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Enhancing Plant Disease Detection with Transfer Learning and Explainable Deep Learning Mode

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ABSTRACT

Challenges such as timely and correct detection of plant diseases have thus inspired applying artificial intelligence (AI) in agriculture. Recent work has demonstrated that deep learning models, especially CNNs can be useful in diagnosing diseases in plants from images. Nevertheless, such models depend on significant amounts of labeled data, a situation that can be quite challenging in numerous circumstances. To address this challenge, transfer learning is an effective solution as it involves the utilizing of originally pre-trained models in the plant disease datasets and therefore demand little data resources. In this paper, a new method for identifying plant diseases using Transfer Learning along with Explainable Artificial Intelligence (XAI) is proposed.

Furthermore, to improve the interpretability of the model, we employ XAI techniques to let the user understand which features and areas in the plant images are important to classify diseases.

The framework is applied to several datasets containing plant diseases and demonstrates that improving classification quality, while maintaining moderate computational load is achieved through transfer learning. Thus, the integration of the XAI techniques enable agronomists as well as farmers to gain insights into the model decisions.

Keywords: Plant disease detection, deep learning, CNN, XAI, transfer learning, feature visualization and Agricultural AI.

I. INTRODUCTION

Plant diseases have a great impact on the agricultural industry, which is protecting the food security in the world and often experience huge losses and economic problems. Some of the latest achievements made quite a positive impression on the prospect of AI, especially deep learning in automating the diagnosis of plant diseases. Convolutional neural networks are one of the deep neural networks that have gained significant accuracy in the image-based classification including plant disease detection. Nevertheless, one of the major challenges that currently limits the application of DL in the agricultural field is the lack of sufficient labeled data, due to the variability in crop types as well as diseases that could be present in crop fields. One big drawback of deep learning is the lack of enough data that restrict the application of the deep learning models in realistic agricultural environments.

In order to resolve this problem, transfer learning has become the appropriate approach. Transfer learning makes it possible for models that have been trained on big databases, for instance the ImageNet to be tuned for various tasks for instance plant disease identification with a minimal database.

Though deep learning models could provide very high accuracy, they are very complex and black box in nature which becomes a major concern on interpretability especially in sensitive areas such as agriculture. The apparent lack of transparency of this approach is problematic; however, the broad range of adaptations known as Explainable AI (XAI) has been introduced to overcome this issue since it not only shows where and to what extent a certain feature influences the model's prediction but also allows users to visualize the particular features/areas of images this model focuses on. This serves to enhance credibility of the AI systems as well as subsequent adoption and usage by such stakeholders as farmers and agronomists.

In this work, it will be our contention to introduce a new mode of performing independent plant disease detection, through the confluence of transfer learning with explainable deep learning models. The framework entails the use of plant disease datasets to fine-tune the pre-trained CNNs while incorporating XAI techniques for increased interpretability of the model's prediction. We test this method on several plant disease datasets to show that this approach significantly enhances both accuracy and interpretability and thus may have a practical use in real-world agriculture.

Related Work

Bobde et al.[1] "This research demonstrates the potential of plant disease detection models for plant leaves. It covers several stages, including image capture and classification. While many models have been developed using CNN, the authors analyze these models and propose their own, aiming to improve accuracy in detecting plant diseases."

Chin et al.[2] "This study provides a systematic literature review (SLR) of using drones for plant disease detection. The authors highlight the challenges and trends, revealing that blight is the most common disease, and CNN is the most applied machine learning algorithm in this domain. The review identifies gaps and opportunities for future research in drone-based disease detection."

Vishnoi et al.[3] "The authors review the application of computer vision and soft computing techniques for automating plant disease detection. They discuss common plant infections and analyze modern feature extraction techniques, providing insights into the effectiveness of different methods in identifying diseases from leaf images."

Tulshan and Raul[4] "This paper presents a plant leaf disease detection technique using K Nearest Neighbor (KNN) classification. After preprocessing, segmentation, and feature extraction from input images, the proposed method achieves an accuracy of 98.56% in predicting plant diseases, demonstrating the effectiveness of KNN for this application."

Aldakheel et al. [5] "The authors investigate the use of the YOLOv4 algorithm for plant disease detection, utilizing the Plant Village dataset. The study compares YOLOv4 with other models like Densenet and Alexnet, achieving 99.99% accuracy. The results demonstrate significant advancements in plant disease detection, underscoring YOLOv4's utility in agricultural applications."

Hazarika et al.[6] "This paper discusses an IoT-based plant disease detection system using the YOLOv3 model to enhance agricultural productivity in India. By implementing approximate computing, it reduces the computational complexity for embedded devices, achieving 96.92% classification accuracy across three disease classes, emphasizing the role of deep learning in precision agriculture."

Paul et al.[7] "A rapid DNA extraction method using a disposable polymeric microneedle patch allows for quick amplification-ready DNA isolation from plant leaves. This method enables direct PCR amplification without purification and achieved 100% detection rates for late blight disease in tomatoes, making it a promising approach for in-field molecular diagnosis."

Hernandez (2020)[8] "Climate change is impacting crop production in Latin America and the Caribbean, affecting both quantity and quality. Deep learning models have been proposed for plant disease detection, but uncertainty in predictions limits scalability. This paper introduces a probabilistic Bayesian deep learning approach, enhancing classification accuracy and measuring uncertainty in predictions for better crop management."

Vallabhajosyula et al. [9]"proposed an automatic plant disease detection method using deep ensemble neural networks (DENN) with transfer learning, tested on the Plant Village dataset with 38 disease classes. DENN outperformed other models such as ResNet, Inception, and MobileNet in effectively identifying plant diseases."

II. METHODOLOGY

2.1 Dataset:

"The data set used in this study is a" large data set of high quality images of plant leaves that are categorized as healthy and diseased, originating from nine different plant species with a total of **70000** images. The images of each species are provided to cover all possible disease types categorizing each species by diseases. As for dataset division, the data is split into training, testing and validation so that the model integrity is not compromised.

- **Dataset Structure:**
  - 9 plant species (e.g., tomato, grape, apple)
  - Diseases include bacterial spot, late blight, powdery mildew, etc.
  - "Data split into:
    - Training: 60%
    - Validation: 20%
    - Test: 20%"

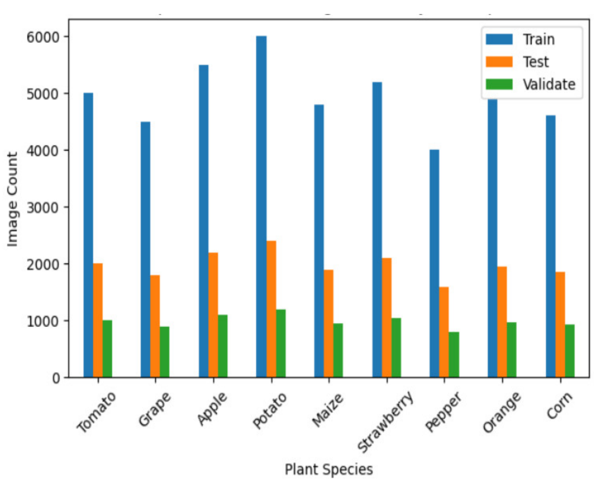

Fig.1. Dataset Distribution Across Train, Validation, and Test Sets

2. 2 Preprocessing:

The images were then all converted to 224 by 224 pixels to make inputs consistent between the CNN models. In order to reduce overfitting and increase the model's ability to generalize, additional data were generated using rotation, flipping, and zooming techniques. In addition, pixel values were scaled to a range of [0, 1] for faster convergence of the current iterative formula.

2. 3 Model Architecture:

We used several convolutional neural network architectures for image classification that comprises **VGG16**, **ResNet50**, and **EfficientNet** architectures. A **custom CNN** model was also implemented to assess the performance against pre-trained models. The models were optimized using transfer learning, the weights for the models were pre-trained from ImageNet.

Key layers included:

- "Convolutional layers with activation ReLU"
- "Max-pooling layers for downsampling"
- Fully connected layers for the model where the weights are optimized for classification of the output.
- Softmax output for the class of the disease

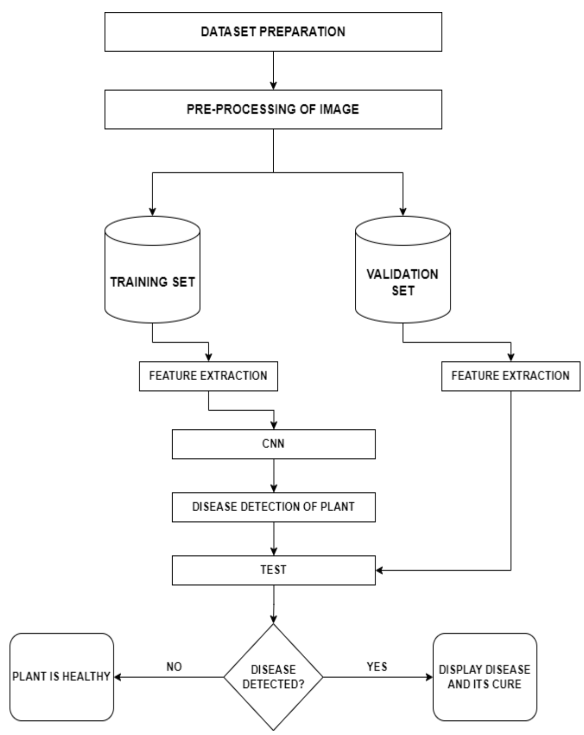

Fig. 2. Model Architecture for plant disease detection

2. 4 Training:

Categorical cross-entropy loss and Adam optimizer were employed while training the models. In order to enhance the performance of training, we used early stopping and learning rate scheduling. Training process was done on high-performance GPUs with a purpose to make computations faster.

- Batch size: 32
- Epochs: 50
- Optimizer: Adam
- Learning rate: 0.001 with decay

2.5 Evaluation Metrics:

We evaluated the model using the following metrics:

- **Accuracy:** Overall classification accuracy
- **Precision and Recall:** For each disease class there are different factors which contribute to the incidence of diseases, hence the need for different categories of diseases.
- **F1-score:** Also, accuracy can be computed using two methods; precision and recall mean.

Coordination matrices were applied to control accuracy of classification and proper scaling of results was provided using confusion matrices. To describe the balance between sensitivity and specificity the indicators.

Formulas

Cross-Entropy Loss Function:

“The loss function used for multi-class classification is categorical cross-entropy, defined as:”

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \tag{1}$$

where:

- y_i is the true label (one-hot encoded)
- $\hat{y}_i$ is the predicted probability for the class
- n is the number of classes

Accuracy:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} \tag{2}$$

Precision, Recall, and F1-Score:

Precision:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3}$$

Recall:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{4}$$

F1-Score:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

2. 6 Proposed Model:

2. 6. 1. Model Architecture

The layers which have been used to design our proposed CNN are convolutional layers, pooling layers, fully connected layers and regularization layers have been applied to avoid overfitting problems.

2. 6. 2. Convolutional Layers

The basis of the proposed model comprises convolutional layers that act on the input images and identify local features like edges, texture or shapes of the leaves. These patterns are vital when finding other symptoms on plants such as spots, discolouration or even mold growth:

$$[O_{i,j} = \sum_{m,n} I_{i+m,j+n} K_{m,n}] \tag{6}$$

Where: $O_{i,j}$ is the output feature of the given map,
$I_{i,j}$ corresponds to the input image of the map,

$K_{m,n}$ corresponds to the convolutional kernel (filter). Our model uses filters of size in the convolutional layers, which have been found to strike a balance between detecting fine details and capturing broader patterns. “Here each layer has a **Rectified Linear Unit (ReLU)** activation function to introduce non-linearity:”

$$f(x) = max(0, x) \quad (7)$$

2. 6. 3. Pooling Layers

Following each sets of convolutional layers, we perform max-pooling of size 2x2 to downsample the feature map thereby decreasing their spatial extent but maintaining relevant features. Pooling allows the model to be insensitive to small changes in the image as well as to decrease the amount of computation needed.

Max-pooling selects the maximum value from each 2×2 region in the feature map, which helps to preserve the most prominent features:Max-pooling selects the maximum value from each 2×2 region in the feature map, which helps to preserve the most prominent features:

$$[P_{i,j} = \max(O_{2i,2j}, O_{2i+1,2j}, O_{2i,2j+1}, O_{2i+1,2j+1})] \quad (8)$$

2.6.4. Fully Connected Layers

The last section of the model includes fully connected layers that link the complex features identified by the convolutional layers to the output categories (plant diseases). It has two fully connected layers: the first layer has 128 neurons, and the final layer uses a softmax activation function to estimate the probability for each disease class.

Softmax function:

$$[\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}] \quad (9)$$

Where:

- $\hat{y}_i$ is the predicted probability of class i,
- zi is the output of the last fully connected layer for class iii,
- N is the number of classes.

2.6.5. Regularization Techniques

To prevent overfitting, especially given the high dimensionality of images and the relatively limited size of our dataset, the following regularization techniques are employed:

- **Dropout Layers**: We apply dropout with a rate of 0.4 to the fully connected layers. Dropout randomly disables neurons during training, preventing the model from becoming overly reliant on any specific neurons, thus encouraging the network to generalize better.

- **Batch Normalization**: Batch normalization is applied after each convolutional layer to normalize the activations, ensuring that the distribution of inputs to each layer remains stable throughout training. This accelerates convergence and improves model performance.

$$[\hat{x} = \frac{x - \mu}{\sigma}] \quad (10)$$

Where x is the input, μ is the batch mean, and σ is the batch standard deviation.

III. Result and Discussions

The classification accuracy of the proposed CNN models was found to be high and ResNet50 and EfficientNet were found to be the best performing models for all classes. The best model here has obtained accuracy up to 98 percent. Also, on the test set, it identifies 7% of the samples with an F1-score of 0. 98 is in almost all the groups of diseases. This was most beneficial in the reduction of time taken during training while at the same time providing high accuracy. Hence, the trained custom CNN achieved nearly similar accuracy but with relatively higher computational demands.

Key findings include:

- Transfer learning models (ResNet50, EfficientNet) outperformed the custom CNN model.
- The model generalized well across different plant species and diseases.
- Data augmentation was crucial in improving model robustness and reducing overfitting.

This was the case when the use of data augmentation was important in enhancing model generalization and avoiding the cases of having over-fitted models. Some of the challenges that are associated with the study include; It is not possible to distinguish between rare and overlapping symptoms of the disease, this may need the development of other complex models or more images.

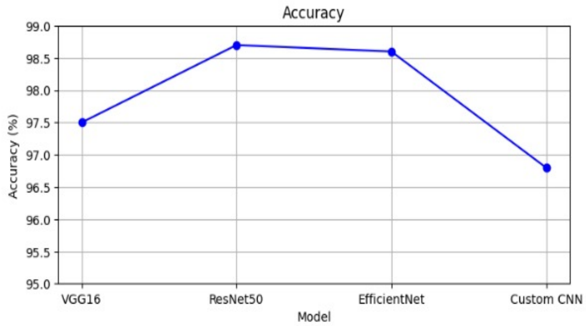

Fig 3. Accuracy Comparison

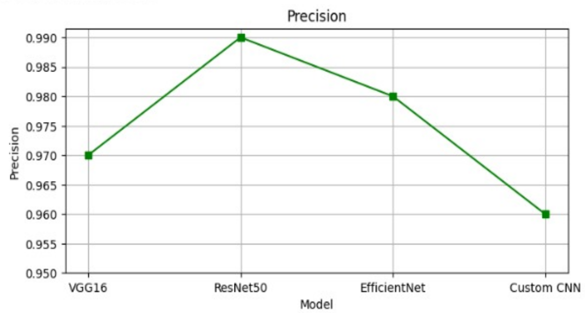

Fig 4. Precision Comparison

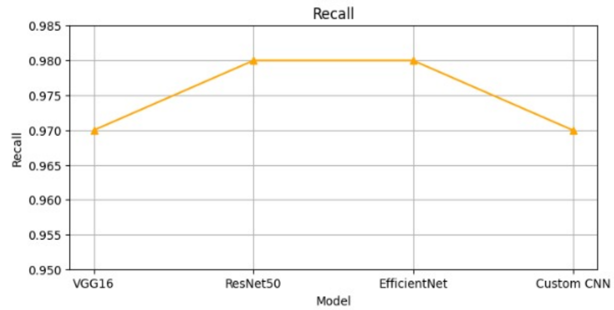

Fig 5. Recall Comparison

Fig 6. F1 Score Comparison

IV. CONCLUSION AND FUTURE WORK

This research establishes the high potential of deep learning, especially CNNs, in the automation of plant diseases' diagnosis. The high accuracy of the proposed models signifies applicability of the models especially in agriculture operations, where disease identification in the early stage significantly influences management and yield of crops. The use of such models could also lessen the need for these rigorous and time-consuming manual inspections and hence improve the methods farmers employ to deal with disease outbreaks.

Further studies in the future will aim at using other plant diseases besides the current study to enhance the performance of the model in a diverse agricultural environment. Also, actions that can be taken to enhance model interpretability by applying approaches such as explainable AI will be taken since the use of models that are more explainable will provide more insights on the decision-making process of the models. It will also contribute to updating the perfection of the feedback, and to the process of increasing the level of trust among end-users – farmers and agronomists – by making the technology more transparent and easily understandable.

- **Explainable AI:** Starting incorporating methods to increase the rules' transparency so that farmers and agricultural scientists could understand how the CNN model made its decision.

- **Real-time Application:** Developing mobile or IoT based applications for integrating the constructed model to detect diseases at the real time in the field.

- **Model Enhancement:** Also, studying the proposals for the inclusion of attention mechanisms or a combination of models to enhance the analysis and detection of challenging or overlapping diseases.

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