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An Innovative Approach for Classifying Plant Diseases Using Deep Learning

Ahmed Solyman[1] and Ismail A. Elhaty[2]*

[1] School of Computing, Engineering and Built Environment, Glasgow Caledonian University, Glasgow, UK.
[2] Department of Nutrition and Dietetics, Faculty of Health Sciences, Istanbul Gelisim University, Istanbul, Turkey.

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Abstract: The classification of plant diseases is essential for the agricultural industry to promptly identify and address crop challenges. The numerous errors and inefficiencies in existing ailment identification approaches prompt the advancement of enhanced methods. This study uses deep learning, namely the EfficientNet method, to strengthen the classification of plant diseases. Through rigorous research and meticulous refinement, the EfficientNet model has been optimized to achieve an impressive accuracy of 99.68%. The findings demonstrate that deep learning can accurately and rapidly categorize plant illnesses, improving agricultural efficiency.

Keywords: Deep learning; Classification; Agriculture.

1 Introduction

Agriculture, the fundamental pillar of worldwide food security, faces challenges in addressing plant diseases that diminish agricultural productivity, quality, and profitability[1]. As per a community report from the Ministry of Agriculture and Farmers Welfare, pests, weeds, and diseases account for 15%–25% of agricultural production losses, with plant diseases being the primary cause [2]. This issue is particularly severe in countries such as India, where 58% of the population relies heavily on agriculture as their primary source of income [3]. Plant diseases negatively impact farmers' profits and the availability and pricing of food for customers [4].

Agricultural professionals perform manual checks as part of conventional disease detection, which can be subjective, inconsistent, and inefficient [5]. Due to the significant time and financial costs and the required specialist expertise, manual diagnosis is not feasible for large-scale agricultural enterprises [6]. Manual diagnosis errors delay treatment and worsen plant diseases [7].

Technology, specifically AI and machine learning, can help detect and categorize plant diseases [8]. Learning, a subset of machine learning, is a powerful technique for categorizing pictures and can enhance and streamline illness detection. Deep learning algorithms efficiently and precisely categorize plant health by analyzing extensive datasets of labeled pictures to recognize intricate patterns and characteristics that signal diseases [9][10].

Convolutional neural networks (CNNs) have been proven helpful in identifying and categorizing plant illnesses in various crops such as tea, apple, tomato, grapevine, peach, and pears, as demonstrated in several types of research [11][12].

However, despite significant advancements, there are still obstacles to reaching high precision, scalability, and resilience standards in agricultural environments[8]. Developing dependable and practical disease classification systems is hampered by variables like changes in ambient conditions, picture quality, and disease presentation patterns[9].

Our research addresses these difficulties by proposing novel plant disease categorization methods based on deep learning and artificial intelligence[10]. A novel deep neural network design is illustrated by adding new layers and altering many EfficientNet levels to boost performance [11].

2 Literature review

This work applies deep learning to plant disease classification investigations. Deep neural networks (DNNs) have shown encouraging results in this area, but their sensitivity to adversarial attacks is problematic [12]. To improve the EfficientNet model's performance and solve the issue, the authors provide a new SimAM-EfficientNet design. This

*Corresponding author e-mail: ahmed.solyman@gcu.ac.uk

architecture uses SimAM attention. Compared to ResNet50 (98.33%), ResNet18 (98.31%), and DenseNet (98.90%), the recommended model achieves 99.31% experimental accuracy on the PlantVillage dataset. The research introduces GP-MI-FGSM, an advanced adversarial attack approach using picture pyramid and gamma correction. Applying the proposed strategy to the model increases performance and reduces errors to 87.6%. With a greater success rate than previous adversarial attack methods like FGSM, I-FGSM, and MI-FGSM, GP-MI-FGSM efficiently evaluates the resilience of deep learning models in plant disease classification tasks.

This study [13] examines plant health care to reduce plant death rates, emphasizing the need for early identification and diagnosis of life-threatening plant illnesses. Predictive models for early plant disease diagnosis are created using machine learning, an artificial intelligence (AI) method. Machine learning techniques are used to classify crops, particularly in the early phases of growth, by analyzing high-resolution optical data collected by drones. Grey-level co-occurrence matrices extract features from grayscale images at the phonological stage. Plant disease detection models are created with machine learning methods such as neural networks, support vector machines, random forest-nearest neighbors, linear regression, and Naive Bayes. Evaluation criteria, including F1-score, accuracy, recall, and true positive and negative rates, are used to assess model performance. The findings indicate that the ensemble plant disease model outperforms previously suggested models in forecasting early disease detection for preventative measures and predictive maintenance.

The study [14] investigates the impact of improper resource utilization and climate change on decreasing agricultural productivity and increasing plant diseases. The study explores deep learning methods for classifying tomato plant illnesses due to the importance of early identification and treatment of plant pathogens to improve crop yield and quality. The Multilevel Feature Fusion Network (MFFN) combines channel, spatial, and pixel attention with ResNet50 and an Adaptive Attention Mechanism. The proposed technique surpasses the existing ones, attaining impressive accuracies of 99.88% in training, validation, and external testing on a tomato leaf dataset. The paper proposes a pesticide prescription module that recommends appropriate pesticides based on the type of leaf disease detected.

This study [15] aims to enhance resource utilization, decrease production inefficiencies, and enhance treatment effectiveness by developing automated methods for identifying and analyzing illnesses in rice crops within the agricultural sector. The system employs computer vision techniques such as deep learning, image processing, and machine learning to identify and categorize rice plant diseases from provided images. This approach groups convolutional neural networks with support vector machines to identify and classify diseases in rice plants, and it uses photo segmentation to find sick parts of the plants. The main discussion points are common diseases, including brown leaf spot, sheath rot, false smut, rice blast, and bacterial leaf blight. With the help of the ReLU and softmax algorithms, modern agriculture relies on accurate diagnosis of plant diseases to increase crop yields, and this study intends to do just that.

Due to the high expense of traditional methods that rely on human feature extraction, there is a growing interest in image-based systems. Problems with backdrop, incorrect photo circumstances, and misclassifications are issues plaguing current methods. To overcome these obstacles, the research [16] presents the Agriculture Detection (AgriDet) framework, which integrates deep learning networks using the Inception-Visual Geometry Group Network (INC-VGGN) and the Kohonen algorithm. Along with image preprocessing and a multi-variate grabcut technique to handle occlusion, an INC-VGGN model has already been trained to detect and categorize plant illnesses. Dropout layers and Kohonen learning provide successful feature learning and minimize overfitting. Statistical study of specificity, accuracy, and sensitivity demonstrates that the proposed framework is more accurate than previous models. The study shows that AgriDet effectively addresses plant disease detection, improving agricultural productivity.

This work [17] proposes an automated technique for recognizing and categorizing plant leaf diseases to overcome human disease inspection disadvantages. The modified PDICNet model uses ResNet-50 for feature extraction and an improved Red Deer optimization algorithm (MRDOA) to provide optimum and conspicuous features. DLCNN classifiers enhance classification accuracy. Simulations show that the PDICNet model works well. On PlantVillage, it had an F1-score of 99.78% and an accuracy of 99.73%. Rice Plant dataset scores were 99.68% and 99.71%. This realistic technique swiftly and accurately identifies and categorizes plant illnesses. This study emphasizes the need to rapidly and accurately detect plant leaf diseases quickly and accurately to prevent further damage to plant development.

The research [18] uses deep learning, namely the Ant Colony Optimisation with Convolutional Neural Network (ACO-CNN), to enhance illness identification and categorization. The proposed method uses convolutional neural networks (CNN) and ant colony optimization to diagnose plant leaf diseases using color, texture, and leaf arrangement information. The proposed approach surpasses the status quo in success and accuracy.

This study [19] shows how deep learning, photo capture, segmentation, noise reduction, and classification may improve plant disease diagnosis.

This study shows that disease severity affects plant quality and yield, vital to agricultural productivity. Despite the extensive use of deep learning, especially CNNs, for species identification, plant disease severity remains seldom studied. The research begins by developing illness severity criteria using data from prior studies. The sixteen CNN-based plant disease severity evaluation studies are examined in three categories: segmentation networks, improved architectures, and classic CNN frameworks. Dataset collection and success indicators are compared in detail. CNN-based severity rating systems have challenges, but the report suggests future research and real-world solutions. This lengthy study attempts to increase our knowledge and abilities in utilizing CNNs to assess plant disease severity.

In the proposed approach in this study [20], the photos are input to a stack of different deep neural networks after being segmented for the area of interest. The deep neural network's output is combined with a machine learning model to diagnose leaf disease. Several mango leaf diseases, including powdery mildew and anthracnose, can be identified using this model. In the experiment aimed at identifying mango leaf illnesses, machine learning, and deep learning models are employed, stacking them together. The suggested model performs better than the most advanced models, scoring 98.57% accuracy. The primary objective of this study [21] is to assist in distinguishing between healthy and sick leaves using Deep Convolutional Neural Network image analysis. PlaNet is a recently created model. Its effectiveness has been contrasted with other widely used CNN models. Eighteen popular CNN models built on deep learning have been tested and verified; one is an ensemble model comprising the top five models. We used four permutations of three commonly used benchmark datasets.

The evaluation demonstrates that the PlaNet model has a high level of efficiency. The highest average performance, in terms of accuracy, was 97.95%. The AUC was 0.9752, the F1-score was 0.9686, the sensitivity was 0.9707, the precision was 0.9576, and the specificity was 0.9456. The studies demonstrate that the deep learning-based system can swiftly and dependably categorize plant leaves. The recommended model performs effectively independently or in conjunction with four combinations of three datasets. The suggested approach exhibits greater flexibility, breadth, and scalability than existing methodologies. The requirement to accurately analyze a botanical leaf image within one second demonstrates its ability to perform in real-time.

3 Methodologies

The study methodologies encompass many stages: data preparation, model architecture selection, fine-tuning, and performance evaluation. Using robust deep learning methodologies accomplishes efficient and precise categorization of plant diseases.

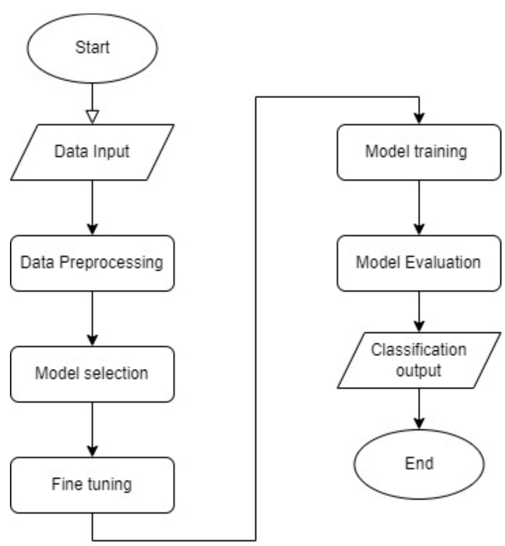

Fig. 1: Our methodology flowchart.

Data Preprocessing

The significance of ensuring high-quality and diverse training data in machine learning and artificial intelligence cannot be overstated. These characteristics significantly impact the effectiveness of models. Researchers and developers have increasingly depended on open-source datasets like the New Plant Diseases Dataset to improve the diagnostic capabilities of machine learning models in identifying plant diseases. It's possible that using the present datasets alone won't always suffice. As a result, preprocessing functions become essential for improving datasets.

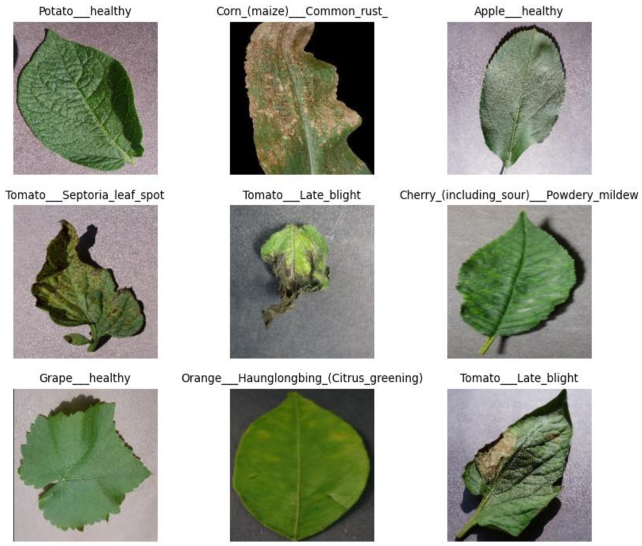

Fig. 2: A sample of the dataset.

Model Architecture

The model architecture must be carefully chosen and optimized for the classification process. The study employed the lightweight and powerful EfficientNetB0 convolutional neural network for picture categorization. The EfficientNetB0 classifier, trained on the ImageNet dataset for the classification of plant diseases, performs better when the weights are employed.

EfficientNet

EfficientNet has transformed convolutional neural networks in the dynamic field of artificial intelligence. EfficientNet is a leader in image classification innovation due to its pursuit of computing economy and cutting-edge performance.

The effectiveness relies on accurate amplitude, width, and magnification level calibration. These three architectural attributes can group diverse photography pictures. EfficientNet has the top position on the list of deep learning architectures due to its ability to balance power and model complexity.

The intricate explanation of the high performance of EfficientNet further ignites my curiosity. Each layer is specifically modified to extract and encode significant details from the photo, resulting in computational harmony. Contrary to its tech restrictions, EfficientNet has expanded its AI capabilities. To a certain extent, the more influential the technology is, the more it indicates how it can be more efficient to allocate resources to improve the outcomes instead of measuring the innovation using computational power. The word EfficientNet depicts the resolve to be efficient and optimize, which is what deep learning is about. This leads to changes in how images are classified and marks the creation of standards for data processing and efficiency among industries and research.

Compound Scaling:

EfficientNet reliably scales the three essential dimensions as opposed to haphazardly doing so. Add α to the network depth. Expand the channels (network width) by β. Resolution: Add γ to the image resolution. Efficiency is preserved via the compound coefficient, which guarantees uniform development across dimensions. The EfficientNet scaling technique consistently and logically scales network width, depth, and resolution using a compound coefficient represented by φ. The equations are as follows:

Depth: Number of layers (L) is scaled by:

$$L' = L \cdot \phi^{1.2} \quad (1)$$

Width: Number of channels © is scaled by:

$$C' = C \cdot \phi^{0.5} \quad (2)$$

Resolution: Image size ® is scaled by:

$$R' = R \cdot \phi^{0.5} \quad (3)$$

Where 1- L', C,' and R' are the new depth, width, and resolution. L, C, and R are the original depth, width, and resolution, respectively. φ is the compound scaling coefficient.

These equations ensure that the increase in the computational cost of the more profound and broader network is balanced by the reduction in computational cost from the lower resolution. This balance allows the model to scale up more efficiently.

Justification for Scaling:

More layers and channels are needed to identify complicated patterns in larger input photos. These factors confirm EfficientNet's scaling technique, improving performance.

Model Customization and Fine-Tuning:

Several changes are made to the original EfficientNetB0 model tailored to the plant disease classification objective. The pre-trained weights are used for launching the model, and then global average pooling and a dense classification layer with softmax activation are added; also, some modifications are made inside the base EfficientNet model, including removing some layers and adding neurons and dropout layers. Notably, to enable the learning of task-specific characteristics while maintaining the valuable representations learned from ImageNet, the EfficientNetB0 base model is fine-tuned by selectively unfreezing layers.

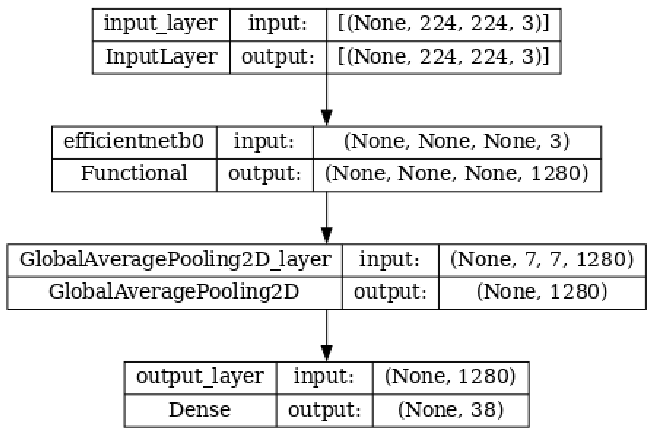

Fig. 3: Our Model Architecture Overview.

Fine-Tuning Strategies:

Fine-tuning is essential to maximize the model's performance on the intended task and prevent overfitting. Early stopping, a decrease in the learning rate on plateaus, and model checkpoint procedures are used together to achieve this balance. When validation loss stops improving, training is stopped early to avoid overfitting. To effectively overcome steep loss landscapes, the learning rate decrease on plateaus dynamically modifies the learning rate. The best-performing model weights are preserved by model checkpointing, facilitating easy restoration and training continuation.

Performance Evaluation:

The model's accuracy and categorical cross-entropy loss are two standard metrics used to assess its performance. These metrics show how well the model can identify plant diseases in various areas. To ensure the model can accurately categorize data that hasn't been seen, its generalization skills are further evaluated using a different validation dataset.

4 Results

The performance of the proposed model was evaluated through training and validation of the dataset. Figure 3 shows the training loss and validation loss over epochs, respectively. The training loss steadily decreases with increasing epochs, indicating effective learning of the model parameters. Similarly, there is a decrease in validation loss, indicating the model's generalization ability to unseen data.

Additionally, Figure 4 presents the training and validation accuracy over epochs, respectively. Figure 4 shows a continuous increase in training accuracy as epochs progress, demonstrating the model's ability to classify training data correctly. A similar rise in validation accuracy is shown, suggesting the model performs well on unseen validation data.

Fig. 4: Training and Validation Loss results.

Note: The blue line was chosen to represent the training loss, while the orange line represents the validation loss.

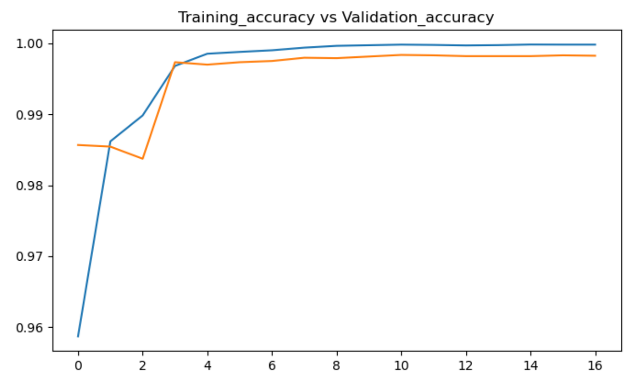

Fig. 5: Training and Validation Accuracy results.

Note: The blue line was chosen to represent the training accuracy, while the orange line represents the validation accuracy.

Also, our model was tested on unseen data to ensure that it was learning effectively without overfitting. As depicted in Figure 5, the test results on a group of plant disease images in the test set were used to observe the model predictions versus actual labels.

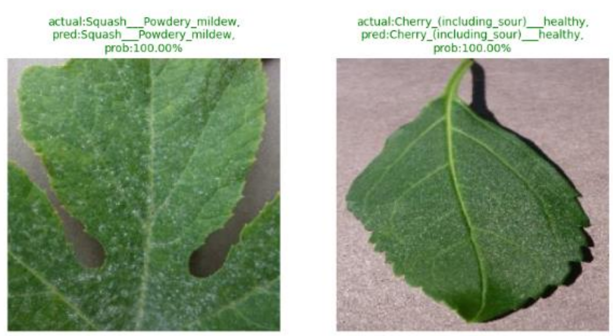

Fig. 6: Model Predictions on test data.

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5 Conclusions

Deep learning, particularly EfficientNet, has improved plant disease categorization. The EfficientNet model has 99.68% accuracy after extensive testing and tweaks. The findings show that deep learning can improve plant disease classification. These technologies enhance agricultural sustainability and output by diagnosing and treating crops early. The discovery affects more than academics. Advanced deep learning helps farmers protect crops from pathogens. Accelerated crop identification using these algorithms reduces crop damage and improves agricultural sustainability and production. The deep learning knowledge of agriculture has been enhanced with this research. Plant disease categorization systems may use real-time data and sensors. Robust, adaptive systems can be created that rapidly respond to environmental changes and new disease threats. Deep learning models that combine real-time data and sensors can improve global food security. Agricultural concerns can be prevented, and international food crop sustainability is ensured by equipping farmers with helpful knowledge and sophisticated warning systems. This branch of study might revolutionize crop management and disease control, laying the basis for a more sustainable and ecologically friendly agricultural future.

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