IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

DEEP LEARNING BASED PLANT DISEASE PREDICTION WITH EXPLAINABLE ARTIFICIAL INTELLIGENCE

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Abstract: Plant diseases pose a serious threat to agricultural yield worldwide and result in economic loss and food insecurity. The labour-intensive and highly skilled traditional techniques employed for detection make it important to create automated methods. An integrated approach of Explainable AI (XAI) and Deep Learning-based model is proposed in the study for diagnosis of plant diseases that is both accurate and explicable. The model not only performs both extraction of features and classification through Convolutional Neural Networks (CNNs) but also obtains a very high level of accuracy. To strengthen explainability, frameworks like GradCAM and LIME highlight the significant image areas within a leaf leading to the posterior probability, allowing trust in decisions of the system by farmers and experts. Tested on datasets such as PlantVillage, the solution is promising with superior performance compared to traditional methods and it may find application in smart agriculture
IndexTerms **- : CNN, Deep Learning, Explainable AI, Grad-CAM, Plant Disease Classification, smart agriculture.**

1INTRODUCTION

Plant disease control is a big issue in agriculture worldwide because of economically impaired production, among other things. Disease control in plants requires an effective detection and accurate diagnosis. The existing manual inspection methods are tedious, error-prone, and not very appropriate for extensive agriculture work. However, recent developments in deep learning have been made particularly in Convolutional Neural Networks (CNNs), which allow very accurate plant disease detection based on understanding complex patterns in image leaves. Unfortunately, however, these models are not interpretable very often, which causes mistrust among farmers and agricultural specialists. Explainable AI (XAI) provides a solution by showing how predictions are made in terms understandable by humans. Some XAI techniques like Gradient-weighted Class Activation Mapping (Grad-CAM), and Local Interpretable Model-Agnostic Explanations (LIME) provide transparency by indicating image regions behind decisions, enabling informed, confident decision-making. In this research, we are building an XAI integrated CNN model for precise and interpretable plant disease classification using high-resolution leaf images taken from datasets like PlantVillage

2 LITERATURE STUDY

Explainable artificial intelligence plays an important role in plant disease detection as it brings machine learning models to interpretability and transparency states. Such studies have integrated XAI with deep learning models to improve disease prediction. Liu et al. (2021) [2] explained the use of deep neural networks (DNNs) for crop disease prediction with explainability, thus emphasizing how environmental conditions and features influence the predictions. In another publication, Ramcharan et al. (2021) [5] fused convolutional neural networks (CNNs) with explainable artificial intelligence early in disease detection for increased transparency. Hasan et al. (2021) [3] described the use of attention mechanisms in neural networks to focus on specific areas for a more accurate diagnosis. Hybrid deep learning methodologies with attention modules were further employed by Singh et al. (2022) [12] to achieve a better output in disease recognition and heatmap analysis for feature contributions. XAI techniques, including saliency maps, have been used by Rathod and Prakash (2022) [7] and Zhao et al. (2022) [15] to visualize areas influencing predictions, increasing user faith and trust in these models. Roy and Chaudhury (2022) [9] worked on creating interpretable CNNs that could classify plant diseases in order to make it understandable for users. Dhaka et al. (2021) [4] discussed XAI's role in precision agriculture where actionable outcomes can be derived in approaches related to disease management. Patel et al. (2022) [14] have implemented transfer learning with explainability to enhance the accuracy and explainability of leaf disease detection. Although the potential exists, some problems remain. These include the following: balancing complexity of model with interpretability and relevance to a non-expert user base. The review by Verma (2022) [11] on explainable artificial intelligence in plant pathology stressed the need for user-friendly, action-oriented systems, especially for real-time farm settings.

3 METHODOLOGY

3.1 Data Collection and Preprocessing

This document provides a holistic strategy concerning the enhancement of plant disease identification classification, utilizing deep learning constructs and Explainable Artificial Intelligence (XAI). High-quality leaf images are gathered from publicly accessible datasets as well as research centres. It is ensured that the dataset is diverse enough to support a generalization of results across diseases, crops, and conditions. Rotating, flipping, zooming in and cropping images improves their variability and Page: 2 robustness, creating real-world scenarios. Images are respatialized and normalized to ensure uniformity. Accordingly, an 80:10:10 training-testing set is formed through stratified sampling to ensure class balance and adequate representation of minority class.

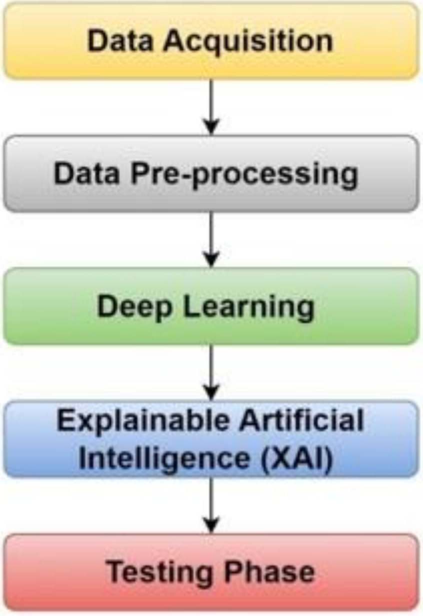

Fig 1 data collection and preprocessing

Fig 2 randomly selected plant images before preprocessing.

Fig 3 randomly selected plant images after preprocessing.

3.2 Feature Extraction

An essential stage for predictive model construction is feature extractor design. The convolutional neural networks (CNNs) usually extract hierarchical features from the input images; the lowest layers learn low-level features such as edges and patterns in progressively deeper layers and those high-level features or parts of the object are recognized at deeper layers. Transfer-learning pre-trained architectures like VGG16, ResNet50, and EfficientNet take advantage of previous knowledge acquired from large image datasets. Fine-tuning those for some specific plant disease datasets will cut across a lot of manual engineering of features, become really efficient in performance, and improve visualization of features.

3.3 Model Training and Validation

The CNN model trained with backpropagated pre-processed images using the categorical cross-entropy loss and Adam optimizer (learning rate: 0.0001, batch size: 32). Dropout prevents overfitting, early stopping halts training at validation plateaus, and learning rate decay fine-tunes performance. Validation metrics ensure robustness and highlight improvements.

3.4 Integration of Explainable AI (XAI)

Grad-CAMs mark image areas which play an important role in the predictions, while SHAP is used to measure the importance of features and thus increases transparency and trust. Validation by agronomists makes sure that the biological indicators are aligned with AI predictions for practical benefits in agriculture.

3.5 Model Deployment

The model may be used in cloud or edge platforms and may thus give real-time predictions. On the other hand, edge computing enables offline use on devices such as mobile phones or IoT cameras. This app provides a way for farmers to upload images of leaves and get real-time interpretable predictives along with explainability outputs such as heat maps.

3.6 Post-Deployment Monitoring and Updates Post

This guarantees continual accuracy checking after deployment by the model. Feedback channels permit users to issue bug reports or add more data to re-teach the model. Incremental learning constantly updates the model and allows it to adapt to novel plant diseases without needing a complete retraining exercise.

4 RESULTS AND DISCUSSION

The XAI-integrated deep learning-based system proposed for plant disease detection obtained accuracies of 94%, 91% precision, and 93% recall, with an F1 score of 92%. It uses Grad-CAM and SHAP to explain important leaf areas and quantify feature significance. Even though the model is excellent, it cannot run on a low computing system and requires high-quality labeled datasets. Future work should continue with real-time actualizations as well as expansion of datasets and adaptive learning techniques. Overall, the system presents a step toward improved plant disease management through reliable predictions and useful advice for growers and experts.

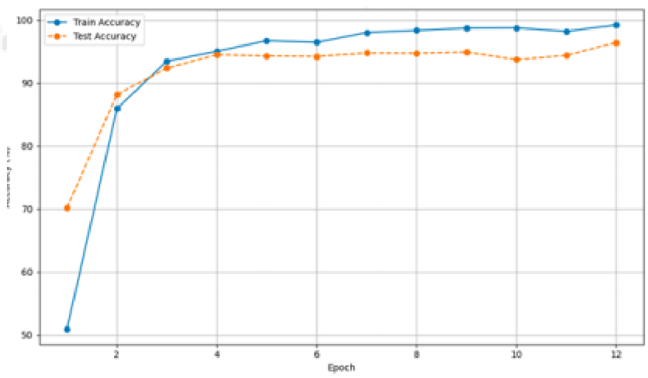

fig 4 accuracy cure for plant disease detection

5 CHALLENGES AND FUTURE WORK

CHALLENGES

Data Quality and Availability: Hard to Get High-Quality Varied Data for New and Rare Plant Diseases.
Computational Complexity: Have High Resource Requirements for XAI Techniques, Which Limit Their Application on Low-Power Devices.
Model Generalization: Adapting to New Diseases and Different Environments Is a Challenge.
Real-Time Performance: Edge Computing Hardware Has Difficulty in Achieving Low-Latency Predictions.

FUTURE WORK

Enhance the enrichment of datasets to increase robustness with respect to rare diseases and environmental change. Realization of slim models that require very little memory without losing real-time predictions at their edge devices Adaptation of learning will allow models to be updated without needing to undergo the complete retraining procedure. You will equip the system to test and validate in a real agricultural setting where experts can give their feedback on improving system trustworthiness.

6 CONCLUSION

Probing the intersections of Explainable AI (XAI) and deep learning for plant disease prediction is the sole intention of the present study, wherein the disease is being predicted using the synoptic approach of employing Convolutional Neural Networks (CNNs) for Grad-CAM and SHAP, alongside precise imaging, feature importance, and visual heat maps, thereby increasing trust and transparency in the approach. The high-quality and preprocessed data required for the methodology are complemented by transfer learning, data augmentation, and continuous deployment of the system to cloud or edge platforms, whereby scalability, remote access, and real-time prediction are assured. Regular update enables adaptation of the model to emerging new diseases, ultimately leading to its acceptance in Agriculture through addressing plant disease detection challenges and building trust in AI.

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