

Explainable AI Based framework for Banana Disease Detection

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Abstract— Due to widespread usage of banana as a staple food crop and susceptibility to numerous illnesses. Bananas require sophisticated detection techniques to support sustainable agricultural practices. Bananas are particularly susceptible to various stem and leaf spot diseases, resulting in significant economic losses within the banana cultivation sector. In this paper, a new XAI framework for banana disease detection and classification is introduced. Our framework uses state-of-the-art AI methods to analyze photos of banana plants. With great precision, it can detect a variety of illnesses like Cordana, Black Sigatoka, Pestalotiopsis, and fusarium wilt. The outcomes show that the framework performs better than current techniques in precisely identifying and categorizing banana diseases. The research employed a Convolutional Neural Networks (CNNs) to detect diseases in banana plants using RGB images of banana leaves. We used pre-trained model called EfficientnetB0 model to evaluate using two datasets BLSD and BDT. For BLSD, the model achieved an accuracy of 99.22%. Next for BDT, on the other hand, demonstrated improved performance with an accuracy of 99.63%.

Keywords—Banana leaf, Machine Learning, Explainable-AI

I. INTRODUCTION

Global food insecurity is raising concern for humanity due to rise in global warming and population led to a demand supply gap in food production [1]. In terms of food security in recent days playing an important role in addressing the root causes associated with yield [2]. Artificial Intelligence(AI) contributed to various field such as biomedical[3][4], agriculture, education and fintech[2][5][6][7]. There is a Tremendous interest towards agrotech field in terms of automated farm management, drone for field inspection followed by spray of pesticide [1][8]. Disease detection is an important stage in consideration of plant life cycle mostly diseases noticed in the stem and leaf, it is a challenging task for

individuals. AI based applications can help in early diagnosis[9]. Early detection of diseases in plants will enhance the yield.

Banana is an important crop grown in tropical or subtropical regions of the world, also has a grater nutrition and economical impact on formers as well as consumers[10]. Banana leaves disease are Panama disease, moko disease, Sigatoka disease, black spot, banana bunchy top, infectious chlorosis, banana streak virus, and banana bract mosaic virus disease[11]. AI based methods are used to tackle banana diseases were introduced in recent years.

Many studies addressed the issues related to automated detection of crop diseases via DL in consideration of leaf for various plants[12]. Where a few recent works focus on banana leaf-based disease prediction via Machine learning and Deep Learning algorithms. The majority of works focus on dealing the issues related to leaf [13], and in recent works, focused on the stem[14].

II. REVIEW OF LITERATURE

Automation in Agri sectors evolved exponentially in recent days due to cost effective sensor followed by improved data acquisition methods, and improved analysis algorithms. In [12]AI based Banana leaf disease detection with DL based methods have shown promising results[15]. Banana disease linked to whole tree are proposed In[14], for leaves, pseudostem, fruit bunch, cut fruits, corm and full plant image data is collected, then fed to DL models ResNetv2 and inception with improved accuracy for classification task. Later, object detection models such as Faster RCNN and SSD with baseline CNN based MobileNetV1, ResNet50 and InceptionV2 were used for object detection for all the cases of banana disease exhibited good performance. In [13], banana leaf diseases(i.e. xanthomonas,

sigatoka) are identified with MFRCNN model composed of modified RCNN, MAGAN model for dataset generation and learning. Ensemble based approach has shown 98% accuracy[16][17].

Explainable AI (XAI) has become crucial in agriculture, allowing farmers and experts to understand and trust AI-based decisions. AI in crop disease detection has seen increased use, with deep learning models like CNNs offering advanced image recognition capabilities. In banana cultivation, AI has been instrumental in detecting diseases such as Black Sigatoka, Fusarium wilt, and Banana Bunchy Top Virus. Studies like Mohanty et al. In [18] demonstrated the effectiveness of deep learning in identifying plant diseases from images. XAI approaches in agriculture, such as LIME and SHAP, have begun addressing the black-box nature of deep learning models. These techniques provide insights into model decision processes, making AI outputs more interpretable for non-experts. Research in banana disease detection often utilizes datasets like PlantVillage but faces challenges due to data variability and scarcity[19]. Recent works [20], have explored transfer learning to mitigate the limited data issue in detecting banana diseases. In [21] Ferentinos, highlighted the potential of deep learning in plant disease detection, emphasizing the need for larger, diverse datasets. The integration of IoT and AI in precision agriculture has also been explored for real-time disease monitoring in crops like bananas. However, the complexity of AI models remains a barrier for end-users, underscoring the need for more intuitive XAI methods. In [22], showed how AI could be made more transparent and trustworthy and can be extended to agriculture. The application of AI in banana disease detection is still nascent, with scope for improvement in accuracy and explainability. There's also an emerging focus on mobile-based AI applications for in-field disease detection, offering accessibility to farmers. The use of drones and satellite imagery in conjunction with AI for disease detection in banana plantations is an evolving area. XAI in this context not only aids in detection but also helps in understanding disease spread patterns. The combination of AI and remote sensing for agricultural disease detection. Despite advancements, the gap between AI explanations and human interpretability remains a challenge. Future research is directed towards more robust XAI models and user-friendly interfaces for non-expert users in agriculture. Overall, the field is progressing towards more accurate, explainable.

III. METHODS AND MATERIALS

This section expands proposed Explainable-AI framework demonstrated for banana disease detection in Fig. 1 Firstly, banana disease images were fed to DL based feature extractor capable of capturing spatial correlation among neighboring pixels in the receptive area defined by the convolution kernel size by overriding directional information inconsideration of distance between the pixels[23] for subsequent steps of framework. Subsequently, from the extracted features via EfficientNetB0[24] for banana disease datasets[25], [26] for disease detection. To address the model explainability we adopt GradCAM visualization for understanding[22].

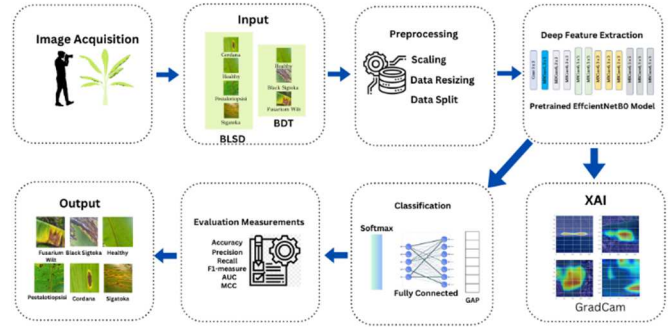


Fig. 1. Proposed X-AI Model for banana disease detection

A. Dataset description

Two standard banana disease image datasets are used. The dataset named Banana LSD (BLSLD) is composed of banana leaves Pestalotiopsis, Sigatoka, Cordana and healthy[25]. In next large scale dataset Banana Dataset Tanzania(BDT) composed of banana leaf and stem images of diseases Black Sigatoka, Fusarium Wilt and healthy images[26]. The proposed work used both dataset for the task of banana disease detection and sample data represented in figure .2.

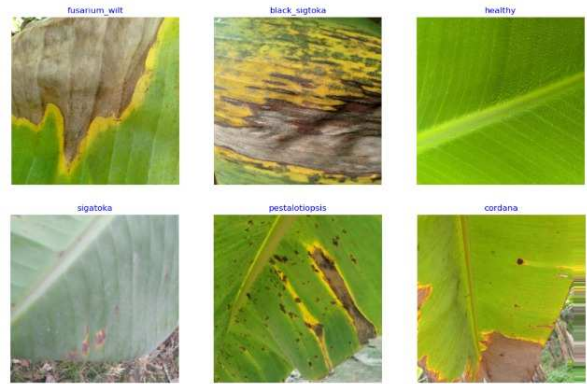


Fig. 2. Sample image dataset for banana disease

B. Data Preprocessing

The XAI framework has preprocessing step where diseased banana images [26] resized to the model's fixed dimensions of 224x224. After resizing of images, we divided the dataset into three segments: 70% for training, 20% for testing, and 10% for validation.

C. Deep Feature Extraction

The proposed work adopted DL based EfficientNetB0 model to extract the high-level features from banana leaf images. EfficientNetB0 model, which is the state of the art model, achieved 84.4% accuracy on ImageNet database with fewer parameters. EfficientNetB0 is one of eight models (B0 through B7) in the EfficientNet family[24]. In contrast to existing convolutional neural network (CNN) architectures, EfficientNet uses a Swish activation function which deviates from the traditional use of Rectifier Linear Unit (ReLU) activation function [24]. The main goal of deep learning architectures is to uncover more effective approaches with smaller model sizes. In contrast to other models, EfficientNet achieves this by

consistently modifying depth, width, and resolution while reducing the model size. The first stage of compound scaling approach involves examining a grid to determine how different scaling dimensions of the baseline network relate to one another under a fixed resource constraint. The appropriate scaling factors for the depth, width and resolution parameters can be found through this exploration. Once the baseline network has been scaled to the intended target network, these coefficients are the applied[24]. The key component of the EfficientNet is inverted bottleneck MBConv which is introduced in MobileNetV2[27], but now has a slightly increased budget for floating-point operations per second (FLOPS). Within MBConv, blocks makeup a layer that first enlarges the channels before compressing them. Direct connections are established between bottlenecks, connecting substantially fewer channels than expansion layers. This architectural design integrates in-depth separable convolutions, which markedly decrease computations by nearly a factor of k^2 in comparison to conventional layers, where k represents the kernel size denoting the width and height of the 2D convolution window[27].

Dropout regularization is then applied to the dense layer to further improve the model's generalization performance. Dropout randomly sets a fraction of input units to zero during training, effectively creating an ensemble of smaller networks and preventing co-adaptation of neurons. This regularization technique has been shown to reduce overfitting and improve the generalization capabilities of deep neural networks.

Finally, a dense layer with a softmax activation function is added to the model to produce class probabilities for multi-class classification tasks. The Softmax function normalizes the output of the network into a probability distribution over the classes, allowing us to interpret the model's predictions as confidence scores for each class.

The model is compiled using the Adam optimizer. The learning rate is set to 0.001, a commonly used value that balances training efficiency and convergence. Categorical cross-entropy is chosen as the loss function, which is well-suited for multi-class classification tasks. Additionally, accuracy is selected as the evaluation metric to monitor the model's performance during training and validation.

In this we adopt python as programming language followed by TensorFlow framework used to implement Explainable banana disease detection model via CNN based feature extraction with EfficientNet-B0[24]. The experiments performed on Intel-i7 with 16 GB ram and NVIDIA RTX 4050 with 6 GB memory. The XAI model is trained for 25 epochs with 32 batch size with Adam optimizer for BLS and BDT datasets, in addition we adopt early stopping condition to mitigate the risk of overfitting.

D. Performance metrics

The performance of XAI frameworks is evaluated using established metrics, among which the Receiver Operating Characteristic (ROC) curve stands out, particularly when applied to the banana standard datasets. This curve offers a visual comparison of the model's ability to correctly identify positives (True Positive Rate, TPR) versus its rate of incorrect positive classifications (False Positive Rate, FPR). True

Positives (TP) indicate accurate predictions, whereas False Positives (FP) signify erroneous predictions. This graphical tool serves to comprehensively summarize the effectiveness of the model at varying levels of decision thresholds, thereby providing a holistic assessment of its classification capabilities.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\text{-score} = 2 * (Precision * Recall) / (Precision + Recall) \quad (4)$$

$$MCC = \frac{(TP * TN - FP * FN)}{\sqrt{((TP + FP) * (TP + FN) * (TN + FP) * (TN + FN))}} \quad (5)$$

E. Explainable AI framework

The proposed framework addresses the classification task for banana leaf diseases has adopted modified EfficientNetB0 based model for feature extraction. The extracted hierarchical CNN features utilized for the task of disease classification[28]. XAI is adopted to address the efficacy and reliability of models learning capabilities. GradCAM visualization is used to understand the learning of the proposed XAI and it is demonstrated in Fig. 4 and Fig. 6 where it is noticed that the heatmap represents the diseased or healthy parts of the banana leaf.

IV. RESULTS

The proposed XAI framework for banana disease classification demonstrated in TABLE I. and TABLE II. where the initial performance of the proposed XAI model for the two distinct banana disease datasets were discussed. We consider 6 key evaluation metrics: Accuracy (*Acc*), Area Under the Curve (AUC), and the Matthews Correlation Coefficient (MCC), Precision (*Prec*), Recall, F1-measure for BLS and BDT. For BLS the results are demonstrated in TABLE I. , the model achieved an overall accuracy of 99.22%, along with high AUC(97.94%) and MCC(99.22%), signaling a very strong correlation between predicted and actual classes. Moving to BDT the results are shown in TABLE II. , the model demonstrated remarkable performance across all three classes, achieving an accuracy of 99.63%, AUC of 99.91% and MCC of 98.32% indicating an exceptionally strong correlation between predictions and actual classes. These findings indicate how well the EfficientNetB0 performs in classifying instances accurately and demonstrates its potential for a range of practical uses.

TABLE I. EVALUATION RESULTS FOR FIRST BLS WITH 4 BANANA DISEASE CLASSES

	<i>Prec</i>	<i>Recall</i>	<i>F1-Score</i>	<i>Acc</i>	<i>AUC</i>	<i>MCC</i>
Cordana	97.22	97.22	97.22	99.44	99.64	99.14
Healthy	100	100	100	100	100	100
Pestalotiopsis	100	100	100	100	100	100
Sigatoka	96.67	96.67	96.67	99.44	99.29	99.65

	<i>Prec</i>	<i>Recall</i>	<i>F1-Score</i>	<i>Acc</i>	<i>AUC</i>	<i>MCC</i>
Overall	98.47	98.47	98.47	99.22	99.73	98.69

	<i>Prec</i>	<i>Recall</i>	<i>F1-Score</i>	<i>Acc</i>	<i>AUC</i>	<i>MCC</i>
Overall	99.36	99.51	99.43	99.63	99.83	99.16

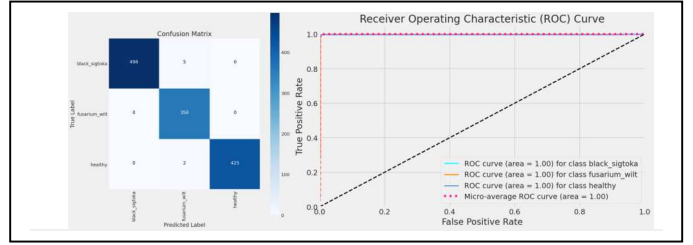
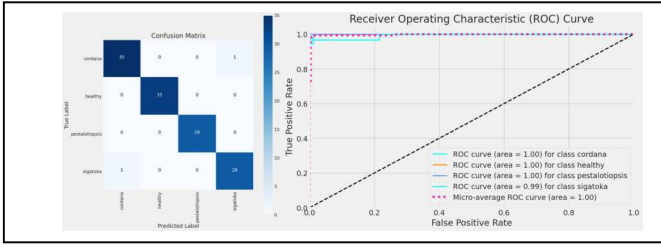


Fig. 3. Confusion matrix and ROC for the 4 class disease classification of banana disease in BLSL

Fig. 5. Confusion matrix and ROC for the 3 class classification of banana disease in BDT

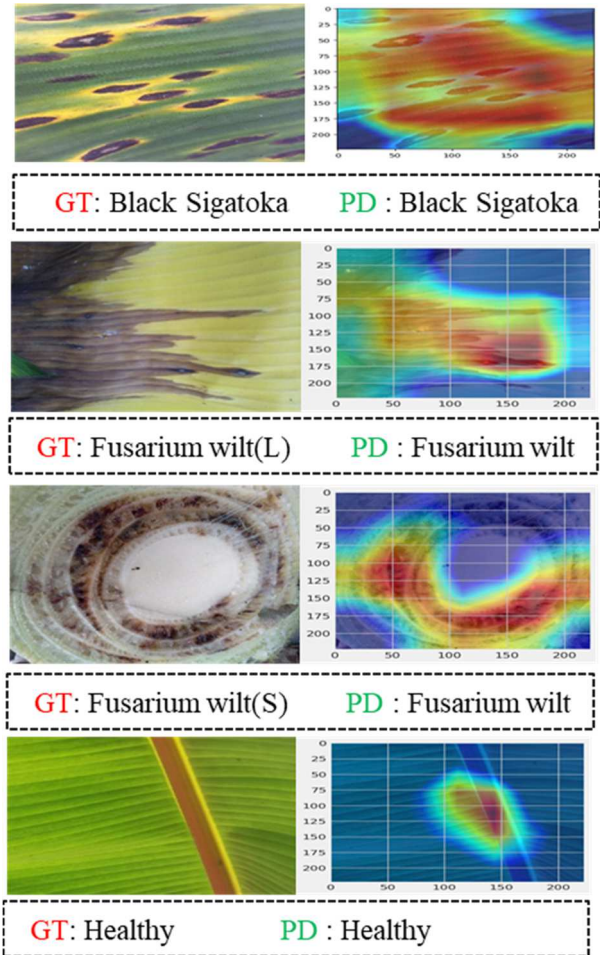
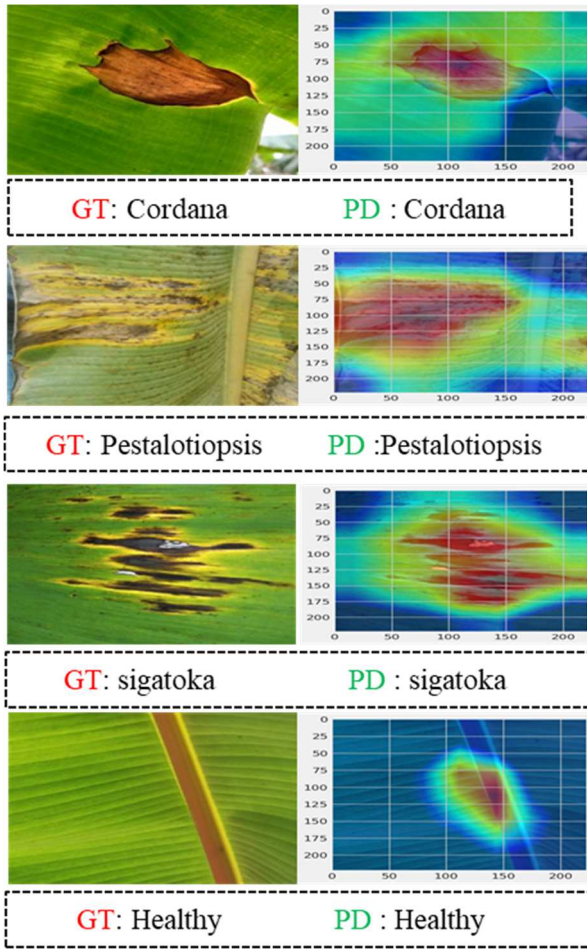


Fig. 4. GradCAM visualization to address the explainability of 4 class banana leaf disease images for BLSL where GT (Ground truth) and PD (Predicted)

Fig. 6. GradCAM visualization to address the explainability of 3 class banana leaf disease images for BDT where GT (Ground truth) and PD (Predicted) as well as Fusarium wilt disease S(stem) and L (leaf) in the BDT

TABLE II. EVALUATION RESULT FOR BDT WITH 3 BANANA DISEASE CLASSES

	<i>Prec</i>	<i>Recall</i>	<i>F1-Score</i>	<i>Acc</i>	<i>AUC</i>	<i>MCC</i>
Black Sigotka	100	99.01	99.50	99.61	99.90	99.19
Fusarium Wilt	98.08	100	99.03	99.46	99.82	98.66
Healthy	100	99.53	99.77	99.84	99.78	99.65

In our study utilizing the EfficientNetB0 model on BananaLSD, we achieved notable performance across different classes. Specifically, we achieved a remarkable 100% accuracy in classifying instances as Healthy and Pestalotiopsis, indicating the model's effectiveness in accurately classifying samples from these categories. Furthermore, for the cordana and

sigatoka classes, the model showed excellent performance with an accuracy rate of 98.68%.

The Fig. 5 shows the Confusion matrix. The EfficientNetB0 model exhibited robust performance by accurately classifying all the images from Healthy, Pestalotiopsis and Sigatoka classes. However, a single image in Cordana is misclassified as Sigatoka. Despite this inaccuracy, the model's overall accuracy is excellent. By extending our research to BDT the EfficientNetB0 model demonstrated the high accuracy result across all the three classes. Fig. 5 illustrates the confusion matrix for BDT providing a thorough analysis of the model's classification performance across three different classes. In particular, the model demonstrated a respectable level of precision by correctly classifying 498 out of 503 images in Black Sigatoka Class, Furthermore, for the Fusarium Wilt class the model accurately classified 351 out of 358 images and for Healthy class 426 out of 427 were correctly identified[10].

These findings highlight the potential utility of the EfficientNetB0 model in applications requiring precise image classification tasks. The results emphasize its effectiveness and warrant further exploration and application in various domains where accurate classification is essential.

The TABLE III. presents the performance of different machine learning models applied to banana disease detection, using various datasets. For the Banana Leaf Spot Disease (BananaLSD), Convolutional Neural Networks (CNN) and SqueezeNet achieved an accuracy of 96.25%. In detecting Fusarium Wilt, a dataset comprising banana images from Southern India was analyzed using both CNN and Support Vector Machine (SVM) methods, resulting in a 99% accuracy rate. The proposed method, employing the BananaLSD and an additional banana dataset BDT with an EfficientNetB0 model, achieved accuracies of 99.22% and 99.63%, respectively. These results underscore the effectiveness of advanced machine learning techniques in the accurate identification of banana diseases, contributing to improved agricultural disease management practices. Moreover, the proposed model shown improvement in learning from the leaf and stem images simultaneously in case of Fusarium wilt disease the detection of disease in stem and leaf images from BDT dataset can be addressed in Fig. 5.

TABLE III. COMPARISON OF PROPOSED MODEL WITH EXISTING WORKS FOR BANANA DISEASE DETECTION

Reference	Dataset	Methods	Performance (Acc)
[10]	BananaLSD	CNN, SqueezeNet	96.25%
[29]	Banana images from southern india	CNN and SVM	99%
Proposed	BananaLSD Banana dataset	EfficientNetB0	99.22% 99.63%

The assessment of the results shown that the XAI framework provides promising results. The explainability of model is quantified with GradCAM visualization method shown in Fig. 4 and Fig. 6 where it can be noticed that the model has learned on important visual markers associated to various diseases of banana leaf and stem.

V. CONCLUSION

This paper presents an Explainable Artificial Intelligence (XAI) framework tailored for detecting and classifying banana images reliable performance for disease identification. The framework outperforms existing methods, demonstrating improved performance. The precise identification of various banana diseases. Leveraging the DL-based EfficientNetB0 model, the framework achieves precise disease identification using RGB images of banana leaves across two distinct datasets. These findings hold promising for enhancing agricultural practices, leading to improved disease management, heightened productivity, and sustained economic growth in the agro-industry. In future endeavors, the scope of the framework will be broadened to include a wider array of banana afflictions, alongside an exploration into the incorporation of real-time surveillance systems aimed at preemptive disease control. Furthermore, there will be a concerted effort towards the enhancement of Explainable Artificial Intelligence (XAI) elements to afford more profound understanding into the rationale behind the model's determinations. This will significantly improve its interpretability and reliability for use in agricultural contexts.

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