Rainfall-Aware Hybrid Ensemble Framework for Risk-Optimized Crop Decision Support

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***Abstract*—Agricultural decision-making has become more challenging due to climatic variability and market conditions, which have rendered traditional crop recommendation systems inadequate for agricultural planning. Most of the traditional crop recommendation systems have focused mainly on yield prediction, without taking into account the associated economic risks, historical production stability, or the associated prediction uncertainties. This paper proposes a rainfall-aware hybrid ensemble approach to an intelligent crop decision support system, which takes into account yield forecasting as well as associated economic risks. The proposed crop recommendation system uses a weighted hybrid ensemble of Random Forest, XGBoost, and LightGBM to predict the crop yield based on rainfall and historical production patterns. A time-based validation approach has been used to prevent temporal leakage, which is essential to render the proposed system practical. Additionally, the proposed system has used a Yield Stability Index, a Price Volatility Index, to quantify the associated historical production stability, as well as the associated market risks, which have been combined to compute the normalized Risk Score and the associated Risk-Adjusted Profit.**

***Index Terms*—Hybrid Ensemble Learning, Rainfall-Based Yield Prediction, Risk-Adjusted Profit, Crop Decision Support, Yield Stability Index, Price Volatility Modeling, Time-Based Validation.**

I. INTRODUCTION

Agriculture is of significant importance to the overall food security of the country and the economy of the country. With the rainfall variability, market conditions, and the uncertainty of the productivity of the crops, the decision-making process of the agriculture sector has become more complex. Farmers have to make decisions on the selection of the crops considering the limited information available to them, where the environmental and economic factors have a significant impact on the profitability of the crops.

With the recent developments in machine learning, the accuracy of the crop prediction models has improved significantly using the historical production and climatic conditions of the crops. Various researchers have used the regression-based algorithms to predict the crop yields more accurately [1]– [4]. Moreover, the hybrid machine learning approaches have also been used to improve the accuracy of the models [5]. Though the machine learning approaches have improved the prediction of the crop yields significantly, they have not considered the economic factors of the crops.

Rainfall variability, in particular, remains one of the most influential environmental factors affecting agricultural output. Multiple rainfall-driven forecasting frameworks have been proposed to model crop productivity under climatic uncertainty [6]– [9]. Although these models account for environmental variability, they largely treat the problem as a pure regression task without integrating economic volatility or historical yield stability into the decision-making process.

Parallel research has been carried out to address the issue of crop recommendation systems using soil, climate, as well as machine learning approaches [10]– [13]. Yet, a large number of crop recommendation systems have been formulated as classification problems, which do not address yield forecasting, market risks, or the overall economic trade-offs of the crop to be planted. Similarly, the literature on economic risk modeling, as well as market volatility analysis, has focused on the price volatility of the crop, without integrating it with machine learning approaches to yield forecasting [14]– [17].

A considerable gap has been identified in the literature, which addresses the need to develop a crop decision support system that incorporates the yield forecasting using rainfall, historical crop production stability, market volatility, as well as the predictive uncertainty of the model. While the literature has focused on developing a decision support system that addresses the predictive accuracy of the model, as well as the overall optimization of the model, there has been little work carried out to incorporate the overall economic risks, as well as the ensemble machine learning techniques, into a single framework.

In order to address the aforementioned gap, this paper proposes the Rainfall-Aware Hybrid Ensemble Framework for Risk-Optimized Crop Decision Support. The proposed system is based on the weighted hybrid ensemble of Random Forest, XGBoost, and LightGBM algorithms for rainfall-affected crop yield forecasting. The proposed framework also includes the Yield Stability Index and the Price Volatility Index, along with the computation of the normalized Risk Score and the Risk-Adjusted Profit, for the multi-objective optimization of crop selection, as opposed to the traditional single-objective optimization of crop selection based solely on the crop yield. The proposed framework also includes the ensemble-based confidence metric for the quantification of the reliability of the proposed crop yield forecasting model.

The proposed Rainfall-Aware Hybrid Ensemble Framework for Risk-Optimized Crop Decision Support is an advancement of the existing crop decision systems by incorporating rainfall-affected crop yield forecasting, hybrid ensemble learning, economic risk modeling, and uncertainty quantification.

II. RELATED WORK

Recent developments in the field of machine learning have impacted agricultural analytics, especially regarding crop yield prediction. Research has investigated regression-based methods like Random Forest, Gradient Boosting, and deep learning for optimizing the accuracy of the forecast results [1]– [4]. The ensemble methods also showed the robustness of the predictor by aggregating different learning algorithms. Although the research has achieved better results for crop yield estimation, the main objective of the work is the minimization of the error, while the economic risk is not addressed adequately. Rainfall modeling has also been given due attention in consideration of the dependency of agricultural productivity on rainfall patterns. Various works have been done on the incorporation of rainfall patterns and related weather characteristics into machine learning models to predict agricultural productivity in the face of climatic uncertainty [6]– [9]. These works highlight the importance of environmental factors such as rainfall in agricultural productivity. However, these works have been limited to the regression analysis of the problem without taking into consideration economic volatility and production stability.

In parallel, crop recommendation systems have been proposed using soil attributes, climatic attributes, and classification-based machine learning models [10]– [13]. Although these systems can be used to recommend crops to the farmers, these works have focused only on the classification of the crop without predicting the expected yield of the crop or determining the profitability of the crop. Additionally, these works have not focused on the uncertainty of the prediction or the variability of the market conditions. The economic risk and price volatility modeling has also been investigated by various researchers, as discussed in separate research articles published in the agricultural research domain [14]– [17]. The main objective of the research articles is to analyze the price volatility of the commodities, predict the trend, and estimate the economic risk of the crops grown in the agricultural domain. Although the research articles have provided immense insights into the behavior of the agricultural market, the research articles have mostly been carried out individually, without integrating the economic risk modeling with the machine learning-based yield prediction models.

Hybrid ensemble learning has been widely investigated in the area of predictive analytics in developing more accurate and robust models [18] – [20]. Weighted ensemble and stacking have demonstrated the effectiveness of these models over single model-based approaches in regression problems. Moreover, recent studies have also been conducted in evaluating the predictive uncertainty of the model using ensemble methods to develop more reliable models [21]. However, the application of these ensemble models in the agricultural domain has mostly been limited to the development of accurate yield prediction models. Further, the application of multi-objective optimization methods has also been studied for the purpose of sustainable crop planning and resource management in agriculture [22]– [25]. Nevertheless, the majority of the methods used were based on traditional optimization methods or linear programming methods without considering the integration of advanced ensemble learning or predictive modeling.

Based on the reviewed literature, it is clear that the majority of the existing research works on yield prediction, rainfall modeling, crop recommendation, economic risk assessment, ensemble learning, and multi-objective optimization have been treated as separate research areas. There is less work that has addressed the integration of rainfall-based yield forecasting, hybrid ensemble modeling, historical stability analysis of production, market volatility modeling, and decision-making under uncertainty into a single model. This indicates a need to fill a research gap in the development of a holistic rainfall-aware hybrid ensemble model, which not only predicts yield but also takes into account the modeling of economic risks, stability, as well as confidence-based uncertainty quantification to support multi-objective crop decision-making. The proposed approach seeks to fill this gap by integrating predictive modeling with optimization of profit using a unified decision intelligence approach.

III. PROPOSED METHODOLOGY

The proposed framework has been developed with the aim of creating an integrated rainfall awareness-based crop decision intelligence system that utilizes the principles of predictive modeling and economic risk optimization. Unlike traditional approaches to crop recommendation, which have relied on single-point predictions, the proposed methodology utilizes the principles of production stability, market volatility, and prediction uncertainty to create a unified decision-making model. The proposed system architecture is based on the integration of several modules, which work together to transform the provided agricultural and market data into a more interpretable decision-making format. The overall aim of the proposed architecture is to move away from single-point predictions and create a structured risk-based crop recommendation mechanism.

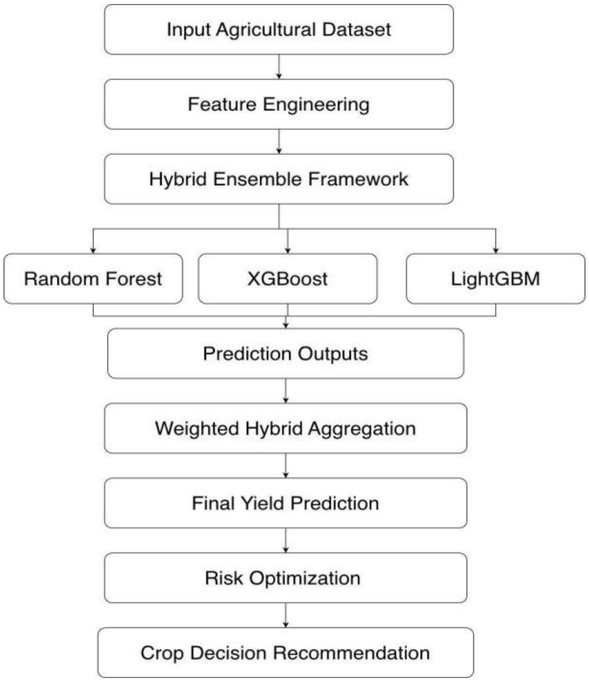

FIG 1. ARCHITECTURE DIAGRAM

A.Data Acquisition Layer

The proposed framework begins with the acquisition of structured data, which is gathered from the following three main agricultural data sources: historical crop production data, rainfall data, and price data. The crop production data includes the quantity of crops grown across various states for different years, providing longitudinal data for the analysis of crop yields. The rainfall data includes the rainfall values for different states across various years, providing the climatic data component for the proposed rainfall-aware crop yield modeling approach. Additionally, the price data is also incorporated into the proposed framework, providing the economic behavior for the different crops grown. The historical price data is used for estimating the economic return, while the price variation is used for estimating the economic volatility for the crops grown. The proposed data acquisition component provides a multi-dimensional data set that is useful for both the proposed crop yield modeling and the economic risk evaluation.

B.Data Integration and Processing Layer

The data integration layer transforms heterogeneous raw datasets into a unified analytical structure suitable for modeling and decision optimization. This layer performs the following key operations:

- Data Cleaning – Removal of inconsistencies, missing values, and formatting irregularities.
- Aggregation – Aggregating state-level data on crop production and prices to maintain consistency in granularity.
- Temporal Alignment – Aligning rainfall, production, and price data for respective years.
- Yield Computation – Derivation of crop yield using:

$$Yield_{c,s,t} = \frac{Production_{c,s,t}}{Area_{c,s,t}}$$

where

C represents crop S represents state and T represent year.

This layer guarantees consistency across different data sources while maintaining their temporal integrity, which is necessary for time series validation in predictive analytics.

C. Feature Engineering and Risk Modeling Layer

The layer of feature engineering and risk modeling turns historic data of production and markets into informative metrics that measure the stability and uncertainty of agriculture over the long run. Unlike existing frameworks based on predicted yield, the new model provides indicators for assessing the consistency of production and risks of the market. Such metrics act as decision-making variables between prediction models and economic optimization. The layer prevents the crop recommendation process from being determined only by expected yields and includes variability and uncertainty of agriculture.

1. Yield Stability Index (YSI)

Productivity in agriculture is necessarily influenced by climate variability, insect infestation levels, and other agronomical factors. Consequently, crops with high yields could still display considerable inter-annual variations. The yield stability could be measured by means of the following index of:

$$YSI_{c,s} = \frac{\sigma(Yield_{c,s})}{\mu(Yield_{c,s})}$$

where:

σ – Standard deviation of past yield data,

μ – Mean yield value.

With the introduction of ratios in the formula for calculating YSI, the measure achieves scale invariance regardless of the magnitude of the crop productivity levels. The larger the value of YSI, the less consistent the production level is. The inclusion of the YSI in the model makes the production level highly variable to be selected even if it has a high average production level.

2. Price Volatility Index (PVI)

Although production stability is critical, economic sustainability also hinges upon market performance. Crop prices tend to be volatile due to supply and demand conditions, seasonal trends, and overall economic factors. The Price Volatility Index is described by the following equation:

$$PVI_{c,s} = \frac{\sigma(Price_{c,s})}{\mu(Price_{c,s})}$$

Like YSI, this ratio is used to measure price change relatively, not absolutely. The crops that have higher PVI values tend to be subjected to greater market uncertainty and thus generate income that cannot be predicted easily. By using PVI, the system proposed in this paper will be able to take economic risk into consideration when making decisions.

3. Risk Normalisation

Normalization is essential since YSI and PVI are generated from two different distributions that may vary depending on crop type and state. Min-max normalization is performed:

$$YSI_{norm} = \frac{YSI - YSI_{min}}{YSI_{max} - YSI_{min}}$$

$$PVI_{norm} = \frac{PVI - PVI_{min}}{PVI_{max} - PVI_{min}}$$

The result is that both measures will have a common range between [0,1] so that they can be combined together.

4. Unified Risk Score

In order to combine production and market uncertainties within a single measure, the following weighted risk metric is used:

$$Risk_{c,s} = \alpha YSI_{norm} + \beta PVI_{norm}$$

where α and β are weights such that $\alpha + \beta = 1$.

α denotes the importance attributed to production uncertainty, whereas β denotes the importance attributed to market uncertainty. Such flexibility ensures that the model can be adapted to suit different needs in agriculture. The risk value obtained represents the uncertainty attached to a given combination of crop and state.

5. Interpretative Role in Decision Framework

While conventional prediction models only go as far as estimating yields, this feature engineering layer provides a method to analyze agricultural risk and economic exposure. The ability to calculate both the consistency of production and variations in prices is key to making risk-informed decisions and not focusing solely on maximizing yields.

D. Hybrid Ensemble Prediction Layer

The role of the hybrid ensemble prediction layer is to perform the estimation of rainfall-aware crop yield by means of supervised learning models. Crop yield prediction is a complex task because of the non-linear relationship between rainfall variation, historical crop yield, and regional crop yield patterns. Though a regression model can perform a specific task in this direction, it may not be capable of performing the task in a generalized manner. To make the crop yield forecasting more reliable, a hybrid ensemble approach has been adopted in this context, wherein multiple tree-based learning models are integrated, and their results are combined in a performance-based manner.

1. Data Preparation and Validation Strategy

Considering that agricultural yield data is affected by temporal and environmental factors, it is important to prepare the data before the model is trained. The data was organized in a way that ensured consistency across years, crops, and states. The feature variables included rainfall and historical production indicators, while the yield acted as the target variable. The data was divided into a training data set and a testing data set for the purpose of evaluating the generalization performance. This ensured that the evaluation of the model did not use information that might have leaked from the training data to the testing data. Model performance was assessed via RMSE and R^2. RMSE was utilized to estimate the extent of prediction error, whereas R^2 was employed to evaluate the level of variance explanation by the model. These measures will help us assess the effectiveness of the model from different angles. The above method of validation will allow us to test the hybrid system using a range of rainfall variability and will reflect its effectiveness in various production situations.

2. Individual Learning Models

Three ensemble regression models are employed to independently estimate crop yield:

a. Random Forest

Random forest is an example of ensemble models where the model used is bagging, and it entails constructing various decision trees based on bootstrapping samples while at the same time randomly selecting attributes.

Formally:

$$\hat{Y}_{RF} = \frac{1}{N}\sum_{i=1}^{N} T_i(X)$$

Where Ti represents the i-th decision tree

Its strength lies in stable performance across noisy agricultural datasets.

b. XGBoost

XGBoost uses gradient boosting and constructs trees incrementally by minimizing a differentiable loss function. Each newly constructed tree tries to minimize residual errors from past iterations.

$$\hat{Y}_{XGB} = \sum_{k=1}^{K} f_k(X)$$

Where each f_k is a regression tree optimised via gradient descent

c. LightGBM

LightGBM is an algorithm for boosting based on gradient that uses histogram-based binning and leaf-wise tree growth for improving the performance while ensuring high prediction accuracy.

$$\hat{Y}_{LGBM} = \sum_{m=1}^{M} g_m(X)$$

It performs well with large-scale agricultural data and heterogeneous feature distributions.

3. Weighted Hybrid Aggregation

To leverage the complementary strengths of individual learning models, a weighted hybrid aggregation strategy is employed. Although Random Forest, XGBoost, and LightGBM are all ensemble-based methods, they differ in learning mechanisms. Random Forest primarily reduces variance through bagging, while XGBoost and LightGBM focus on sequential error minimization through gradient boosting. These structural differences lead to diverse predictive behavior across climatic and regional conditions.

Rather than selecting a single best-performing model, the proposed framework combines their outputs to enhance stability and reduce model-specific bias. The final hybrid yield prediction is computed as:

$$\hat{Y}_{hybrid} = w_{RF}\hat{Y}_{RF} + w_{XGB}\hat{Y}_{XGB} + w_{LGBM}\hat{Y}_{LGBM}$$

where the weights satisfy:

$$w_{RF} + w_{XGB} + w_{LGBM} = 1$$

Instead of assigning equal weights, performance-driven weighting is adopted. The weights are computed inversely proportional to validation error:

$$w_i = \frac{\frac{1}{RMSE_i}}{\sum_j \left(\frac{1}{RMSE_j}\right)}$$

This way of calculating weights gives more importance to those models whose errors in predictions are less. This is because the algorithm uses an approach based on performance rather than choosing an arbitrary criterion.

4. Prediction Confidence Estimation

Even though the use of a hybrid aggregation method increases the accuracy, a point estimate for the yield might be insufficient for decision-making in agricultural scenarios. The use of rainfall variability might result in uncertainty, and understanding the reliability of the prediction is essential for economic optimization. For understanding the reliability of the prediction, a confidence metric based on ensemble agreement has been proposed. The idea is that when all the models agree, the prediction is more reliable, and when they disagree, it is less reliable.

The confidence score is computed as:

$$Confidence = 1 - \frac{\sigma\left(\hat{Y}_{RF}, \hat{Y}_{XGB}, \hat{Y}_{LGBM}\right)}{\mu\left(\hat{Y}_{RF}, \hat{Y}_{XGB}, \hat{Y}_{LGBM}\right)}$$

Where σ denotes the standard deviation and μ denotes the mean of model predictions.

E. Risk Optimization and Multi-Objective Decision Layer

While yield prediction provides an estimate of expected production, agricultural decision-making cannot depend solely on productivity. Farmers must also consider economic return and the stability of that return. A crop with high predicted yield may still expose farmers to financial risk if its production history is unstable or if its market prices fluctuate significantly.

1. Expected Profit Estimation

The economic value of the expected yield from the hybrid ensemble model is calculated by using historical average price data. The expected profit is calculated by multiplying the expected yield with the historical average price of the crop in the state where the crop is grown. This step makes the prediction economically viable by giving an economic value to the expected production.

2. Risk-Adjusted Profit

Since agricultural returns are influenced by both production stability and market volatility, expected profit is adjusted using the unified risk score.

Risk-adjusted profits are computed as follows:

$$\textit{Risk-Adjusted} = \textit{Expected Profit} \times (1 - \lambda \cdot \textit{Risk Score})$$

where λ is the risk sensitivity factor.

This equation makes sure that the estimated profits are adjusted down according to the stability of the crop yields and price levels. In turn, this means that:

- Crops with stable yield and prices keep their estimated profits intact.
- Highly unstable crops are appropriately penalized.
- High-risk crops are therefore not prioritized over low-risk crops.

3. Final Decision Scoring

For ranking recommendations, the framework considers the following:

- Risk-adjusted profit
- Prediction confidence from the ensemble

All these factors are weighted in the final decision-making process based on profit, sustainability, and prediction accuracy.

The crop scoring highest in all aspects is recommended for planting under the stipulated rainfall pattern.

4. Practical Interpretation

Unlike conventional yield prediction systems, the proposed approach evaluates crops through three dimensions:

1.Productivity (Predicted Yield)
2.Economic Stability (Risk Score)
3.Predictive Reliability (Confidence)

It is an integrated approach that offers a more balanced and practical recommendation, assisting in agricultural planning under rainfall variability.

IV.RESULTS

The performance of the hybrid ensemble method was evaluated in this study using multiple regression measures such as RMSE, MAE, and R². However, apart from the aforementioned measures, tolerance-based accuracy measure was also employed in order to assess the effectiveness of the predictions being made. Tolerance accuracy measures the correctness of predictions based on whether they lie within an acceptable deviation range of the true yield.

The dataset was divided into a training dataset and test dataset, after which different individual models including Random Forest, XGBoost, and LightGBM models were designed to forecast the yield of the crop based on rainfall and yield history. Later, hybrid approaches were employed in order to blend the results obtained from these models.

The quantitative assessment outcomes are presented in Table I. Among all the models, the best performance is attained by LightGBM model, which has an RMSE of 0.700 and an R² of 0.655. Nevertheless, it is noted that the developed hybrid ensemble model outperforms other models in terms of performance, as its RMSE is the lowest at 0.699 while R² is the highest at 0.656.

TABLE I. EVALUATION TABLE

Model	*RMSE*	*MAE*	R^2	*Accuracy*
Random Forest	0.750	0.524	0.604	0.82
XGBoost	0.727	0.517	0.628	0.83
LightGBM	0.700	0.501	0.655	0.84
Hybrid Ensemble	0.699	0.497	0.656	0.87

The accuracy that was attained from the tolerance-based perspective proves just how effective the suggested system would be when applied. It should be noted that obtaining exact prediction accuracy would not be easy when making predictions in agriculture because of the variations in the environment; however, the hybrid system was able to attain 87% accuracy using ±0.9 tons per hectare as the tolerance level.

Besides yield predictions, the system includes economic factors by utilizing metrics that incorporate risk. These two metrics include the Yield Stability Index and the Price Volatility Index that were applied to measure production stability and price volatility. Both measures were then aggregated into a Risk Score that was subsequently converted to the Risk-Adjusted Profit.

The scatterplot of Risk Score against Risk-Adjusted Profit indicates a clear example of risk-reward tradeoff. The crops that entail a low-risk environment have the highest risk-adjusted profits, thus necessitating the need to take into consideration the risk factors while choosing crops to grow. Furthermore, the confidence level of the ensemble model was remarkably high at 91%. The high consensus makes the forecast more reliable and reduces the level of uncertainty that would otherwise result if just one model was used. The above results demonstrate that the proposed rainfall-aware hybrid ensemble system works effectively. Not only does it give accurate forecasts for the yield but it also provides economic insight that can be used to make decisions.

V.CONCLUSION AND FUTURE WORK

In this study, an intelligent decision support system for crop selection depending on rainfall variations was suggested. This decision support framework is an ensemble decision support framework with the integration of yield prediction models using machine learning techniques and risk assessment of economic parameters of the crop in selecting suitable crops. Weighted hybrid ensemble learning models with random forest, XGBoost, and Light GBM algorithms were used to improve the accuracy and robustness of the forecasting model, whereas other variables, including stability of yield, volatility of price, and risk-adjusted profit, were used as economic parameters of the crops. Through experimental results, it was observed that the hybrid ensemble model performed significantly better than the single model in terms of accuracy and stability.

However, despite its efficacy, the suggested model can still be improved along various lines. Adding more climatic and environmental parameters, like temperature and humidity levels, can increase the accuracy of predictions as well as the flexibility in use in different regions. Integrating weather forecast can contribute even more to the practicality of the model in question.

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