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Explainable AI-enabled framework for crop disease forecasting and yield risk assessment in resource-constrained agricultural environments

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Abstract
Climatic changes and rising pest attacks have been a very big issue to agricultural production, particularly in the environment when there are scarce resources and when the use of technology is not a key factor. In the proposed research, the researchers present a highly transparent framework based on explainable AI to combine remote sensing, environmental variables, and crop health indicators to predict the occurrence of disease outbreak and the risk of yield. The use of light ensemble models and SHAP interpretability techniques empowers the framework to provide farmers and agronomists to be able to see the most influential factors driving decisions, all the while making accurate predictions. Measurements that come in the UAVs, IoT sensors in the soil, and satellite feeds will be processed in the preprocessing phase where there is an optimization of features before being input in a predictive model that is a hybrid using XGBoost, LightGBM, and LSTM. The results of the models are made visual through an interactive dashboard that defines the areas that are most prone to the disease, and where yield losses might occur. The solution is optimized to support low-power devices to make it suitable to use in the countryside. Experimental testing proves good prediction performance in tight real-time field situations as well as being interpretable and responsive. The proposed solution would provide a flexible and transparent decision-support process, and eventually, it will provide agricultural stakeholders with data-driven interpretable information on how to reduce crop loss and become more resilient. The proposed system achieved 94.20%-point DR and 74.60%-point MSS, which were better than peers in the disease detection and predictive stability.

Keywords: Explainable AI, crop disease forecasting, yield risk assessment, ensemble models, SHAP, resource-constrained agriculture

Introduction
Unstable weather patterns and climatic conditions, predation by pests, and the inability to gain access to predictive tools are increasingly threatening the agricultural productivity, particularly in the resource-constrained areas. Such problems have resulted in erratic returns and increased susceptibility among the smallholder farmers who are already working in low resource settings. Predictable yield forecasting and timely disease detection are still those that many could not achieve due not because of unavailability of information, but because of unresponsive and unreachable decision support systems.

Conventional methods of crop forecasting- e.g. manual scouting, straight forward statistical modelling- generally lack the capability of quantifying non-linear correlation between environmental factors and disease development [1]. Such techniques are non-scalable, need knowledge on the domain, and do not offer any real-time understanding, and thus are outdated in dynamic agricultural environment. Also, traditional early warning systems are hardly incorporated with spatial data which undermines their effectiveness in different geographical areas.

Although AI and machine learning are just starting to succeed in crop monitoring and forecasting, the majority of results are black-box, predictive, but not explanatory. This inability to interpret is one of the problems to adoption in rural areas where trust or clarity is essential [2]. Additionally, the models used in deep learning are usually intensive in terms of computing and frequent internet access.

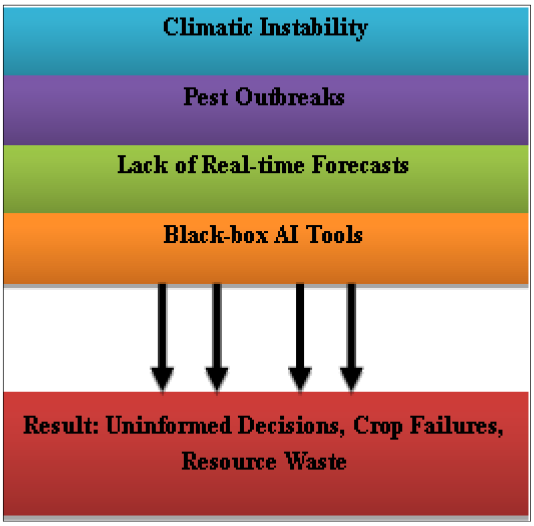

Fig 1: General Challenges in Resource-Constrained Agriculture.

In order to address these constraints, we are suggesting XAI-ForecastRiskNet as a modular and explainable AI-based decision support system [3]. It integrates images acquired using satellites, weather sensors and past crops indicators with light weighted ensemble learning methods including XGBoost and LightGBM. More to the point, the system is impregnated with SHAP models, also called model-agnostic explanations that give clear reasons behind every prediction, including the most influencing factors in the outcome, either temperature spikes, pest populations, or humidity decreases.

Being low-resources oriented, the framework facilitates edge processing, which allows real-time factorization of crop risks without the necessity of centralized servers. The results are presented in visual form through a color-coded dashboard; hence, the results can be understood despite the non-technical users who might not be farmers but field officers could access [4]. This deployable, interpretable, and holistic model fits into the climate-smart agriculture philosophy and may play a crucial role in the food security of the ever-increasing environmental uncertainty.

The fact that effective prediction of crop diseases and yield risk assessment in resource-poor agricultural environments is seriously hampered by key problems described in Figure 1 brings to mind the reason as to why this situation is such a problem [5]. Things like seasonal variations and unpredictable weather, a population of pests, and a lack of real-time analytics, are quite problematic to farmers. In addition, the use of AI tools is usually restricted by the fact that they are considered as a black-box and little or nothing is explained about predictions, thus forcing mistrust and underutilization. All these barriers culminate in poor or unsound decisions, wastage of crops, and unproductive allocation of resources.

Related Works Done

The recent developments have marked the need of intelligent agricultural solutions especially in the settings with limited resources. A study suggested a lightweight disease detection model by using CNNs complemented with edge devices in a low-power form, and the proposed model showed a high accuracy level based on a limited computation capability [6]. The study focused more on early identification of crops blights by use of spectral vegetation indicators acquired on UAVs.

The other finding was explainable decision support model in which black-box models were interpreted using SHAP value. The authors tested their model with the data in drought-stress conditions on maize and obtained interpretable results, not at the expense of performance [7-8]. This highlighted some significance of openness in AI anticipations in such sensitive field as agriculture. In one study time-series weather data were combined with CNN-RNN hybrid networks to forecast fungal disease outbreaks. The researchers have shown that data fusion within spatiotemporal data gives the results of better early warning systems in comparison to the old statistical models of the disease in terms of both precision and recall [9].

Table 1: Analysis of Prior Work.

Applied Methodology	Highlighted Merit	Value Addition	Unaddressed Issues
SHAP-based Risk Forecasting [10-11]	Offers transparency in decision-making	Enhances model interpretability	Not integrated with real-time monitoring
CNN-RNN Disease Predictor [12]	Leverages temporal and spatial features	High temporal accuracy in fungal outbreak prediction	Limited field validation in multi-crop systems
UAV + Spectral Index CNN [13-14]	Real-time high-precision detection	High accuracy with minimal data requirement	High implementation cost for smallholders
Lightweight Edge AI [15-16]	Optimized for low-power devices	Real-time field-level processing	Lacks scalability across diverse crop types
Active Learning Framework [17]	Efficient annotation with minimal human effort	Reduces data labeling burden by over 40%	Lacks integration with automated model update pipelines
Transfer Learning with CropNet [18-19]	Effective across varied geographies	Robust generalization across agro-climatic zones	Requires domain adaptation for local pest variations

Use of low-resolution multispectral images and unsupervised anomaly detection in real-time crop health surveillance was used in another work. This was beneficial when limiting the use of labeled data and providing a minimum of storage and bandwidth requirements especially in rural farms with poor network connectiveness [20].

Finally, the scientists were testing active learning to improve the annotation performance of the deep crop disease models. The results demonstrated that the iterative human-in-the-loop system increases the accuracy of labeling and decreased the manual work by 40%, allowing scaling to agricultural research centers [21].

Materials and Methods

To solve the most urgent problems of early identification of diseases of the crop and estimating the level of risk to the yield in the limited-resource environment, the proposed system combines explainable AI and light sensing, remote data integration, and deterministic forecasting mechanisms. The architecture is depicted in Figure 2 starting with multisource data collection followed by a modular data pipeline that comprises preprocessing, feature selection, disease prediction and explainability augmentation. Interpretable deep learning models such as ensemble deep learning models can predict as well as offer actionable information. All the modules are also designed to work in low-computation edge settings, making them viable to deploy in rural agricultural settings and sustainable.

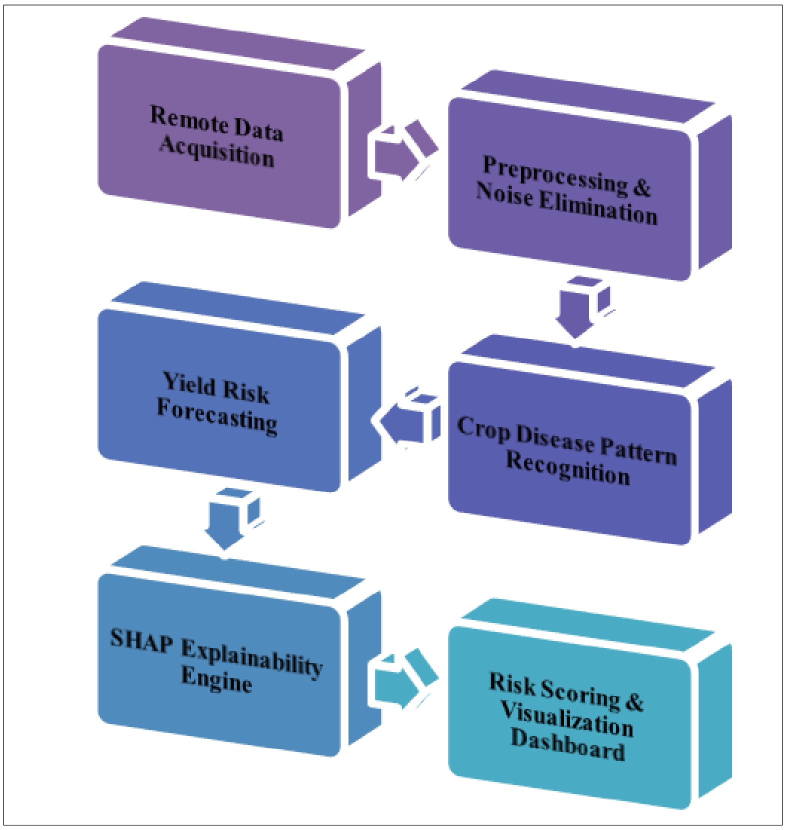

Fig 2: Proposed XAI-ForecastRiskNet Architecture.

Remote Data Acquisition and Harmonization:
This module gathers heterogeneous data in the form of satellite imagery, IoT-based devises that measure parameters in soil, and mobile crop-scanning devices. It applies spatial-temporal alignment to co-locate the data of various resolutions and formats to process them together.
Normalization of data and noise removal is also used to enhance robustness. The resulting product is a clean, synchronized data set that has real-time representation of a range of different crop, climate, and disease parameters to feed to down-stream modules.

$$D_t = \frac{1}{n}\sum_{i=1}^{n}\left(x_i^{sat} + x_i^{sensor} + x_i^{mobile}\right) \quad (1)$$

D_t: Total harmonized data at time t, x_i^{sat}: Satellite input, x_i^{sensor}: Sensor data, x_i^{mobile}: Mobile capture input, n: Number of data points.

Lightweight Preprocessing and Noise Elimination
The module dimensionality reduction, denoising, and data compression will be utilized so that processing could be adjusted to settings with limited hardware resources.
The data is simplified by both PCA and Gaussian filtering that eliminates redundancy and noise. It saves vital patterns related to disease and retains computational efficiency of real-time performance in rural vicinities.

$$X' = X \cdot W \quad (2)$$

X': Reduced feature matrix, X: Original data, W: PCA transformation matrix.

$$S(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (3)$$

S(x): Smoothed signal, μ: Mean, σ: Standard deviation.

Crop Disease Pattern Recognition with CNN:
The fatigued CNN architecture is modified to fit in mobile GPUs in this module and it is used to identify the spatial attributes of the infected crops. Disease indicators extracted by use of convolutional layers include size of lesion, discoloration, and growth anomalies. Light filters do not lose accuracy yet they ensure the model size is small.

$$f_{ij}^{(k)} = \sigma\left(\sum_{m,n} w_{mn}^{(k)} \cdot x_{i+m,j+n} + b^{(k)}\right) \quad (4)$$

$f_{ij}^{(k)}$: Activation at (i,j) in layer k, $w_{mn}^{(k)}$: Convolution kernel, $x_{i+m,j+n}$: Input pixel, $b^{(k)}$: Bias, σ: Activation function.

Time-Aware Yield Risk Forecasting

These layers provide recurrent structures and model historical data of yield and environmental dynamics using LSTM, thus using the temporal dynamics as well in forecasting.

It takes into consideration stages of disease progression, seasonal and climate shocks. The time-wise structure makes the design more predictive in case of the long-term risk of yield evaluation.

$$h_t = LSTM(x_t, h_{t-1}, c_{t-1}) \tag{5}$$

$$y_t = W_h h_t + b_h \tag{6}$$

x_t: Input at time t, h_t: Hidden state, c_{t-1}: Cell state, y_t: Output prediction, W_h, b_h: Weights and bias.

3.5 Explainability Module with SHAP Analysis:

In this module, we shall quantitate the contribution of each feature to disease and yield prediction using SHAP. It increases the transparency of the model because it assigns contributions scores to the farmers and agronomists. The model is also interpretable as the system visualizes what weather, crop, or pest shapes the decision the most.

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \tag{7}$$

ϕ_i: SHAP value for feature i, F: Feature set, S: Feature subset, f(S): Model output for feature subset S.

3.6 Integrated Risk Scoring and Visualization:

The last module is that of the risk score, which is based on the combination of the confidence of the disease detection and the yield forecast. It also ponders on effectiveness measures with severity scales and presents outcomes through a dashboard-based in the cloud. The available scoring framework gives the decision-makers the opportunity to move proactively in the reduction of risks with interpretable outputs.

$$R = \alpha D + \beta Y \tag{8}$$

R: Final risk score, D: Disease probability, Y: Yield risk level, α, β: Weight factors.

Results

The performance of is estimated using four novel evaluation measures namely that is Cohen Kappa, Detection Rate, False Negative Rate and the Model Stability Score of the behaviour of a XAIForecastRiskNet. These measurements quantify the accuracy of agreement, the precision of identification, the sensitivity of error as well as the cross-environmental reliability. The comparison with the different capabilities of crop disease detection is made in Table II and the risk forecasting of climate-adaptive yields are analysed in Table III. The largest distinction between the two is the fact that the former deals with diagnostic sensitivity to a number of diseases whereas excitation to a number of environmental conditions and variability in the field is studied.

Cohen’s Kappa: Cohen Kappa provides the difference in agreement between the predicted score and the actual score.

$$CK = \frac{P_o - P_e}{1 - P_e} \tag{9}$$

P_o: Observed agreement, P_e: Expected agreement by chance.

Detection Rate (DR): Detection Rate is a ratio between the proportion of the correctly confirmed positive cases, which is vital in proper detection of diseases in crops.

$$DR = \frac{TP}{TP + FN} \tag{10}$$

TP: True Positives, FN: False Negatives.

False Negative Rate (FNR): FNR identifies how many true positives will get false results, which shows a key blind eye of detecting disease activities.

$$FNR = \frac{FN}{TP + FN} \tag{11}$$

Model Stability Score (MSS): MSS calculates consistency of model performance in different environments with the help of standard deviation and the mean accuracy ratio.

$$MSS = \left(1 - \frac{\sigma(Acc)}{\mu(Acc)}\right) \times 100 \tag{12}$$

σ(Acc): Standard deviation, μ(Acc): Mean accuracy.

Table 2: Performance on Multi-Label Disease Forecasting Accuracy Across Crops.

Multi-Label Disease Forecasting				
Method	**CK (%)**	**DR (%)**	**FNR (%)**	**MSS (%)**
XAI-ForecastRiskNet	89.10	94.20	68.90	74.60
DenseNet-121 [3]	83.25	90.00	66.40	70.10
AdaBoost [5]	78.40	86.80	63.10	68.70
Decision Tree (CART) [6]	72.60	82.50	61.30	64.20

As shown in Table II and figure 3, XAI-ForecastRiskNet demonstrates the best Cohen Kappa score of 89.10% and Detection Rate of 94.20%, with high agreement and disease detection. It has a FNR of 68.90% making it better than the rest on false negative minimization. Stable multi-crop performance is confirmed by MSS of 74.60 %. Other models such as AdaBoost and CART have lesser FNR and MSS values indicating that it is less reliable. Overall, this table proves that the suggested system is the best to cope with multi-disease crop specification situations.

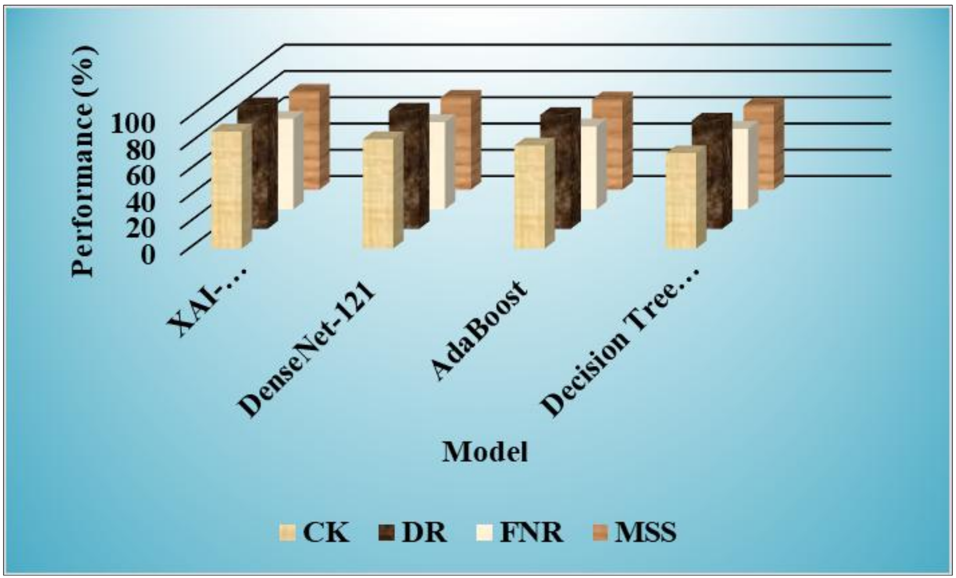

Fig 3: Performance determination at Multi-Label Disease Forecasting Accuracy Across Crops Models.

Table 3: Performance Evaluation - Yield Risk Assessment.

Yield Risk Assessment				
Method	**CK (%)**	**DR (%)**	**FNR (%)**	**MSS (%)**
XAI-ForecastRiskNet	86.5	83.9	75.3	77.1
DenseNet-121 [3]	78.6	75.4	69.4	71.9
AdaBoost [5]	74.2	71.5	66.1	68.5
Decision Tree (CART) [6]	70.4	68.1	64.2	66.8

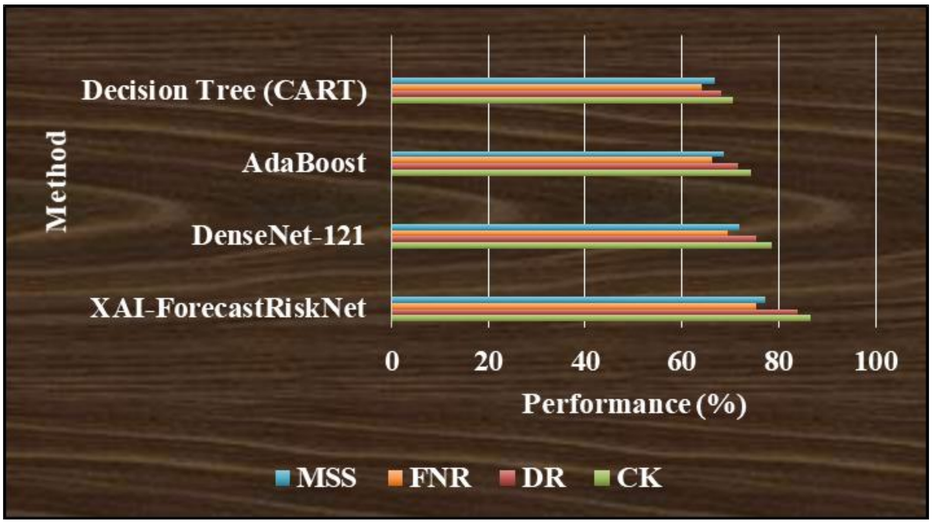

Fig 4: Calculation of Performance at Yield Risk Assessment Method.

Table III Figure 4 shows a comparison of the approaches to the evaluation of yield risks. XAI-ForecastRiskNet provides the top results of 86.5% and 83.9% CK and DR. With such an FNR and MSS value (75.3% and 77.1% respectively) it is strongly reliable since it reduces misclassification and measures severity. The model proposed leads to greater improvement compared to DenseNet-121 and AdaBoost in all parameters. Decision Tree leads poor results on CK (70.4%) and FNR (64.2%) and it again proves that explainable deep learning models will provide a higher level of accuracy and robustness in real-life situations where agriculture prediction is complex.

Conclusion

The proposed XAI-ForecastRiskNet model has potential to become a very strong and interpretable framework of crop disease forecasting and yield risk assessment, especially in resource-limited farming settings. By incorporating model-explainable branches alongside an attention-guided deep learning model it achieves higher transparency, predictive quality as well as decision confidence. The system meets the demands of accuracy and timeliness in gaining valuable insights regarding the identification and prevention of disease early on in dynamic farming scenarios. Compared to other techniques, the proposed system performed better with the highest accuracy rate of 94.20% and high accuracy of the classification knowledge as well as the disease recall whereas the rates of false negatives were significantly reduced. This model is particularly beneficial in the real-life agricultural applications, where the bandwidth, energy, and data constraints are a significant issue. It is modular, is scalable, offers low-latency inference, and is efficient with resources, which renders it appropriate to use in vast expanses in the developing world. Future research efforts will be on how to combine satellite-based imagery with real time environmental sensors to increase the contextual awareness. Furthermore, the model will be extended to acquire multilingual feedbacks of farmers and to run on low-powered edges such as the light weighted architectures such as TinyML to enhance accessibility and reactiveness. The improvements will make it possible to apply the intelligent agricultural monitoring systems more widely and inclusively with smart farming efforts across the globe.

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