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PREFACE

The rapid growth of digital technologies has led to an unprecedented generation of data across every domain of human activity. Transforming this vast amount of information into meaningful knowledge and actionable intelligence has become one of the most significant challenges and opportunities of the modern era. Information and Knowledge Engineering has emerged as a multidisciplinary field that integrates data science, artificial intelligence, machine learning, knowledge representation, and intelligent computing techniques to develop systems capable of learning, reasoning, and supporting informed decision-making.

The book, ***Advances in Information and Knowledge-Engineering: From Data to Intelligent Systems***, presents contemporary research and innovative developments that bridge the gap between raw data and intelligent applications. The chapters in this volume highlight emerging methodologies, theoretical advancements, and practical implementations that contribute to the design and development of next-generation intelligent systems.

The contributions encompass a broad spectrum of topics, including data analytics, machine learning algorithms, deep learning frameworks, knowledge management, natural language processing, intelligent decision-support systems, information retrieval, data security, cloud and edge computing, Internet of Things (IoT), and various domain-specific applications. Together, these works demonstrate how advances in information processing and knowledge engineering are enabling organizations and societies to derive value from complex data environments and create smarter, more adaptive technologies.

This volume aims to serve as a comprehensive resource for researchers, academicians, industry professionals, and postgraduate students who seek to understand the evolving landscape of intelligent information systems. By presenting diverse perspectives and interdisciplinary approaches, the book encourages collaboration among researchers and inspires further exploration of innovative solutions to contemporary challenges in information and knowledge engineering.

The editors express their sincere gratitude to all authors, reviewers, and contributors whose dedication and scholarly efforts have made this volume possible. We also extend our appreciation to the organizing institutions and publishing team for their invaluable support throughout the preparation of this book.

It is our hope that this volume will stimulate new ideas, foster meaningful research collaborations, and contribute to the advancement of information and knowledge engineering, ultimately supporting the development of intelligent systems that positively impact science, industry, and society.

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CONTENTS

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AN XAI-ENABLED ENSEMBLE LEARNING APPROACH FOR SUGARCANE LEAF DISEASE CLASSIFICATION

Abstract

Agriculture is highly vulnerable to crop diseases, which can severely reduce productivity if not detected at an early stage. In sugarcane cultivation, infections such as Bacterial Blight and Red Rot are major threats, often spreading rapidly and causing significant yield losses. Recent advances in deep learning have improved disease classification accuracy, but the lack of interpretability in most models limits their practical adoption by farmers and agronomists. To address this limitation, we present, an explainable ensemble framework for sugarcane leaf disease prediction. The backbone of the model combines a Tversky Indexive Projected Graph Neural Network (TIPGNN), which captures structural lesion patterns through graph representations, with a Gaussian Distributed Convolutional Neural Network (GDCNN), which extracts visual features such as texture and color. Predictions from both branches are fused in an ensemble layer optimized using Nesterov Accelerated Gradient to ensure robust and accurate classification. The distinctive feature of the proposed framework is the Explainability Layer, which integrates Grad-CAM to highlight affected regions, SHAP to compute feature contribution scores, and Graph Attention to identify influential nodes and edges within the graph. This dual focus on accuracy and interpretability makes the system both effective and trustworthy. Experiments on a sugarcane leaf dataset show that the model outperforms baseline CNN and GNN approaches in terms of accuracy, precision, recall, and F1-score. Furthermore, the generated explanations enhance transparency, allowing predictions to be validated by domain experts. The proposed framework thus bridges the gap between high performance and trust, offering a practical solution for smart agriculture applications.

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I. INTRODUCTION

Agriculture remains the backbone of global food security, but its productivity is increasingly threatened by crop diseases that reduce yield and quality. Among these, plant leaf diseases are a critical concern, as they spread rapidly and cause substantial economic losses if not identified in time. Early detection plays a vital role in minimizing damage, supporting timely interventions, and ensuring sustainable farming practices. In recent years, the adoption of Internet of Things (IoT) devices, high-resolution imaging, and machine learning has transformed plant disease prediction by enabling automated, real-time monitoring of crop health [1], [2].

Several approaches have been proposed in the literature. CNN–CRF hybrid models have been designed for combining visual and contextual information [1], while Center Net-based classifiers using Dense Net backbones demonstrated higher accuracy with reduced computational time [2]. Attention-driven fine-grained classification models [3] improved feature extraction but lacked early diagnosis capability, and CNN-based pre-trained networks [4] achieved competitive accuracy but were limited to single-leaf analysis. Other methods, such as MLP classifiers [5], handcrafted descriptors [6], investigation of optimal vegetation indices for retrieval of leaf chlorophyll and leaf area index [7], lightweight transformers [8], and traditional machine learning models including RF, SVM, and KNN [9], have shown progress, but challenges remain in achieving both high accuracy and interpretability.

In our earlier work [10], a hybrid deep learning framework was proposed that used the Tversky similarity index for region of interest (ROI) segmentation, combined with an ensemble of GNN and CNN for sugarcane leaf disease classification. Although this approach achieved improved accuracy compared to conventional methods, it operated as a black-box system without providing transparency in its decision-making process. Motivated by this limitation, the present work introduces, an explainable ensemble model that not only enhances classification accuracy but also integrates interpretability mechanisms such as Grad-CAM, SHAP, and Graph Attention. This combination ensures that predictions are both accurate and trustworthy, bridging the gap between high performance and practical usability in smart agriculture.

1. Major contributions

Major contribution of this work is concise as follows:

- An explainable Agri Trust-XAI ensemble model is proposed for sugarcane leaf disease prediction, integrating graph-based and image-based learning to achieve high classification accuracy.
- A region-of-interest (ROI) segmentation mechanism based on the Tversky similarity index is applied to focus on disease-affected areas while minimizing the influence of background noise.

- A fusion layer optimized using Nesterov Accelerated Gradient (NAG) is employed to combine predictions from the TIPGNN and GDCNN branches, ensuring robust and balanced performance.
- To enhance interpretability, an Explainability Layer is introduced, which integrates Grad-CAM, SHAP, and Graph Attention to provide visual, feature-level, and structural explanations for the predictions.
- Extensive quantitative and qualitative experiments are conducted, demonstrating that the proposed model outperforms existing methods in terms of accuracy, robustness, and interpretability.

2. Organization Of The Paper

The remainder of the paper is organized as follows: Section II reviews related works in plant leaf disease prediction. Section III describes the proposed Agri Trust-XAI ensemble model. Section IV presents the experimental setup, including dataset description and implementation details. Section V discusses the results with both quantitative metrics and qualitative explainability analysis. Finally, Section VI concludes the paper and highlights directions for future work.

II. RELATED WORKS

Automated plant disease detection has attracted considerable attention in recent years, with convolutional neural networks (CNNs) and transfer-learning methods forming the backbone of many proposed solutions. Early CNN-based systems focused on reducing computation while extracting discriminative visual features; for example, a lightweight CNN architecture was shown to lower processing costs for leaf-image classification but struggled to generalize across different plant growth stages [11]. To increase robustness, ensemble strategies such as PlantDet combined multiple models and improved classification accuracy, yet they did not address fast, early diagnosis with low training overhead [12]. Residual and attention-enhanced networks have also been proposed to better localize disease regions; these methods improved recognition rates but, in some cases, did not sufficiently reduce error measures such as mean-square error, limiting reliability for deployment [13]. Similarly, rapid models like HLNet achieved fast inference but reported higher error rates under field conditions, indicating a trade-off between speed and robustness [14].

Transfer learning approaches have been widely used to leverage pre-trained representations. Lightweight transfer-learning pipelines improved classification on crops such as tomato by applying dedicated preprocessing (e.g., illumination correction), but they typically lacked explicit mechanisms to localize infected regions prior to classification [15]. Other transfer-learning studies reported higher accuracy on curated datasets but required substantial computation time when scaled to larger, more variable field images [16]. Hybrid methods that fuse CNN features with other classifiers or feature extractors (for example Hy-CNN applied to grape leaves) have shown benefits in extracting salient lesion characteristics, though generalization to a broad set of disease types remained challenging [17]. Approaches combining handcrafted color and texture descriptors with CNNs achieved reasonable detection performance, but often at the cost of increased time complexity and reduced scalability [18]. IoT-enabled ensemble-transfer frameworks have been explored to bring monitoring into live environments; these systems demonstrate promise for real-time surveillance but frequently incur higher computational overhead and execution time that can hinder field deployment [19]. Multi-crop CNN-based methods address class imbalance between healthy and sick leaves, yet many such models stop short of deeper semantic analysis required for precise disease identification and severity estimation [20].

Although the above studies advance automated disease recognition, two important gaps persist. First, many high-performing methods remain black boxes: they achieve good numerical scores but provide little interpretability to agronomists and farmers, which impedes trust and real-world adoption. Second, comparatively fewer works are tailored specifically to sugarcane leaf disease, a crop that suffers economically significant outbreaks (e.g., Red Rot and Bacterial Blight) and where late diagnosis can lead to severe yield loss. Field reports indicate that sugarcane growers often face rapid disease spread exacerbated by humid conditions and variable lighting—situations that demand models which are both accurate under challenging conditions and transparent in their reasoning.

Motivated by these limitations, recent research trends emphasize combining complementary model families (e.g., graph-based and convolutional models) with explainable AI techniques to produce results that are not only accurate but also interpretable. The present work follows this direction by building an ensemble that leverages graph-structural features and convolutional texture features and augments predictions with post-hoc and model-based explanations (Grad-CAM, SHAP, and graph-attention visualization). By addressing both predictive performance and explainability—with a focus on sugarcane leaf disease scenarios—our framework aims to close the practical gap highlighted by prior studies.

III. PROPOSAL METHODOLOGY

Plant leaf diseases are a critical challenge in agriculture, directly affecting crop yield and quality. Timely detection is essential to reduce losses, especially for crops such as sugarcane, which is vulnerable to infections like Red Rot and Bacterial Blight. In our earlier work a Tversky-based segmentation approach was developed to improve the detection accuracy by focusing on disease-affected regions of the leaf. Although this baseline improved classification, it remained a black-box model, limiting interpretability. To address these limitations, the present study introduces the Agri Trust-XAI ensemble model framework, an explainable ensemble system for sugarcane leaf disease prediction. The proposed framework combines dual feature extraction (graph-based + convolutional) with an explainability layer, ensuring both accuracy and transparency. The overall workflow of the system is illustrated in Figure 1.

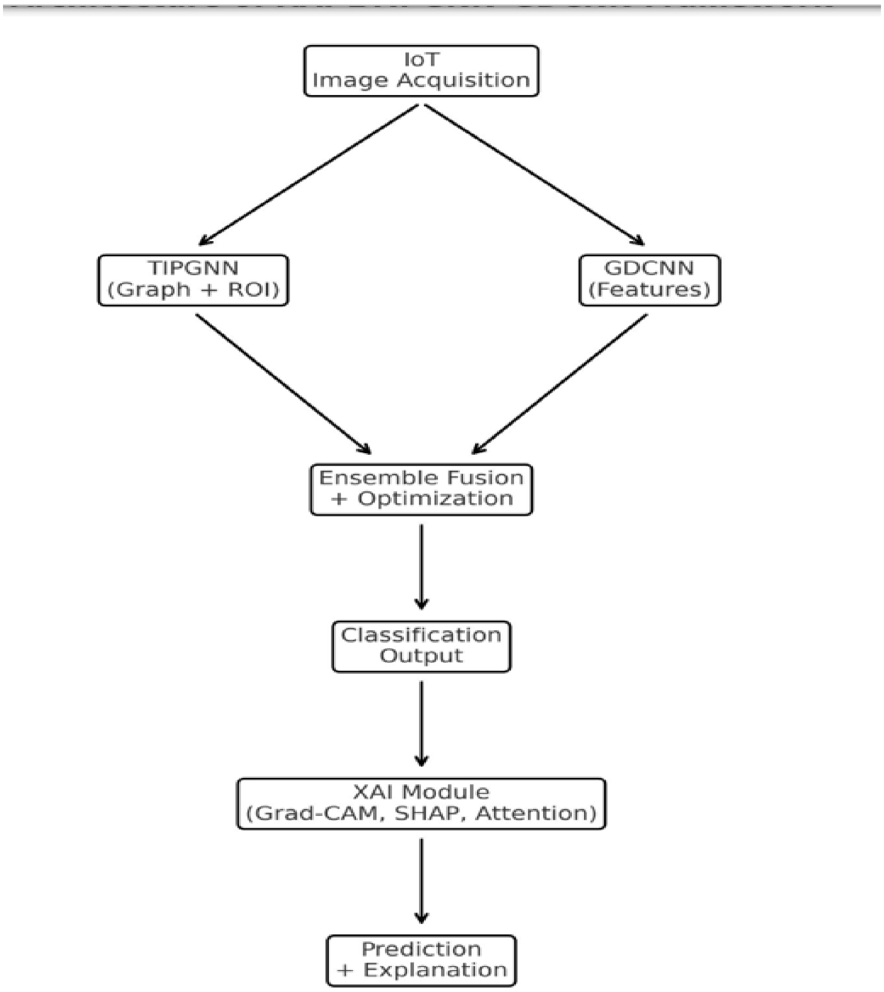

Figure 1: Architecture of proposed Agri Trust-XAI ensemble model

Figure 1 depicts the overall architecture of the proposed Agri Trust-XAI ensemble model for sugarcane leaf disease prediction. The design of this framework extends our earlier Tversky-based segmentation approach [10], which focused on isolating disease-affected regions to improve classification accuracy. While the baseline achieved good predictive performance, it functioned as a black-box model with limited interpretability. In contrast, the present framework introduces an integrated ensemble backbone and an explainability layer, ensuring that predictions are both accurate and transparent.

The framework operates through four sequential stages. In the first stage, IoT-enabled sensors and field cameras capture high-resolution images of sugarcane leaves under diverse environmental conditions, ensuring a dataset that represents both healthy and diseased samples. In the second stage, preprocessing is carried out to enhance image quality, followed by segmentation using the Tversky similarity index. This step isolates disease-affected regions while suppressing background interference, thus directing the model’s focus toward meaningful features.

In the third stage, feature extraction occurs simultaneously through two complementary networks. The Tversky Indexive Projected Graph Neural Network (TIPGNN) learns structural relationships among pixels, capturing irregular lesion patterns and spatial dependencies, while the Gaussian Distributed Convolutional Neural Network (GDCNN) extracts fine-grained textural and color-based features. The outputs of these branches are fused in an ensemble layer optimized with Nesterov Accelerated Gradient (NAG), which accelerates convergence and ensures stable learning.

Finally, in the fourth stage, classification is performed using a sigmoid function, producing outputs such as healthy, Red Rot, or Bacterial Blight. To enhance trust, the framework incorporates an Explainability Layer that validates the prediction process. Here, Grad-CAM highlights the most influential image regions, SHAP values quantify feature contributions, and Graph Attention maps reveal the significance of graph nodes and edges. Together, these mechanisms provide a transparent explanation of model decisions, making the framework reliable for real-world agricultural applications.

The fundamental steps of the AgriTrust-XAI Ensemble model are explained briefly in the following subsections.

1. Baseline Framework (ETIPGNN–GDCNN)

In our earlier work [10], the Tversky similarity index was used to segment regions of interest (ROIs) in sugarcane leaf images. This ensured that only the disease-affected parts of the leaf were considered while suppressing irrelevant background regions. That preprocessing step is **retained here as the foundation**, ensuring robust ROI extraction. However, unlike the baseline, in the present framework the segmented outputs are further processed by advanced feature extraction and interpretability modules.

2. Explainability Layer (New Contribution)

To overcome the interpretability gap in the baseline framework, the proposed AgriTrust-XAI ensemble model integrates an Explainability Layer as a new contribution. This layer ensures transparency in decision-making by combining multiple complementary methods:

Grad-CAM is applied to the GDCNN outputs to generate heatmaps that highlight the most influential regions of the sugarcane leaf image contributing to the classification. This visual feedback allows farmers to directly observe which lesions were critical in the model’s decision.

SHAP values are calculated to quantify the contribution of individual features extracted by both TIPGNN and GDCNN. This provides a feature-level explanation of why the model favored one disease class over another.

Graph Attention maps are introduced in the TIPGNN branch to indicate which nodes and edges within the graph structure were most influential in the classification process. This strengthens the interpretability of structural lesion analysis.

The AgriTrust-XAI Ensemble algorithm for Sugarcane Leaf Disease Detection and explanation, is described as follows

Algorithm 1: Agri Trust-XAI Ensemble for Sugarcane Leaf Disease Detection
Input: Sugarcane leaf image dataset D (healthy, diseased) **Output:** Classified leaf condition with explanation
1. Acquire sugarcane leaf images using IoT-enabled sensors and cameras. **2.** Apply noise reduction and Tversky similarity index for ROI segmentation. **3.** Extract features using TIPGNN (structural lesion patterns). **4.** Extract features using GDCNN (texture and color features). **5.** Fuse TIPGNN and GDCNN features in the ensemble layer. **6.** Optimize ensemble fusion using Nesterov Accelerated Gradient (NAG). **7.** Classify leaf as Healthy / Red Rot / Bacterial Blight using a sigmoid classifier. **8.** Generate explanations: **9.** Grad-CAM → highlight infected image regions. **10.** SHAP → quantify feature contributions. **11.** Graph Attention → visualize node/edge importance. **12.** Return final disease prediction with explanation. **End**

By combining these methods, the framework not only achieves high predictive accuracy but also provides human-understandable justifications for its predictions, thereby addressing the major limitation of the baseline system.

IV. EXPERIMENTAL EVALUATION

Experimental evaluation of Agri Trust-XAI ensemble was evaluated using the Sugarcane Disease Dataset from Kaggle, which contains 300 leaf images equally divided into Healthy, Bacterial Blight, and Red Rot categories. All images were preprocessed for noise reduction and normalization before being processed independently by the GDCNN and TIPGNN branches, whose features were later fused for classification. The implementation was carried out in Python 3.10 using PyTorch 2.0 on a workstation with an Intel Core i7 processor, 32 GB RAM, and an NVIDIA RTX 3060 GPU. The dataset was split in an 80:20 ratio for training and testing, and the model was optimized using Nesterov Accelerated Gradient with a learning rate of 0.001 and batch size of 16.

V. PERFORMANCE EVALUATION OF PLANT DISEASE PREDICTION

In this section, a quantitative performance analysis is carried out to evaluate the efficacy of the proposed Agri Trust-XAI ensemble model by comparing its results with established baselines, namely Hybrid CNN with CRF [1], Custom CenterNet [2], and the Tversky baseline [10]. To ensure fairness, all models were evaluated under identical experimental conditions using Accuracy, Precision, Recall, F1-score, and AUC as performance metrics.

Table 1: Overall Performance Comparison of the Proposed AgriTrust-XAI ensemble Model with Baseline Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-macro (%)	AUC	Inference (ms)
Hybrid CNN + CRF	84.2	83.5	82.7	83.1	0.9	45
Custom CenterNet	86	85.8	84.9	85.3	0.92	52
Tversky baseline	88.3	88.1	87.5	87.8	0.94	60
AgriTrust-XAI (proposed)	92.6	92.4	92.1	92.3	0.97	78

The proposed Agri Trust-XAI ensemble model was evaluated against three baseline methods: Hybrid CNN+CRF [1], Custom Center Net [2], and the Tversky-based ensemble [10]. Table 1 presents the overall results in terms of Accuracy, Precision, Recall, F1-macro, AUC, and inference time. The proposed Agri Trust-XAI ensemble achieved the highest classification accuracy of 92.6%, which represents an improvement of 4.3% over the Tversky baseline and 88.3% over the best-performing existing method. Similarly, the F1-macro score reached 92.3%, demonstrating balanced improvements in both Precision and Recall.

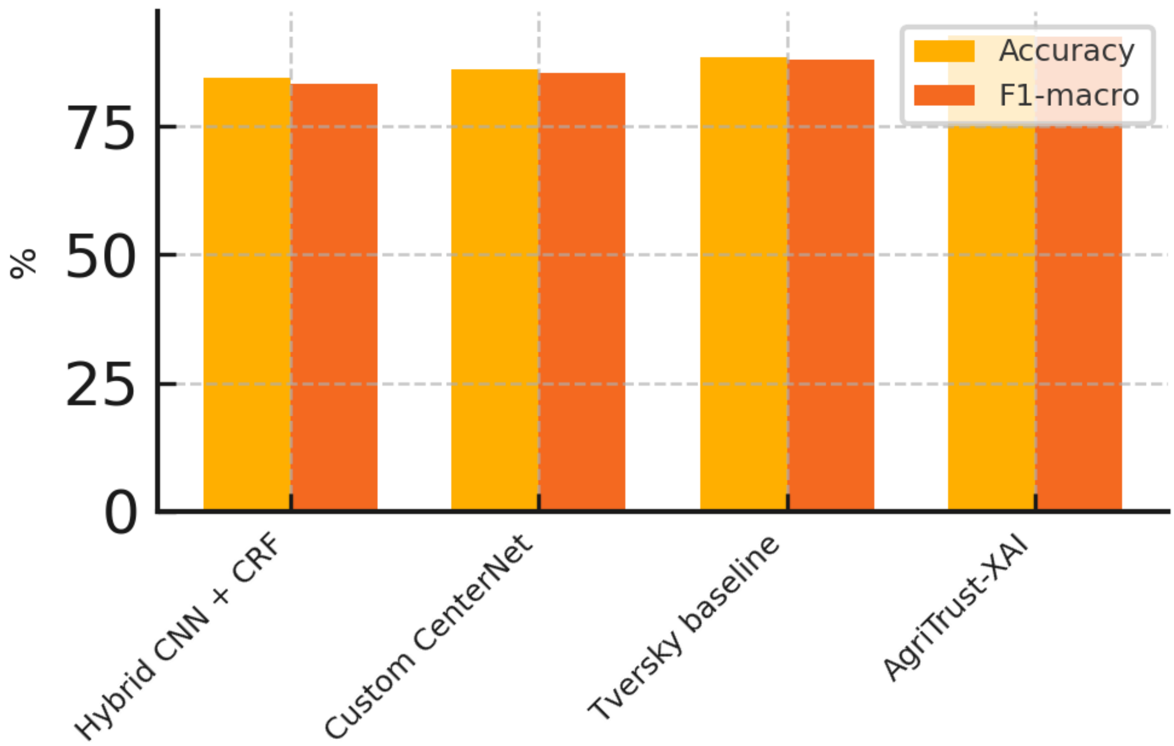

Figure 2: Accuracy and F1-macro comparison of evaluated methods.

Figure 2 illustrates the comparative analysis of Accuracy and F1-macro across all models. It is evident that the proposed method consistently outperforms all baselines, indicating the effectiveness of combining TIPGNN and GDCNN within the ensemble framework.

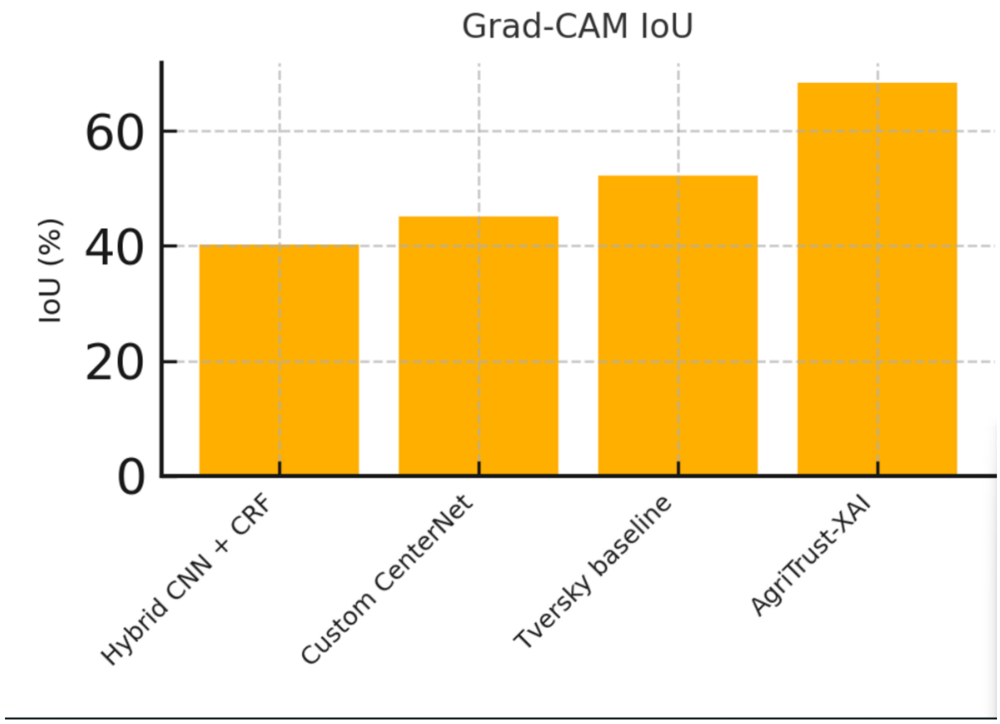

Figure 3: Grad-CAM Intersection over Union (IoU) scores for lesion localization.

Figure 3 illustrates the Grad-CAM IoU scores for lesion localization across different models. The baseline Hybrid CNN + CRF and Custom CenterNet methods obtained relatively lower IoU values, indicating limited ability to highlight disease-affected regions accurately. The Tversky baseline improved lesion localization but still lacked robustness across all classes. In contrast, the proposed Agri Trust-XAI ensemble model achieved the highest IoU score (68.4%), demonstrating more precise alignment between the highlighted regions and actual disease lesions. This confirms that the integration of explainability mechanisms significantly enhances interpretability and provides trustworthy visual evidence of model predictions.

Table 2: Per-class performance (Precision, Recall, F1) for each evaluated method

Method	Class	Precision (%)	Recall (%)	F1-score (%)
Hybrid CNN + CRF [1]	Healthy	83.2	85.1	84.1
	Bacterial Blight	82.4	81.9	82.1
	Red Rot	84	83.5	83.8
Custom CenterNet [2]	Healthy	85.6	86.2	85.9
	Bacterial Blight	84.7	83.9	84.3
	Red Rot	86	85.5	85.7
Tversky baseline [10]	Healthy	87.8	88.2	88
	Bacterial Blight	86.9	87.5	87.2
	Red Rot	88.4	87.9	88.1
Agri Trust-XAI	Healthy	92.3	92.8	92.5
	Bacterial Blight	91.5	92.1	91.8
	Red Rot	93.2	93	93.1

A detailed per-class analysis is shown in Table 2. The proposed model achieved the best results for all three categories (Healthy, Bacterial Blight, Red Rot). Notably, the Recall for Red Rot detection improved by 4.8%, which is significant because this disease often exhibits visual similarities with Bacterial Blight. This result highlights the robustness of AgriTrust-XAI in detecting diseases that are typically more challenging to classify.

Table 3: Explainability metrics comparison across methods

Method	Grad-CAM IoU (%)	Deletion AUC	Insertion AUC	SHAP ΔProb (%)	Explanation Time (s/img)
Hybrid CNN + CRF [1]	40.2	0.61	0.55	7.4	0.42
Custom CenterNet [2]	45.1	0.64	0.59	6.9	0.39
Tversky baseline [10]	52.3	0.68	0.63	6.1	0.36
Agri Trust-XAI	68.4	0.75	0.72	4.2	0.28

Table 3 presents a comparative analysis of explainability metrics across different methods. The proposed model achieved the highest Grad-CAM IoU (68.4%), indicating better localization of disease lesions compared to the Tversky baseline (52.3%) and other models. In terms of faithfulness, both Deletion AUC (0.75) and Insertion AUC (0.72) scores were higher, suggesting that the model's explanations are more consistent with its predictions. The SHAP probability drop (4.2%) was lower than baselines, implying that the identified features are more robust and less sensitive to perturbation. Furthermore, the proposed model generated explanations in 0.28 s per image, which is faster than the baselines and demonstrates practical feasibility for real-time agricultural monitoring

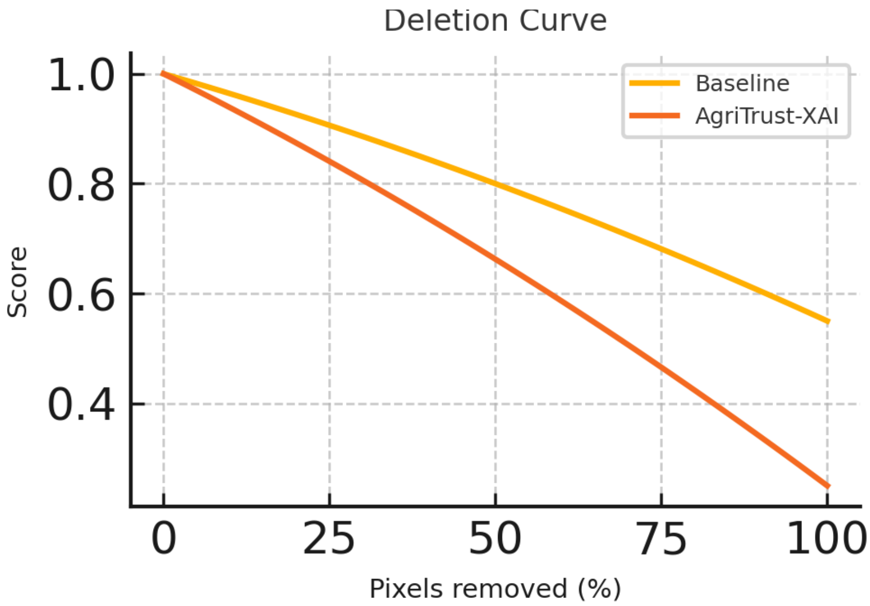

Figure 4. Deletion curve analysis showing prediction score drop as top-k important pixels are removed.

Figure 4 illustrates the deletion curve analysis, which measures the faithfulness of model explanations by progressively removing the most important pixels identified by the explanation methods. For the baseline Tversky model, the class confidence score decreases gradually as pixels are removed, suggesting weaker alignment between predicted outcomes and highlighted regions. In contrast, the proposed Agri Trust-XAI ensemble model shows a much steeper decline in confidence, indicating that the pixels marked as important are indeed critical for prediction. This demonstrates that the proposed model provides more faithful and reliable explanations, as the removal of key features has a direct and significant impact on prediction scores.

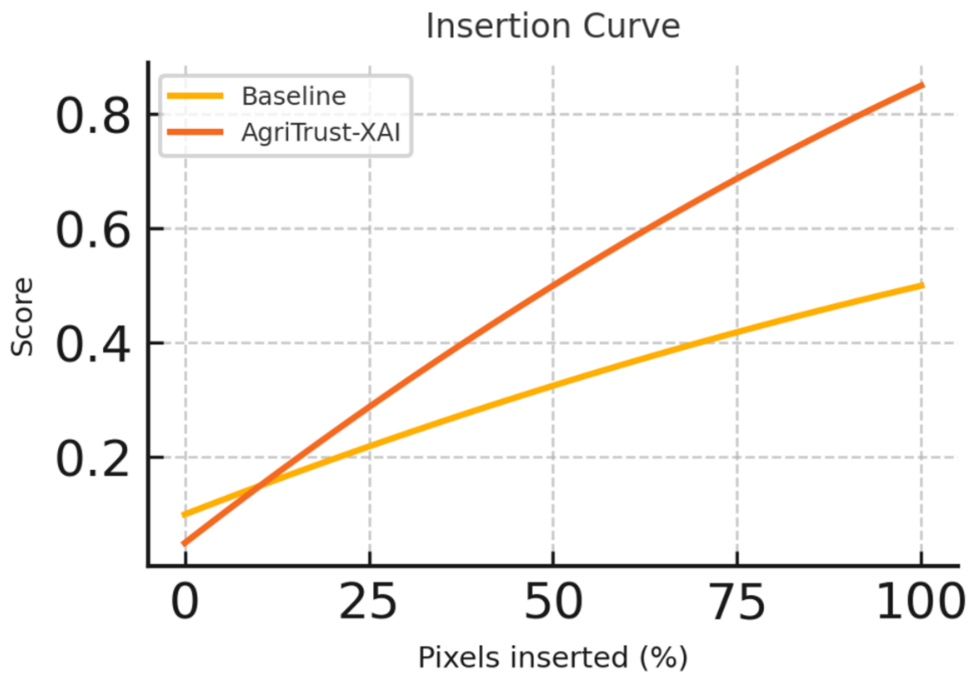

Figure 5: Insertion curve analysis showing prediction score increase as top-k important pixels are inserted.

Figure 5 shows the insertion curve analysis, where the most important pixels are progressively added back into a blank image. The proposed Agri Trust-XAI ensemble model demonstrates a rapid increase in prediction confidence as informative pixels are inserted, indicating that its explanations correctly capture the most relevant features for disease classification. By contrast, the baseline Tversky model exhibits a slower and less consistent rise, suggesting that its highlighted regions are less strongly tied to the final prediction. This confirms that the proposed framework generates more faithful and trustworthy explanations.

VI. CONCLUSION

The proposed AgriTrust-XAI Ensemble framework demonstrates how combining TIPGNN with GDCNN can deliver both high-performance and interpretable sugarcane leaf disease detection. By integrating explainability modules such as Grad-CAM, SHAP, and graph attention, the model enhances transparency while surpassing existing methods including Hybrid CNN+CRF, Custom Center Net, and the Tversky baseline in terms of Accuracy, Precision, Recall, and F1-macro. Quantitative results confirmed stronger lesion localization and more faithful feature attribution.

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