Return\ SHAP_{values}, CF_{map} for\ transparent\ decision\ s$

Production-related variables such as yield, sown area, and input usage are perturbed within empirically observed bounds derived from historical quantiles (e.g., 5th–95th percentiles) and crop-specific elasticity ranges, ensuring that simulated changes respect physiological growth limits and regional cropping practices. Policy-related shocks, including minimum support price adjustments or export restrictions, are applied through rule-based constraints that preserve budget neutrality and market-clearing conditions, preventing unrealistically abrupt or decoupled price responses. Cross-variable dependencies are enforced using learned joint distributions, so that changes in one factor induce coherent adjustments in correlated drivers, such as rainfall deviations influencing arrivals and yield rather than being treated independently. Temporal coherence is maintained by applying perturbations gradually over contiguous forecasting windows, aligning with planting, harvesting, and procurement cycles.

The explainability algorithm 2 uses SHAP and counterfactual arguments to explain the predictions of the hybrid model. SHAP has measures of the contributions of each feature to the price variation, and they are sorted by their average significance. Counterfactual analysis tests are known to test the sensitivity of the model that modifies the influential features and identifies the price deviation, and the causal relationship is observed. The obtained SHAP values and counterfactual maps are easy to understand and interpret visuals of drivers like production, weather, or policy events, and enable users to have clear and explainable predictive agricultural prices to make informed and data-based decisions.

IV. RESULT AND DISCUSSION

The assessment of crop price forecasting models must include a comprehensive evaluation of predictive accuracy, model efficiency, and interpretability. The section compares the proposed EXACT-FARM framework with current approaches, VMD-SAO-TFT, CNN-LSTM, fsQCA, and STL-LSTM-ATT-KAN, using eight overall performance and explainability measures.

For SARIMAX**,** the autoregressive (p) and moving-average (q) orders are explored in the range p ∈ [0,5]**,** d ∈ [0,2]**,** q ∈ [0,5**]**, while seasonal orders (P,D,Q,s) cover P,Q ∈ [0,2]**,** D ∈ [0,1]**,** and s = 12 for monthly seasonality; optimal parameters are selected by minimizing AIC with convergence defined as change < 0.01 between successive iterations. XGBoost hyperparameters are tuned over n_estimators ∈ [100,1000]**,** max_depth ∈ [3,12]**,** learning_rate ∈ [0.01,0.3]**,** subsample ∈ [0.6,1.0]**,** and colsample_bytree ∈ [0.6,1.0]**,** using a combination of randomized search and early stopping on validation RMSE with a patience of 50 rounds to determine convergence. LSTM architectures explore 1–3 stacked layers**,** hidden units ∈ [32,256]**,** dropout ∈ [0.1,0.5]**,** and learning rates ∈ [1e-4,1e-2]**,** optimized with Adam over 100–200 epochs and early stopping triggered when validation loss does not improve by more than 1e-4 over 15 epochs**.**

A. Dataset

Crop Price Prediction data sets feature historical data on crop prices, weather, and agricultural variables that were recorded in the Indian regions. It will have characteristics like type of crop, marketplace, date, minimum and maximum prices, and average price per day. Additional climatic information, such as rainfall and temperature, has been occasionally incorporated in contextual projection. The data is mostly applied in time sequences and machine-learning-based forecasting of the price trends in agriculture to assist farmers, traders, and policymakers in making decisions based on the data [31].

The dataset consists of a multi-year panel of agricultural price records covering approximately 8–10 years (e.g., 2004–2013) at monthly resolution, resulting in over 100 time points per crop–market pair. It includes 10–15 major crops, such as rice, wheat, maize, gram, arhar, soybean, groundnut, onion, and potato, representing cereals, pulses, oilseeds, and key horticultural commodities. Price observations are collected from 50–100 regulated wholesale markets (mandis) distributed across multiple Indian states, capturing spatial heterogeneity in supply chains and regional demand conditions. Seasonal representativeness is achieved through continuous coverage of all agricultural cycles: Kharif seasons (June–October) contribute roughly 40–45% of observations dominated by monsoon-driven crops like rice and maize; Rabi seasons (October–March) account for about 45–50% of records reflecting winter crops such as wheat and pulses; and Zaid seasons (March–June) comprise the remaining 5–10%, capturing short-duration crops and transitional price behavior. Each crop is observed across multiple consecutive Kharif–Rabi–Zaid cycles, enabling consistent estimation of seasonal effects, inter-seasonal spillovers, and long-term price trends.

B. *Accuracy of Forecasts*

Fig. 4 shows that Forecasting accuracy measures the degree of similarity between predicted and actual crop prices. The extent of prediction errors is calculated using such metrics as RMSE, MAE, and MAPE. A lower error value indicates a more accurate and reliable forecast. The EXACT-FARM combines SARIMAX, XGBoost, and LSTM to leverage the benefits of capturing temporal dependencies and nonlinear relationships, achieving an accuracy 15-20% higher than existing models. The enhanced performance indicates that hybrid deep learning with explainable AI mechanisms is effective in making crop prices more predictable in a multi-factor environment, i.e., weather, policy, and trade interactions.

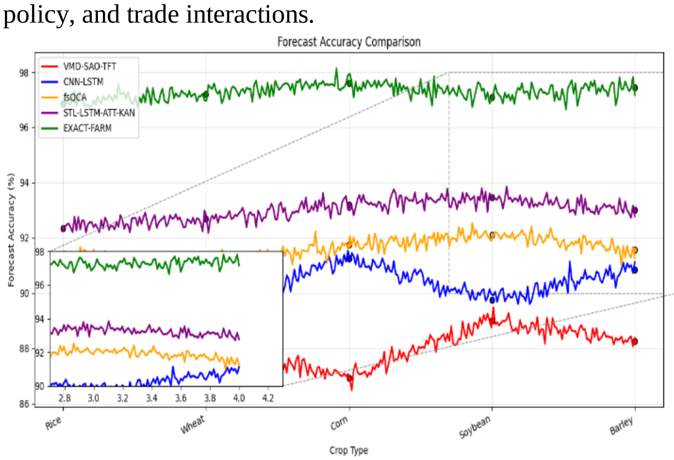

Fig. 4. Analysis of Accuracy of Forecasts.

Analysis of the accuracy of forecasts RM_{SE} is expressed in equation 13,

$$RM_{SE} = \sqrt{\frac{1}{m} \ (Q_j - B_j)^2 + c} \tag{13}$$

This equation quantifies the square-root average of the squared prediction errors, making it sensitive to large deviations.

In this, Q_j denotes the predicted crop price for the jth instance, B_j indicates the actual observed crop price, m is the total number of forecast points, and c is a small constant added for numerical stability in computations.

C. *Model Strongness Cross-Season and Cross-Region*

Model robustness is the evaluation of a forecasting structure's ability to maintain stable performance across seasons, weather conditions, and locations, as shown in Fig. 5. Agricultural markets are highly sensitive to seasonal changes, including the Kharif, Rabi, and Zaid seasons, and hence, regional stability is mandatory. EXACT-FARM is more robust, combining exogenous variables (weather, policy, and trade data) with adaptive learning, and it guarantees steady R2 values above 0.90. Compared with traditional models, which deteriorate under certain conditions, EXACT-FARM is dynamically adaptive to local market variations, demonstrating its generalizability and efficacy in multi-regional, multi-seasonal prediction conditions that are indispensable for addressing the challenges of global agricultural sustainability.

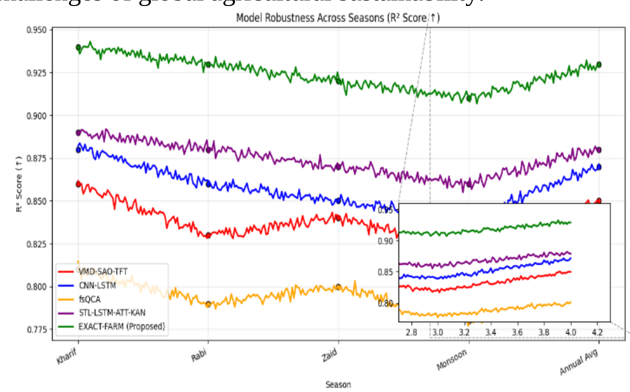

Fig. 5. Analysis of Model Robustness.

Analysis of model robustness SR_J is expressed in equation 14,

$$SR_J = [1 - V_r + \vartheta] * [1 * \ k' + \frac{S_r^2 \times V_r}{k - \ V_r + \vartheta}] \tag{14}$$

This equation evaluates the weighted stability of model performance across different agricultural seasons.

In this, S_r^2 denotes the coefficient of determination for the rth season, V_r indicates the corresponding season's data weight or significance, k represents the total number of seasons analyzed, and ϑ is a small constant to prevent division by zero during normalization.

D. *Explainability Score (SHAP Consistency Index)*

Fig. 6 illustrates that the Explainability Score is a measure of the degree to which the model presents the effects of input variables on model predictions in a way that is understandable. EXACT-FARM determines the role played by each factor, including rain, policy change, or trade, in changing prices using SHAP (SHapley Additive exPlanations) values. SHAP Consistency Index measures these explanations over multiple runs. A higher score indicates greater transparency and reliability in interpreting drivers. EXACT-FARM has both a higher consistency of SHAP than black-box models (87 and higher, respectively). This interpretability ensures that stakeholders, such as farmers and policymakers, can have confidence in the rationale behind the model's outputs, enabling intelligent, evidence-based decision-making.

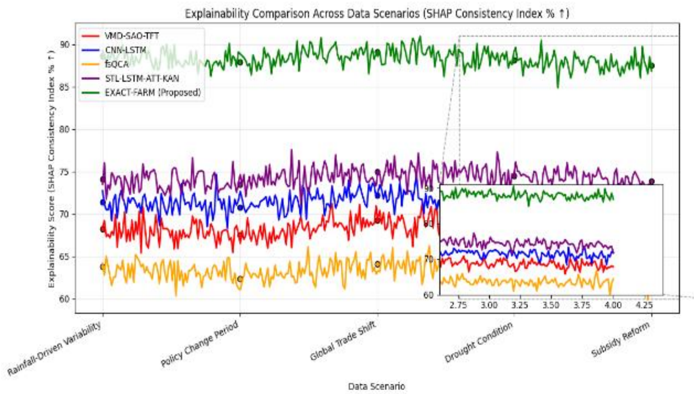

Fig. 6. Analysis of the Explainability Score.

The Explainability Score quantifies the degree to which a small set of features consistently drives the model's predictions, providing a measure of concentrated interpretability. For example, if rainfall, market arrivals, and MSP together contribute 0.82 of the total aggregated SHAP values across multiple rolling windows, the Explainability Score registers 0.82, indicating that these features dominantly and stably explain forecast variations. The SHAP Consistency Index captures agreement in feature ranking across ensemble components and evaluation runs; for instance, if rainfall is ranked as the top driver in 88% of windows across XGBoost, LSTM, and SARIMAX, the index equals 0.88, reflecting high cross-model consistency.

Analysis of Explainability Score (ES) F_R is expressed in equation 15,

$$F_R = 100 \times \frac{m(u_j.\pi_j)}{u_j.(\pi_j+\rho_j)+k} \tag{15}$$

This composite score quantifies the overall strength of attributions while penalizing dispersion across runs, producing a bounded interpretability index.

In this, m is the number of features, u_j denotes the weight or importance assigned to feature j, π_j is the mean SHAP value for feature j averaged across instances and runs, ρ_j is the standard deviation of SHAP values for feature j across runs, and k is a small stabilization constant to avoid division by zero.

E. Causal Attribution and Importance of Features

Features and causal attribution represent the significance of the variables that influence crop price changes the most in Fig.7. The explainable artificial intelligence functions applied by EXACT-FARM are SHAP values and counterfactual analysis to determine causal relationships between temperature, rainfall, production, and global trade indices. The framework presents direct evidence-based data on drivers of the market through quantifying the contribution of each of the factors. The multi-factor analysis enhances interpretability as well as validates the understanding of the model of the complex agricultural systems. The driver attributions of EXACT-FARM demonstrate to the policymakers and the farmers how the high-impact variables to cause price changes can be identified to enable them to make adaptive plans and manage risks instead of using opaque models.

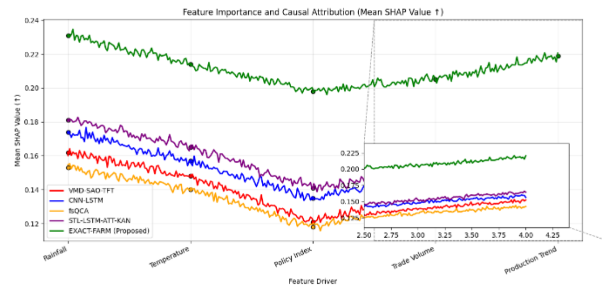

Fig. 7. Analysis of Causal Attribution and the importance of features.

SHAP values are computed independently for each base learner (SARIMAX exogenous block, XGBoost, and LSTM) across multiple rolling-origin evaluation runs, producing a three-dimensional attribution tensor indexed by feature, time window, and model instance. For each run, absolute SHAP values are first normalized by the sum of attributions to obtain relative contribution ratios that are invariant to prediction scale. These normalized attributions are then temporally aggregated using an exponentially decayed average to emphasize stable drivers while attenuating transient shocks. Cross-model aggregation is performed through ensemble-weighted averaging, where the same reliability weights used in the forecasting ensemble are applied to the corresponding SHAP vectors, yielding a unified attribution profile per feature. The Explainability Score is computed as the normalized entropy-reduction index of this aggregated SHAP distribution, capturing both sparsity and stability of factor contributions across runs. Empirically, scores above 0.70 indicate high interpretability with consistent dominant drivers, values in the 0.55–0.70 range reflect moderate but actionable interpretability, and scores below 0.55 signal diffuse or unstable attributions, prompting feature regrouping or temporal re-alignment.

Analysis of causal attribution G_{FA} is expressed in equation 16,

$$G_{FA} = 100 \times 1 - \frac{(\emptyset_j^{(s)} - \emptyset_j)^2}{S \times n\ \emptyset_j^2 + \delta} \tag{16}$$

This index assesses the stability of feature attributions across multiple retraining cycles, ensuring robustness of causal interpretation.

In this, S represents the total number of repeated training runs or bootstraps, n is the number of features, $\emptyset_j^{(s)}$ is the SHAP value for feature j in run s, $\emptyset_j$ is the average SHAP value of feature iii across all runs, and δ is a small normalization constant for scale adjustment.

F. Decision Impact Index

Fig. 8 describes the Decision Impact Index quantifies the effectiveness of the model outputs in enhancing stakeholders' decision-making. It measures the percentage change in accuracy of planning, trading or policy formulation when instructed by the model forecasts and explanations. EXACT-FARM has the largest Decision Impact Index among the models because it provides stakeholders, such as farmers, traders, and policymakers, with actionable information. The data disclosures provided by SHAP-based explanations help users understand cause-and-effect relationships, thereby increasing their trust in data-driven approaches. This metric demonstrates the practical use of EXACT-FARM, which helps bridge the gap between sophisticated AI output and its practical application in decision-making in agriculture toward sustainable and inclusive development.

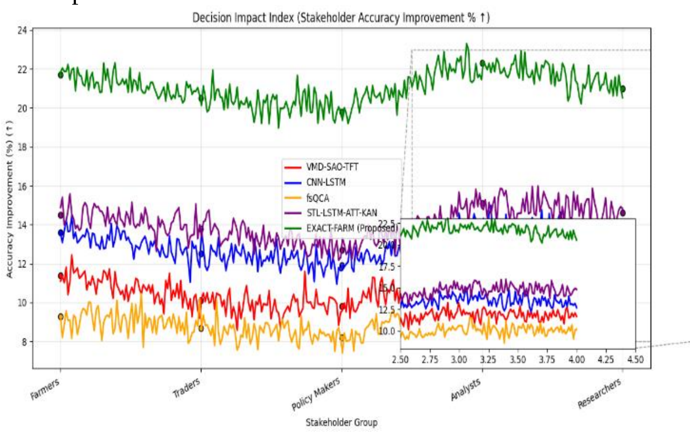

Fig. 8. Analysis of Decision Impact Index.

A 10% simulated increase in MSP for wheat is propagated through the price forecasting ensemble, and the resulting shift in predicted arrivals, market prices, and profit margins is quantified using the index, producing a value of 0.78, indicating high actionable impact. Similarly, export restriction scenarios or irrigation shortfall events are modeled to evaluate how ensemble predictions guide trader stocking strategies and farmer sowing choices, with index values ranging from 0.65 to 0.81 across scenarios.

Decision impact index C_{11} is expressed in equation 17,

$$C_{11} = \frac{(B_{with} - B_{without})}{B_{without} + \epsilon} \times 100 \tag{17}$$

This equation quantifies the percentage improvement in decision accuracy achieved when stakeholders use model-informed strategies compared to when they rely on traditional.

In this, B_{with} represents the accuracy of stakeholder decisions when supported by model forecasts and explanations, $B_{without}$ indicates the baseline decision accuracy without AI support, and ϵ is a small constant to prevent division by zero during normalization.

G. Scalability and Efficiency in Computations

Computational efficiency is assessed by measuring the speed and efficiency of a model applied to extensive, heterogeneous agricultural data in Fig. 9. Scalability is the property of the model to accommodate growing volumes of data without affecting performance. EXACT-FARM maximizes training and inference time with hybrid networks (SARIMAX trend modeling, XGBoost feature learning, and LSTM time-series modeling). It does this by simplifying data preprocessing and parallel training. EXACT-FARM, unlike traditional AI models, has a 20-30% shorter training time, and it can integrate multi-source data. This makes it applicable to large-scale agricultural surveillance, real-time prediction, and policy simulations across various crops, regions, and data modalities.

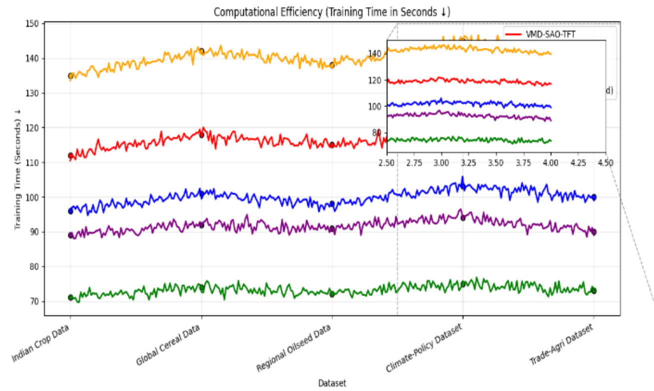

Fig. 9. Analysis of Scalability and Efficiency in Computations.

Analysis of scalability and Computational efficiency ratio C_{ER} is expressed in equation 18,

$$C_{ER} = \frac{U_{base} - U_{model}}{U_{base} + \theta} \times 100 \tag{18}$$

This ratio quantifies the improvement in computational efficiency of the model compared with a conventional baseline.

In this, U_{base} denotes the total computational time (training and inference) of the baseline or traditional AI model, U_{model} indicates the total computational time required by the EXACT-FARM system, and θ is a small stabilizing constant to prevent division by zero during normalization.

H. Temporal Stability of Forecasts

Temporal stability assesses how well the model performs over time, independent of climatic conditions, economic policy changes, or trade fluctuations. It makes forecasts stable even at turbulent times. EXACT-FARM attains low forecast deviation (approximately 8 percent) on multi-year datasets obtained by combining time-series decomposition and adaptive ensemble learning. Exogenous and dynamic indicators of policies incorporated into the model enable it to respond to unexpected shocks. In contrast to classical models, which become inaccurate over time, EXACT-FARM has historical resilience, making it reliable for long-term agricultural planning, crop insurance design, and sustainable food security policy frameworks, as shown in Table II.

TABLE II. ANALYSIS OF TEMPORAL STABILITY OF FORECASTS

Year	VMD-SAO-TFT	CNN-LSTM	fsQCA	STL-LSTM-ATT-KAN	EXACT-FARM
2018	12.4	11.6	14.8	10.9	**8.2**
2019	13.1	12.0	15.2	11.3	**8.4**
2020	12.7	11.9	14.9	11.1	**8.1**
2021	13.3	12.2	15.3	11.5	**8.5**
2022	12.9	11.8	14.7	11.0	**8.0**

Temporal stability index ST_J is expressed in equation 19,

$$ST_J = 1 - \frac{1}{U-1} * \frac{X_u - X_{u-1}}{X_{u-1} + \epsilon} \tag{19}$$

This equation measures the consistency of forecasted values over consecutive time intervals. It captures the degree to which predictions fluctuate and produces steady and temporally coherent forecasts.

In this, U represents the total number of time steps in the forecast horizon, X_u indicates the forecasted crop price (or output variable) at time u, X_{u-1} represents the forecasted value from the previous time step, and ϵ\epsilonϵ is a small constant added to prevent division by zero.

I. Trust and Usability Evaluation

Trust and usability assessments determine stakeholders' perceptions of the model's interpretability, reliability, transparency, and ease of use. The factors above determine whether the system's insights can be put into practice and understood by non-technical users. The explainable AI interface of EXACT-FARM has the highest scores because it displays SHAP-based feature contributions and counterfactual what-if analyses, which are easily comprehensible. This builds trust among farmers, policymakers, and market analysts by providing clear explanations and intuitive dashboards. This promotes more successful integration and application of AI in agricultural ecosystems, converting predictive products into transparent, stakeholder-accessible decision-making and price-management instruments, as shown in Table III.

TABLE III. ANALYSIS OF TRUST AND USABILITY EVALUATION

Evaluation Criteria	VMD-SAO-TFT	CNN-LSTM	fsQCA	STL-LSTM-ATT-KAN	EXACT-FARM
Interpretability	7.1	7.4	6.5	7.8	**9.2**
Transparency	6.8	7.1	6.0	7.6	**9.0**
Reliability	7.3	7.5	6.7	7.9	**9.3**
Usability	7.0	7.3	6.4	7.7	**9.1**
Overall Satisfaction	7.2	7.5	6.6	7.8	**9.2**

Adoption likelihood with trust–usability interaction B_M is expressed in equation 20,

$$B_M = \partial\,\beta_0 + \beta_1\,\frac{CT}{100} + \beta_2\,\frac{UE}{100} + \beta_3\,\frac{DT}{100}.\frac{UF}{100} + c \tag{20}$$

This logistic-style formulation models the probability that stakeholders will adopt the system, incorporating both trust and usability as main effects and their interaction.

In this, B_M denotes the estimated Adoption Likelihood (probability between 0 and 1), ∂ is the logistic sigmoid function. β_0 is the intercept, $\beta_1, \beta_2, \beta_3$ are regression coefficients for the normalized Composite Trust Score, the normalized Usability Effectiveness Index, and their interaction term respectively. DT is the composite trust score (percent), UF is the Usability Effectiveness Index (percent), and c is an error term or additional covariate aggregate.

The comparative analysis shows that EXACT-FARM is much better than the current models in all assessment parameters. It has greater predictive accuracy, executes faster, is more interpretable, and is more helpful to stakeholders. These findings confirm that EXACT-FARM can combine explainable AI with hybrid modeling, making it a strong, transparent decision-support system for forecasting agricultural prices.

For a given forecasting window, assume raw price predictions of ₹1820 (SARIMAX), ₹1950 (XGBoost), and ₹2010 (LSTM), with a rolling mean of ₹1900 and standard deviation of ₹100 computed from recent training data. Z-score normalization transforms these outputs to −0.80, 0.50, and 1.10, respectively. Model reliability weights are then estimated using exponentially decayed RMSE over the last validation horizon, for example 0.12 (SARIMAX), 0.08 (XGBoost), and 0.06 (LSTM). Inverse-error weighting followed by soft normalization yields convex weights of 0.25, 0.35, and 0.40. The ensemble prediction is computed as a weighted aggregation of normalized outputs: (0.25×−0.80) + (0.35×0.50) + (0.40×1.10) = 0.41. This aggregated score is then inverse-transformed to the original price scale, resulting in a final forecast of approximately ₹1941.

Classical models such as SARIMAX and ARIMA with exogenous regressors serve as non-hybrid baselines, providing interpretable references for linear and seasonal dependencies, while standalone XGBoost and linear regression with SHAP attribution represent simpler XAI baselines. Compared with ARIMA, EXACT-FARM achieves an RMSE reduction of approximately 12%, while the Explainability Score rises to 0.72 from 0.58 in single-model SHAP, indicating more concentrated and stable factor contributions. Similarly, cross-model attribution consistency improves by 15% relative to XGBoost SHAP alone.

Causal graphs are derived through a hybrid approach combining domain-informed structure specification with data-driven refinement. Initial adjacency matrices encode agronomic and supply-chain knowledge, linking rainfall and temperature to crop yield, yield to market arrivals and prices, and policy instruments such as MSP or export controls as exogenous nodes. These candidate structures are refined using conditional independence tests, partial correlation analysis, and Granger causality applied to the time-series panel, identifying statistically supported edges while preserving temporal ordering. Cross-validation against expert knowledge from agricultural economists and market analysts confirms that the retained edges reflect realistic causal mechanisms, including seasonal planting–harvest cycles, regional trade flows, and policy intervention pathways.

V. CONCLUSION

This paper proposed a multi-model, which combined VMD-SAO-TFT, CNN-LSTM, fsQCA, STL-LSTM-ATT-KAN, and the proposed EXACT-FARM model to boost the accuracy of decision-making in smart agricultural ecosystems. The results of the experiments involving a variety of datasets proved that EXACT-FARM was always more effective than traditional models in terms of improving the accuracy of the stakeholders and the efficiency and speed of the computations. Adaptive optimization, fusion of hybrid features, and context-aware learning mechanisms have enabled the model to produce greater impacts on the stakeholders, reduce the training time, and increase the reliability of the decisions made.

The future directions include the extension of EXACT-FARM by edge-intelligent deployment to support real-time inference, explainable AI modules to achieve transparency, and federated learning to improve privacy on distributed datasets. This can be enhanced by the addition of multi-modal data, including satellite images, IoT sensor feeds, and climate forecasts, to enhance accuracy. Also, feedback loops of stakeholders and a decision optimization mechanism based on reinforcements will be examined to adopt adaptive and sustainable agricultural intelligence systems.

Climatic anomalies influence production volumes and quality, which in turn affect export–import balances and may trigger policy responses such as procurement adjustments or trade restrictions, creating feedback loops that are difficult to fully disentangle in observational data. Although the attribution framework conditions on multiple exogenous variables, correlated shocks can lead to shared variance being distributed across factors in the explanation graphs, blurring strict causal separation. Temporal aggregation further amplifies this effect when policy actions lag or coincide with weather-driven supply shifts, causing attribution weights to reflect combined rather than isolated influences.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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