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RESEARCH ARTICLE

EfficientNetB3-Adaptive Augmented Deep Learning (AADL) for Multi-Class Plant Disease Classification

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ABSTRACT Plant diseases can significantly impact agricultural productivity if not promptly identified and treated. Traditional plant disease classification methods are often challenging and time-consuming, making the identification of diseases a challenging task. This paper aims to bridge research gaps and address challenges in existing methodologies by proposing an efficient, effective multi-class plant disease classification approach. The research explores the application of pre-trained deep convolutional neural networks (CNNs) in this classification task, utilizing an open dataset comprising 52 categories of various diseases and healthy plant leaves. This study evaluated the performance of pre-trained deep CNN models, including Xception, InceptionResNetV2, InceptionV3, and ResNet50, paired with EfficientNetB3-adaptive augmented deep learning (AADL) for precise disease identification. Performance assessment was conducted using parameters such as batch size, dropout, and epoch counts, determining their accuracy, precision, recall, and F1 score. The EfficientNetB3-AADL model outperformed the other models and conventional feature-based methods, achieving a remarkable accuracy of 98.71%. This investigation highlights the potential of the EfficientNetB3-AADL model in offering accurate, real-time disease diagnostics in agricultural systems. The findings suggest that transfer learning and augmented deep learning techniques enhance the accuracy and performance of the model.

INDEX TERMS Adaptive augmented deep learning, convolutional neural network, deep learning, plant disease classification, transfer learning.

I. INTRODUCTION

Agriculture plays a vital role in global economy and serves as the backbone of every developed nation. The production of food, which is essential for human survival, is dependent on agricultural practices [1]. Whether living in urban or rural areas, everyone relies on agricultural production for survival [2]. However, like any field, agriculture faces challenges, with plant diseases being a significant problem for crop production [3]. Despite technological advancements in various domains, farmers often rely on outdated methods of disease detection, physically inspecting plants visually. This farmers' experience-based approach has several limitations [4].

This strategy may help a farmer identify specific plant diseases with which he is already familiar. However, it is less effective for identifying novel and unknown plant diseases. The inability to identify several plant diseases results in a loss

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of food production [5], [6]. Plant disease development may occur due to climate change or due to some type of infection. The two primary forces impacting the ecosystem are biotic and abiotic factors. The abiotic factors [7] encompass elements such as sunlight, air, moisture, minerals, and soil. All non-living, chemical, and physical components present in the atmosphere are referred to as abiotic factors. In contrast, biotic factors [8] pertain to all the living organisms (fungi, viruses, insects, and bacteria) present in an ecosystem [9], [10].

Plant illnesses and diseases can significantly affect the quality and quantity of different plants. In nations where agriculture is the primary source of income and employment, such diseases can have damaging economic effects. Therefore, it is essential to identify, recognize, and treat plant diseases in their early stages to protect the plants from damage and maximize the quality and quantity of the harvest [11].

In recent years, plant disease classification has become increasingly important to prevent the significant losses suffered by various plant species due to harmful diseases. These diseases, which reduce food production and lower plant productivity, can be caused by factors such as global climate change and pollution as displayed in Figure 1. Various technologies, including computer vision [12], machine learning [13], and deep learning-based technologies [14] have been used to identify plant diseases. Convolutional neural networks (CNNs), the most popular deep learning method, have found success in various Computer Vision applications, including traffic detection [15], medical image recognition [16], [17] segmentation images [18], [19], and others.

However, existing studies leveraging deep learning techniques face limitations. These include the use of large datasets with redundant data, small datasets representing only one type of disease, and the utilization of complex models leading to extended training times and increased computational costs. To address these issues, the focus should shifts toward the utilization of compact, efficient datasets and the application of augmentation techniques for more accurate classification. Our research aims to address these gaps by proposing a more efficient and effective approach to plant disease classification, drawing on deep learning-based methodologies prevalent in existing studies [20].

The goal of this research is to assess the performance of pre-trained deep CNN models (Xception [21], InceptionV3 [22], InceptionResnetV2 [22], [23], and Resnet50 [24]) along with the EfficientNetB3-AADL model. This study incorporates 52 classes of various plant diseases for classification, which is a larger number of classes than previous studies have considered. The research aims to demonstrate the effectiveness of our proposed model, emphasizing the potential for improved performance with proper implementation. Additionally, it highlights the advantage of using deep learning algorithms for feature extraction, thus reducing the human effort and time required to establish automated and efficient systems for classifying plant diseases. The contributions to this paper are described below:

- Evaluating the performance of pre-trained deep CNN models (Xception, InceptionResNetV2, InceptionV3, and ResNet50) in conjunction with EfficientNetB3-adaptive augmented deep learning (AADL) for multi-class plant disease classification.
- Investigating the influence of transfer learning [25], [26] on the performance of pre-trained CNN models.
- Implementation of EfficientNetB3-AADL to enhance the robustness of the proposed model, thereby enabling a more comprehensive and reliable classification of various plant diseases.
- Conducting a thorough analysis of existing studies on plant disease classification and highlighting the novelty of the current study using AADL.

The remainder of the paper is structured as follows: Section II reviews related work of existing studies. Section III details the dataset and the proposed approach used and implemented in our research. Section IV presents the results of the experimental evaluation. Section V discusses the results achieved by our model and compares them with existing studies. Finally, Section VI concludes the paper, suggesting potential avenues for further research.

II. RELATED WORK

Plant disease classification presents a significant challenge to farmers worldwide. Traditional methods for identifying plant diseases are often labor-intensive and time-consuming, potentially impacting overall crop productivity. Therefore, early-stage detection of diseases is paramount to prevent widespread contamination. Numerous approaches have been proposed to identify and analyze plant diseases. This section reviews existing researcher on plant disease classification.

Agarwal et al. [27] proposed CNN based architecture for tomato plant disease identification. The accuracy of their model varied from 76% to 100% due to differences in tomato image classes, with an average accuracy rate of 91.2%. However, the study could benefit from extending its research scope to include other diseases and not restrict itself to a single plant species [28].

Srinivas et al. [29] proposed a neural network architecture named AlexNet [30] for disease classification. Their research employed AlexNet with rectified linear units (ReLU) in place of the tanh function. The use of ReLU confers the advantage of six times faster execution than a CNN using the tanh activation function, and the model achieved an overall accuracy of 94%. Alguliyev et al. [31] presented a deep learning model based on a combination of CNN and gated recurrent units (GRU) for the identification of plant leaf diseases across 14 different species, representing 38 different classes. Both the CNN and GRU models were trained together to enhance classification accuracy, which culminated in a 91.19% accuracy rate for the CNN + GRU model.

FIGURE 1. Class-wise sample images of the dataset.

Chen et al. [25] proposed an enhanced VGG model (INC-VGGN) built upon the VGG framework. It incorporated two inception modules, a pooling layer, and replaced the activation function, which led to an average accuracy of 92% for corn plant leaf disease. Xu et al. [32] utilized the VGG16 pre-trained CNN model [33] with a transfer learning strategy proposed to detect maize leaf disease (healthy, leaf blight, and rust) in complex field backgrounds with small dataset sizes. The weight parameters from the VGG16 model, pre-trained on ImageNet, were fed into the model, achieving an average accuracy rate of 95.33%.

In study [34], a deep learning model, specifically a CNN, was trained on the Plant Village dataset, comprising over 55,000 images with 38 classes across 14 different plant species, to classify various plant diseases. The CNN model was compared to pre-trained models such as VGG, ResNet, and DenseNet, achieving an overall accuracy of 94.58%. The deep learning model outperformed manual plant leaf disease detection in both speed and accuracy.

CNN was used by Kim et al. [35] to construct an apple leaf classification algorithm that achieved a 92.43% accuracy rate on the Plant Village dataset. A model for categorizing diseases in grape and mango leaves using a pre-trained AlexNet model was proposed by [36]. The authors of [37] proposed a hybrid model that combines a deep learning model with principal component analysis (PCA) and the whale optimization algorithm for diagnosing tomato diseases. Their dataset, derived from Plant Village, contained 18,160 images of tomato leaves divided into 10 different classifications. The hybrid model achieved a testing accuracy of 86% with the Adam optimizer and 94% with the RMSprop optimizer.

Arsenovic et al. [38] presented a CNN architecture for classification of plant diseases using photographs taken in actual environments with varying angles, weather conditions, and backgrounds. The proposed model achieved an accuracy of 93.67%. In [39], the authors used an online dataset of 3,248 images of 14 plant diseases and employed image data augmentation techniques to increase the dataset's size to over 30,000 images. With minor changes in model parameters, their CNN model achieved a 94% accuracy rate.

In [40], using 2,816 images, researchers evaluated the performance of various deep learning models, including EfficientNet, VGG, ResNet, AlexNet, Inception v4, SqueezeNet, and DenseNet, for classifying cucumber diseases using 2,816 images. They also used image augmentation to increase the dataset size to 20,256 images. The EfficientNet-B4 model achieved a testing accuracy of 90.45% with the Adam optimizer, 85.37% with the SGD optimizer, and 94.81% with the RMSprop optimizer.

In study [41], the authors used a CNN based architecture for classifying cucumber disease. The dataset contained 14,208 leaf images of cucumbers. The model achieved an overall accuracy of 93.4%. Harte et al. [42] demonstrated how CNN models can assist small-scale farmers in detecting and diagnosing plant leaf diseases by analyzing healthy and diseased leaf tissue. Conversely, Reddy et al. [43] proposed a framework for distinguishing between healthy and diseased leaves, using image processing techniques in the preprocessing stage.

In conclusion, the significant challenge for researchers is to develop a robust deep learning-based framework for plant disease classification that addresses common issues with minimal limitations and produces accurate results. The literature review indicates that existing studies in this field have limitations, such as using various datasets of different sizes and sources, which often contain redundant data, and employing complex models, which lead to extended training times and higher computational costs. These issues manifest in problems such as overfitting, high computational costs, and a need for improvements in accuracy and computation time.

The objective is to develop an efficient deep learning-based CNN framework that yields reliable results with the fewest limitations.

III. MATERIALS AND METHODS

The following section presents the architecture of the deep learning model and the materials used for the experiment in this study. The description will cover every technology used and all the necessary background knowledge needed to understand the proposed approach.

A. DATASET

The dataset used in this research comes from Kaggle and contains 58 classes of healthy and unhealthy plants, with a total of 59,809 images. The dataset was filtered to include only classes with a significant sample size, implying that only classes with at least 36 images were included in the dataset, and any classes with fewer than 36 images were excluded. The dataset was then divided into training, validation, and test sets using the train test split function from the sci-kit-learn library. Here, 90% of the data was used for training, and the remaining 10% was evenly split between validation and test sets. All images in the dataset have dimensions of $256 \times 256 \times 3$, indicating that each image has a width and height of 256, with three channels representing the RGB format. These images were then resized according to network requirements. Some of the sample images available for each class of plant diseases have been shown in Figure 1.

B. DATA PREPROCESSING

The data preprocessing in this research included the following steps:

1) Importing the dataset from Kaggle to Google Colab.
2) A trim function was defined in the experiment to limit the size of the dataset and balance the number of images per class. This function adjusted the number of samples to be between a maximum of 200 and a minimum of 36.
3) The AADL technique [44], [45] was used to further balance the dataset. This function applied visual transformations such as horizontal flipping, rotation, and zooming to generate augmented and balanced images. The goal of AADL was to achieve the desired number of samples per class.
4) After data preprocessing, the resulting dataset included 10,400 images of 52 classes in the training set, 3,323 images in the validation set, and 3,323 images in the test set.

The dataset used in this research includes a wide range of images, creating a large dataset. Training on such a large dataset demands considerable resources and can be time-consuming. To overcome this challenge, we employed the proposed AADL method to reduce the dataset size and balance it for our model. Table 1 illustrates some images in our dataset before and after applying the data augmentation method. These techniques aim to decrease computational cost and prevent overfitting. The term ‘‘adaptive’’ in AADL suggests that when there is a large dataset, our framework automatically balances it by reducing its size, making model training more manageable. Thus, our approach sets itself apart from traditional models by incorporating AADL and using a data trimming method. Table 2 lists the methods set for data augmentation.

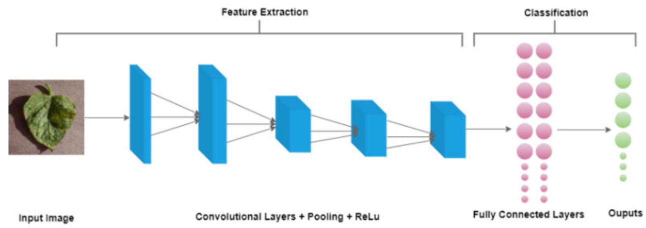

FIGURE 2. Representation of convolutional neural network architecture.

C. METHODOLOGY

1) CONVOLUTIONAL NEURAL NETWORKS

CNN is among the most recognized and extensively used algorithms in the field of deep learning (DL). The primary advantage of CNN over its predecessors is its ability to autonomously recognize unique features, without the need for human intervention. CNNs have been massively utilized across various domains, including computer vision [46], speech processing [47], face recognition [48], [49], image segmentation [50], image classification [51], and video analysis [52], among others. The architecture of CNNs is inspired by neurons in the human and animal brain, similar to a standard neural network.

A CNN architecture consists of several convolution layers that precede subsampling (pooling) and fully connected (FC) layers at the end. CNNs are feed-forward neural networks, meaning data flows from the input layer to the output layer without looping back. As depicted in Figure 2, the CNN framework is comprised of input, hidden, and FC (output) layers. The hidden layers include convolutional, ReLU, and pooling layers, which are combined to form a single network [53].

Let us examine the CNN architecture by considering an input, x, divided into three dimensions: height (m), width (m), and depth (r), where the height is equal to the width. The depth is also referred to as the number of channels. For example, the depth (r) of an RGB image is three. Similar to the input image, each convolutional layer's kernels (or filters) denoted by k, have three dimensions ($n \times n \times q$), where n is smaller than m, and q is equal to or smaller than r. The convolutional layer performs a dot product between its input and weights, as depicted in (2), although the inputs are half the size of the original image.

ReLU is the most commonly used activation function in the CNN environment. It transforms all negative inputs to zero. ReLU is advantageous over other functions because it requires less computational resources. By setting all negative

TABLE 1. Data preprocessing of 52 classes of plant diseases.

Plant Disease	Before AADL Methodology	After AADL Methodology
Apple scab	1814	200
Apple black rot	1789	200
Apple cedar apple rust	792	200
Apple healthy	1184	200
Bacterial leaf blight in rice leaf	36	200
Blight in corn leaf	1031	200
Blueberry healthy	1082	200
Brown spot in rice leaf	36	200
Cercospora leaf spot	57	200
Cherry (including sour) powdery mildew	758	200
Cherry (including sour) healthy	616	200
Common rust in corn leaf	1175	200
Corn (maize) healthy	837	200
Garlic	44	200
Grape black rot	3398	200
Grape esca black measles	3985	200
Grape leaf blight Isariopsis leaf spot	3100	200
Grape healthy	305	200
Gray leaf spot in corn leaf	517	200
Leaf smut in rice leaf	36	200
Orange Haunglongbing citrus greening	1561	200
Peach healthy	259	200
Pepper bell bacterial spot	897	200
Pepper bell healthy	1065	200
Potato early blight	900	200
Potato late blight	900	200
Potato healthy	110	200
Raspberry healthy	267	200
Strawberry leaf scorch	799	200
Soybean healthy	3665	200
Strawberry healthy	328	200
Tomato bacterial spot	1914	200
Tomato early blight	900	200
Tomato late blight	1718	200
Tomato leaf mold	857	200
Tomato Septoria leaf spot	1594	200
Tomato spider mites two spotted	1508	200
Tomato target spot	1264	200
Tomato mosaic virus	336	200
Tomato healthy	1146	200
Algal leaf in tea	102	200
Anthracnose in tea	90	200
Bird eye spot in tea	90	200
Brown blight in tea	102	200
Cabbage looper	70	200
Corn crop	94	200
Ginger	40	200
Healthy tea leaf	67	200
Lemon canker	55	200
Potato hollow heart	54	200
Red leaf spot in tea	129	200
Potato crop	36	200

pixels to zero, ReLU introduces nonlinearity into the network. The output is then fed into the subsequent layer [53].

$$f(x)_{ReLU} = \max(0, x) \tag{1}$$

Next, upon applying an activation function to the output of the convolution layer, we obtain the following results:

$$h^k = f(W^k * x + b^k) \tag{2}$$

Then, in the pooling layers, each feature map is down-scaled, thereby reducing the network parameters, amplifying the training process, and mitigating the overfitting problem. A pooling function (such as max or average) is applied to a local region of size p × p (where p is the kernel size) for each feature map. For classification, the network "flattens" the 2D visual data into a 1D vector that represents image-level features via FC layers. The final layer uses the softmax activation function to produce classification scores. Each score

TABLE 2. Settings used for data augmentation.

Method	Quantity
Flipping	Horizontal
Rotation range	20
Width shift range	0.2
Height shift range	0.2
Zoom range	0.2

corresponds to the probability of a specific class. The softmax activation function is described by (3).

$$\sigma(\overrightarrow{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{3}$$

The input vector of the softmax function is represented as $(\overrightarrow{z})$, where z_i refers to the input vector's i^{th} element, which can be any real number. The normalization factor at the bottom of the equation ensures that all the output values of the function sum to 1, creating a proper probability distribution. K refers to the number of possible classes in the dataset.

2) TRANSFER LEARNING APPROACH

In the field of DL, the practice of using a network that has already been trained on a particular task is known as transfer learning [25]. Transfer learning is especially popular in DL due to its capability to train the network with less input and with higher accuracy. It allows a machine to use information gained from one task to perform better on a different, yet related task. In transfer learning, the last few layers of the trained network are replaced with new ones. These can be FC and a softmax classification layers with the number of classes utilized in this study [26].

There are several advantages to transfer learning. Firstly, the network can be trained with less data. It enhances learning by transferring knowledge from a previously learned task to the new task at hand. Many studies have used transfer learning in their disease detection strategies. Another benefit is the reduction in training time, generalization error, and the computational cost associated with building a DL model [25]. In this study, we adopted the concept of a transfer learning strategy by using pre-trained CNN models for the classification task.

D. PROPOSED FRAMEWORK

The primary contribution of this research lies in the evaluation of the performance of pre-trained DL models [54], particularly contrasting them with our proposed EfficientNetB3-AADL model that utilized AADL. The AADL method applies transfer learning, fine-tuning, and data augmentation techniques [44], [45] to balance the large dataset size. The model can classify 52 classes of plant diseases, though the input size of the images may vary based on the architecture. To prevent overfitting, fine-tuning parameters such as batch normalization, dropout, L1 and L2 regularization [55], and adjustments to the learning rate are used.

Data augmentation and trimming techniques increase the diversity of the training data. The last three layers of each pre-trained model are replaced, ensuring that the final output layer aligns with the number of classes in the dataset. The EfficientNetB3-AADL model is customized by adding extra layers such as convolutional and max pooling layers, to make it more robust and reliable for multi-class plant disease classification. The proposed framework of our research is depicted in Figure 3.

1) EFFICIENTNETB3-AADL

EfficientNet [56] is a CNN architecture that comes in various versions, ranging from EfficientNetB0 to EfficientNetB7. To achieve maximum model accuracy, EfficientNet models are built on the principle of compound scaling, which scales up the convolution network model size in a balanced way to the desired size. Compound scaling is a technique that uses a compound coefficient to uniformly scale all dimensions. This method allows for balanced scaling across the width, depth, and resolution of the network.

The EfficientNet model comprises mobile inverted bottleneck convolution blocks MBConv, with varying kernel sizes of 3 × 3 and 5 × 5. This architecture significantly reduces computation by a factor of f^2 where f is the filter size, compared to traditional convolution [57]. With the application of a compound scaling coefficient, the network's depth, width, and resolution are uniformly extended. We utilized EfficientNetB3 for our classification task since larger networks with increased width, depth, or resolution generally result in higher accuracy. The EfficientNetB3 model has a depth of 210 layers, consists of 11.1 M parameters, and has an input shape of 300 × 300 × 3. Due to its deeper network, the EfficientNetB3 model better understands complex features and generalizes to new tasks [56], [58].

The proposed EfficientNetB3 model was customized by adding a convolutional layer with 32 filters defined with a kernel size of 2 × 2, and a max pooling layer of 2 × 2 kernel size with stride 2 to make the model more robust than the standard EfficientNetB3 model. We also fine-tuned parameters such as replacing the final three layers of this model, with the requirement that the final output layer matches the number of classes in the dataset. A batch normalization layer, and L1 and L2 regularization techniques were employed to prevent overfitting.

A dropout layer was added to enhance the reliability of the model for classification. Furthermore, a dense layer with 256 neurons was added to our model. Given the large size of the dataset used in this study, training the model on the entire dataset was challenging due to the computational resources and time required. To address this, we proposed a method called AADL to reduce the dataset size and balance it for the

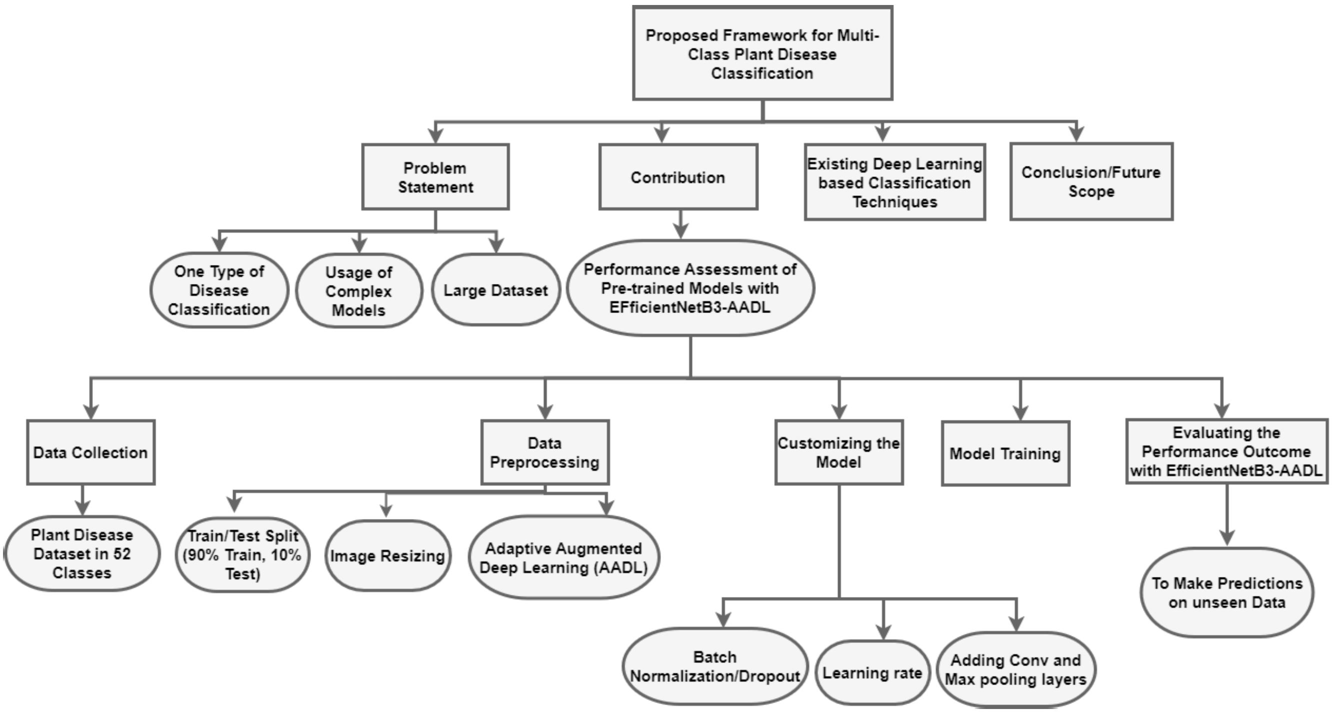

FIGURE 3. Representation of proposed framework.

model. The aim of using this method is to decrease computational time and avoid overfitting. This method includes data trimming to make our model more robust in achieving high accuracy. The method also aims to increase the diversity of the training data through augmentation.

The term ''adaptive'' in augmented DL method signifies the automatic adjustment capability of the framework to balance a large dataset by reducing its size, facilitating more efficient model training. The AADL methodology in this paper showcases the efficacy of transfer learning and data augmentation techniques in enhancing the accuracy of plant disease classification. The architectures utilized were chosen due to their recent designs, specifically developed to improve performance on image classification tasks.

These architectures have proven to be more efficient and outperform their predecessors. The distinctive characteristic of EfficientNetB3-AADL is its application of the compound scaling method, which concurrently scales network depth, width, and resolution. Compared to traditional scaling techniques that primarily focus on a single network dimension, this leads to a noticeable enhancement in performance. EfficientNetB3-AADL integrates a lightweight convolutional layer along with an efficient architecture, reducing computational requirements while maintaining good accuracy. Figure 4 shows our proposed model architecture. The novelty of this research lies in the application of our customized model and AADL methodology to bolster the efficiency, effectiveness, and robustness of the EfficientNetB3-AADL model. This enhances its accuracy in classifying 52 classes of plant diseases. Furthermore, it is clear that this model has fewer parameters than other architectures utilized for experimental comparisons.

E. IMPLEMENTATION

The study primarily focused on performance evaluation of pre-trained CNN models and the EfficientNetB3-AADL in the classification of plant diseases. The input images were resized to meet the network's requirements, and the number of classes was set to match the output classification layers. Training images were passed through multiple filters at varying resolutions, with the output of each convolution serving as the input for the succeeding layer.

The layer progression in the model led to increasingly complex features that differentiate leaf objects from others. The model was trained to classify diverse plant diseases into distinct categories. Each image output yields a probability score for each disease, with the model selecting the disease having the highest probability as its classification result. Listed below are the primary features and algorithmic steps of the proposed approach:

1) Load the image dataset comprising 52 classes of varied plant diseases. Filter the list to only include classes having a minimum number of images. Classes with a smaller number of images are omitted from the dataset.
2) Utilize the train_test_split function to divide the dataset into training, validation, and testing datasets, such that 90% of the data is allocated for training and the remaining 10% for testing and validation. The AADL

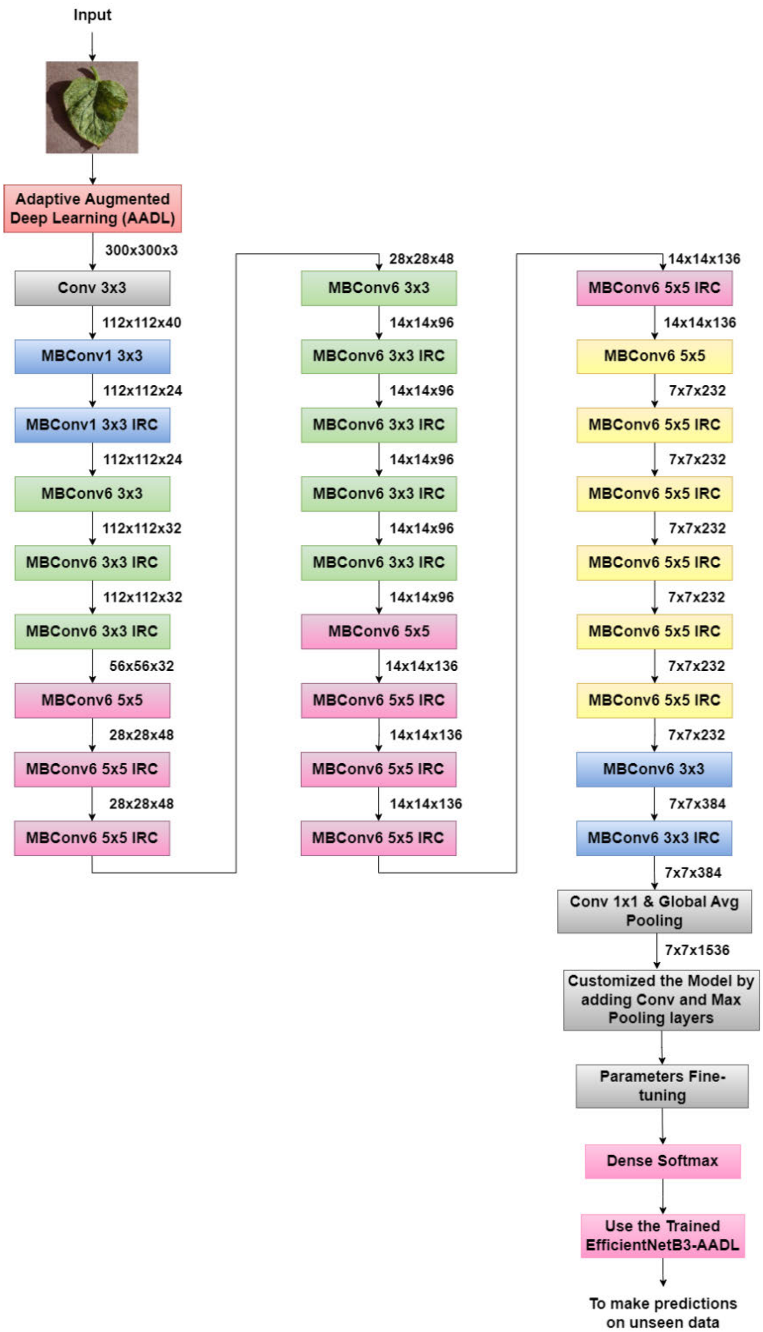

FIGURE 4. Proposed EfficientNetB3-AADL architecture.

methodology is applied to balance and reduce the size of the dataset.

3) Use EfficientNetB3-AADL as the base model.
4) Customize the EfficientNetB3-AADL model by adding a convolutional layer with 32 defined filters, each of kernel size 2 × 2, and a max pooling layer of 2 × 2 kernel size with stride 2, enhancing the model's robustness.
5) Add a batch normalization layer to the output of the base model. Flatten the output of this layer and add a dense layer with 256 neurons employing L2 and L1 regularization, and a ReLU activation function.
6) Integrate a dropout layer with a rate of 0.4 and a final dense layer with the number of neurons equivalent to the number of classes. Use a softmax activation function.

7) Define a model that accepts the base model's inputs and gives the final dense layer's outputs. Compile the model using the Adamax optimizer and categorical cross-entropy loss function.
8) Train the EfficientNetB3-AADL model with an initial learning rate of 0.001. Utilize the LR_ASK callback function and Adamax optimizer for enhanced training performance and control.
9) Train the model for 10 epochs and evaluate its performance using the testing dataset.
10) Compare the performance of the EfficientNetB3-AADL model with pre-trained models and make predictions on new data.

It is important to note that in our experiment, our model did not require more than 10 epochs of training. We achieved our threshold accuracy within 10 epochs. The visualization of results from our proposed model is presented in the results section, further demonstrating the potential effectiveness of our approach.

IV. EXPERIMENTAL RESULTS

This section discusses the experimental setup, model performances, and results. It also elucidates the performance of our DL models on the dataset in terms of accuracy, precision, recall, and F1 score. We will compare our pre-trained models with the EfficientNetB3-AADL model and visualize the results achieved in this research.

A. EXPERIMENTAL SETUP

The study juxtaposed the performance of pre-trained CNN models with the EfficientNetB3-AADL model using the adaptive augmented deep learning technique for plant disease classification. The models were trained and evaluated on the Google Colab platform, leveraging a GPU, Python 3.7, Tensorflow, Scikit learns, and Keras library on an Intel Core i3 CPU. The plant disease dataset was split into training, validation, and testing datasets, and augmented DL was utilized to mitigate the risk of overfitting.

The data augmentation technique was applied to the training set, whereas the testing and validation sets comprised 3,323 images spanning 52 classes. The training set contained 10,400 images across 52 classes. All images were resized to meet the model's requirements. Table 1 delineates the original dataset size before applying the AADL methodology and the augmented dataset size post-AADL methodology. This approach comprises data trimming to bolster the model's robustness in achieving high accuracy, as well as enhancing the diversity of the training data via augmentation.

Following the application of the AADL methodology to the dataset, the model architecture was constructed by adding various convolutional and max pooling layers, leveraging CNN ImageNet weights [59]. Various hyperparameters were established for training and evaluation as displayed in Table 3. The Adamax optimizer [60], [61] was used for data training and the ReLU activation function was employed to avoid the vanishing gradient problem. Regularization techniques, including batch normalization, L1 and L2 regularization, and dropout [55] were utilized to prevent overfitting. The model was trained for 10 epochs with a learning rate of 0.001, and a batch size of 20. Another novelty of our research is the introduction of an LR_ASK callback class that allows users to continue training, halt training, or adjust the learning rate value.

TABLE 3. Hyperparameters and other characteristics of proposed model.

Parameters	Values
Batch size	20
Epochs	10
Dropout rate	0.4
Learning rate	0.001
Loss function	Categorical cross-entropy
Momentum	0.99
L1 regularization	0.006
L2 regularization	0.016
Optimizer	Adamax

The categorical cross-entropy loss function was employed to assess the model's performance. Typically, this function was used to evaluate our model's performance. The categorical cross-entropy loss function was applied when altering the model's weights during training, with the goal of minimizing the loss; lower loss means higher model accuracy. This loss function calculates the difference between output probabilities and true values. It is defined in (4):

$$\textit{Categorical Crossentropy Loss} = -\sum\nolimits_{i-1}^{n} t_i \log(p_i) \quad (4)$$

where n denotes the number of classes in the dataset, t_i represents the actual label, and p_i is the softmax probability for i^{th} class.

The Adamax optimizer, another variation of the Adam optimizer [61], was chosen due to its proficiency in handling sparse updates and achieving superior accuracy compared to other optimizers. The choice of optimizer can significantly impact the model's accuracy, and the Adamax optimizer has proven to deliver the highest accuracy in such cases. The equation for Adamax can be seen in (5):

$$\begin{aligned} m_t &= \beta_1 m_{t-1} + (1-\beta_1)\, g_t \\ v_t &= \beta_2 v_{t-1} + (1-\beta_2)\, g_t^2 \end{aligned} \quad (5)$$

where g represents the gradient on the current mini-batch, m and v denotes moving averages, and the β represents the recently introduced hyperparameters of the method. Each of them has excellent default values of 0.9 and 0.999, which are seldom altered in practice. At the beginning of the iteration, the moving average vectors were initialized with zeros.

Having set up the training environment required for our experiment; we trained our EfficientNetB3-AADL model on the dataset. However, our model did not need to be trained for more than 10 epochs in any of our experiments. We were able to achieve our desired accuracy at 10 epochs, further demonstrating the potential of our suggested approach. After training the model, we evaluated our model's performance against four other pre-trained models and concluded that our proposed model outperformed the pre-trained models. We selected the EfficientNetB3-AADL as the optimal model for classification due to its outstanding performance. A visual representation of our best model during the training phase is provided in Figure 5.

Figure 5 clearly demonstrates that the EfficientNetB3-AADL model achieved the highest accuracy during the training phase. This model reached a training accuracy of 0.9914, which is notably higher than the other pre-trained models used in this study. These results establish that the performance of this model surpasses that of the other pre-trained models during the training phase.

B. EVALUATION METRICS

Evaluation metrics are crucial in DL endeavors to identify the most effective classifier [62]. We assessed our models using the accuracy, precision, recall, and F1-measure metrics.

1) ACCURACY

The accuracy metric quantifies the ratio of correctly predicted classes to all samples analyzed.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

2) PRECISION

Precision identifies how accurately the predicted patterns in a positive class represent positive patterns.

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

3) RECALL (SENSITIVITY)

Sensitivity, or recall, calculates the percentage of correctly identified positive patterns.

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

4) F1 SCORE

The F1-score measures the harmonic average of recall and precision rates.

$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

5) CONFUSION MATRIX

Confusion matrices provide counts of predicted and actual values. They present four primary categories: true positive (TP), false positive (FP), true negative (TN), and false negative (FN). A confusion matrix, also referred to as an error matrix, is a table showing various combinations of predicted and actual values, which demonstrates how a classification model is performed on a test dataset.

TABLE 4. Performance Comparison of efficientnetb3-aadl model with other pre-trained models.

Network	Accuracy	Precision	Recall	F1 score
InceptionV3	97.08%	97.26%	97.08%	97.08%
InceptionReNetV2	97.74%	97.95%	97.74%	97.75%
ResNet50	95.94%	95.53%	95.94%	95.98%
Xception	98.50%	98.68%	98.50%	98.52%
EfficientNetB3-AADL	**98.71%**	**98.85%**	**98.71%**	**98.72%**

Upon evaluating each pre-trained CNN model and the EfficientNetB3-AADL model using the test dataset, we found that the EfficientNetB3-AADL model achieved the highest accuracy compared to the other models in our research. The performance evaluation of the utilized pre-trained models and the EfficientNetB3-AADL model, using the test dataset, in terms of accuracy, precision, recall, and F1 score is described in Table 4.

The performances of all models were observed to be comparable and statistically significant. However, the EfficientNetB3-AADL model outperformed the others in terms of accuracy, precision, recall, and F1 score. After generating a classification report for the proposed models, a confusion matrix was created to evaluate their performance on the test dataset. Figure 6 presents the confusion matrix of the EfficientNetB3-AADL model, which according to the performance metrics, delivered the best results. Based on these outcomes, visual assessment of the proposed model's performance can help identify the classes that are prioritized by our proposed model's neurons. The columns of the matrix correspond to the actual class while the rows represent the predicted class. The diagonal cells are associated with correct classification, whereas the off-diagonal cells denote misclassifications.

The aim of this research was to compare the performance of state-of-the-art pre-trained models (Xception, Inception-ResNetV2, InceptionV3, and ResNet50) with the customized EfficientNetB3-AADL model for classifying plant disease images. The study featured the use of transfer learning and data augmentation techniques, model customization through addition of convolutional and max pooling layers, training with the Adamax optimizer, performance evaluation via the categorical cross-entropy loss function and accuracy metric, and comparison to determine the best-performing model. The EfficientNetB3-AADL architecture was found to achieve the highest accuracy of 98.71%.

Furthermore, the study aimed to emphasize the importance of using balanced datasets coupled with augmentation techniques for classification tasks. It suggested that future research could benefit from testing these models on

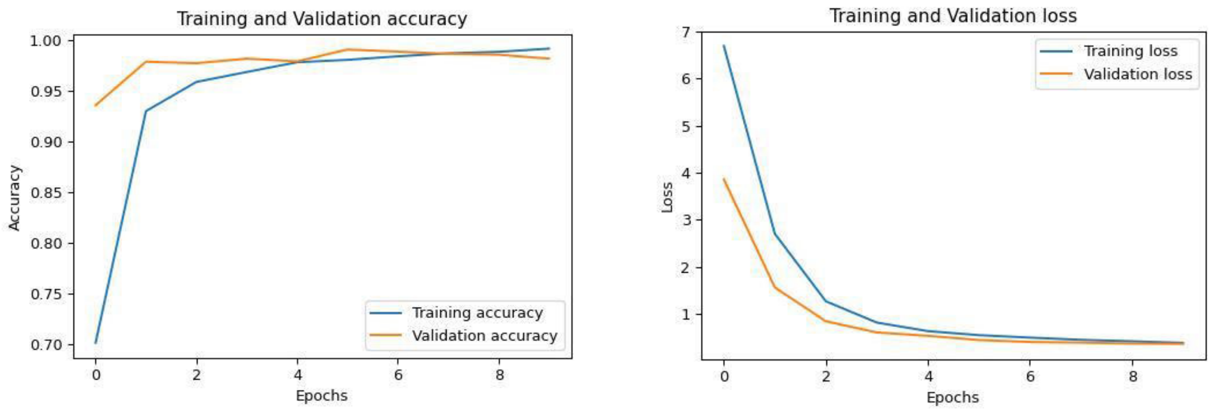

FIGURE 5. Performance of proposed EfficientNetB3-AADL.

TABLE 5. Comparison of different state-of-the-art-work with our proposed model.

Study	Dataset	Model	Accuracy	Precision	Recall	F1 score
[27]	17,500 tomato images in 10 classes	CNN based model	91.2%	-	-	-
[34]	38 classes of 14 different plant species	CNN based model	94.58%	-	-	-
[35]	Apple leaf disease	CNN based model	92.43%	-	-	-
[37]	18,160 tomato images in 10 classes	Hybrid deep model with Adam optimizer, Hybrid deep model with RMSprop optimizer	86% 94%	- -	- -	- -
[38]	Different classes of plant diseases	CNN based model	93.67%	-	-	-
[29]	87,000 plant images	CNN based AlexNet model	94%	-	-	-
[31]	87,867 plant images in 38 classes	CNN + GRU (gated recurrent units)	91.19%	92%	91.20%	91.26%
[39]	30,000 images of 14 different plant diseases	CNN model	94%	-	-	-
[41]	14,208 images of different plant disease	CNN based model	93.4%	-	-	-
[25]	Corn plant leaf disease	VGG with inception modules (INC-VGGN)	92%	-	-	-
[40]	20,256 images of plant diseases	Pre-trained EfficientNetB4(Adam), Pre-trained EfficientNetB4 (RMSprop), Pre-trained EfficientNetB4 (SGD)	90.45% 85.37% 94.81%	- - -	- - -	- - -
Our Study	17,046 plant images in 52 classes	**EfficientNetB3-AADL**	**98.71%**	**98.85%**	**98.71%**	**98.72%**

real-time environmental images. Overall, this study contributes significantly to the field of image classification, highlighting the importance of suitable techniques for achieving high accuracy in classification tasks and suggesting potential avenues for future research to further advance the field.

V. DISCUSSION

This research utilized transfer learning and deep learning (DL) techniques [63] for plant disease classification. The proposed EfficientNetB3-AADL model was compared to pre-trained models (Xception, InceptionResNetV2, InceptionV3, and ResNet50). Through hyperparameter

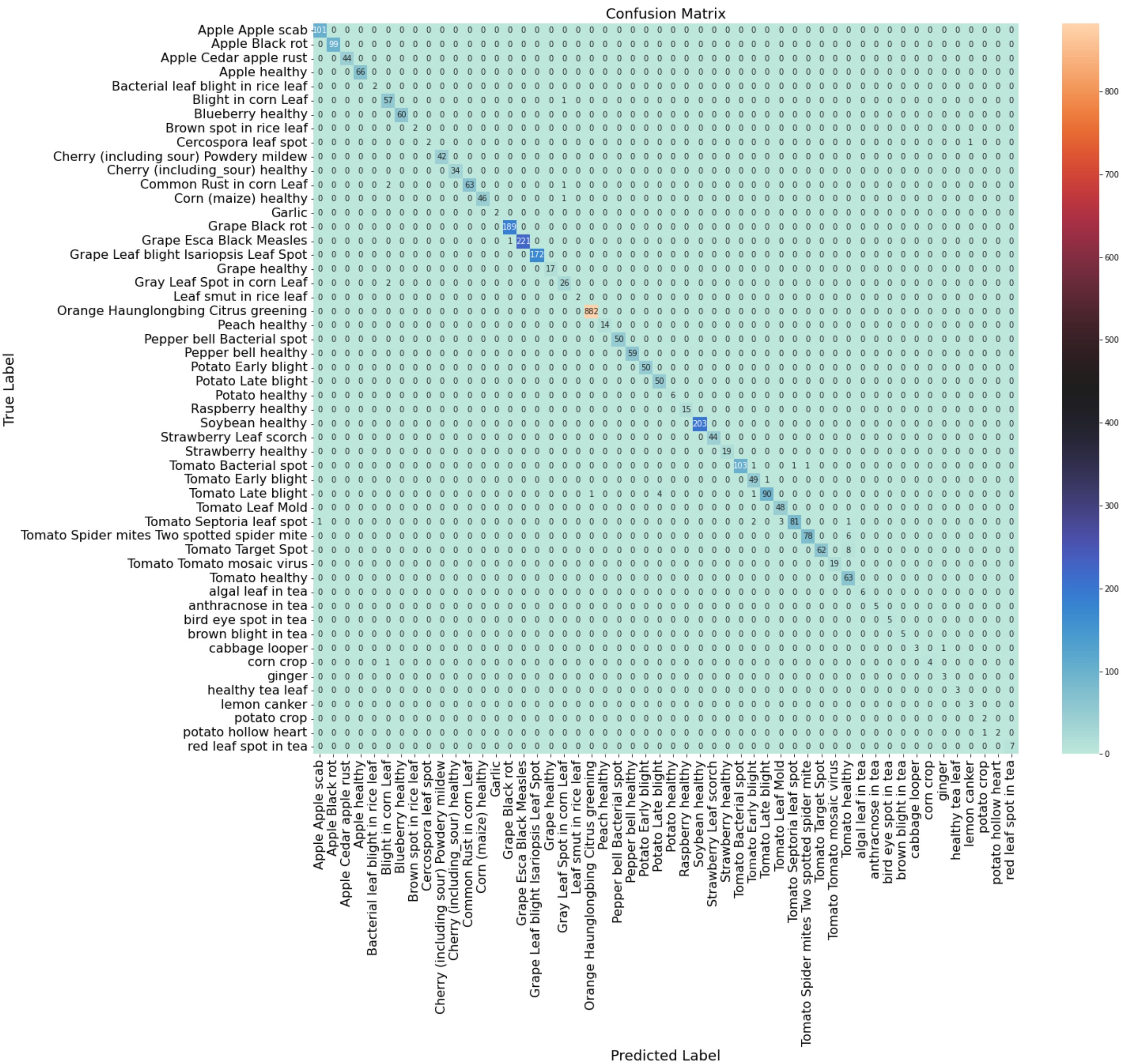

FIGURE 6. Confusion matrix for EfficientNetB3-AADL model.

optimization and augmented DL, EfficientNetB3-AADL achieved the highest accuracy of 98.71%, outperforming other methods.

The uniqueness of this research lies in a dataset consisting of 52 different plant disease classes, the implementation of transfer learning for leveraging the feature extraction capabilities of pre-trained models, and the application of augmented DL techniques with Adamax optimization to enrich the diversity of the training data. Our model was also customized with additional convolutional and max pooling layers, which contributed to the achieved high accuracy in disease classification. The superior accuracy of the EfficientNetB3-AADL model can be attributed to its optimized structure, which strikes an excellent balance between accuracy and efficiency. With fewer parameters compared to other models and a unique architecture optimized for scale, including efficient building blocks and a compound scaling method, EfficientNetB3-AADL is an optimal choice for large-scale image classification tasks. Consequently, it achieved an accuracy of 98.71%, outperforming the other pre-trained models.

However, the study has certain limitations. For instance, the misclassification of some sample images occurred due to minor noise. The test images were captured in a laboratory setting rather than real-time field conditions, which could

FIGURE 7. Prediction results of proposed EfficientNetB3-AADL.

potentially affect the model's generalizability. Moreover, the use of pre-trained models significantly slows down the training process, particularly on machines without a powerful GPU.

Future work could concentrate on integrating recent advancements in DL to enhance the model's accuracy and efficiency further. The study underscored the importance of employing balanced datasets with augmentation and data trimming techniques for classification tasks and proposed that subsequent research could mitigate some of the limitations of this study by testing the models on real-time environmental images. The study makes valuable contributions to the field of image classification, emphasizing the significance of employing suitable techniques for high accuracy in such tasks. It also suggests directions for future research that could further advance the field. A comparison of our findings with those of previous studies is presented in Table 5.

A. PREDICTION PERFORMANCE OF OUR PROPOSED APPROACH

To evaluate the performance of our model, we made predictions on the test dataset to assess how well our proposed model performs on unseen data. Figure 7 showcases the predictions and results made by our proposed model. The actual label of each class is also provided along with the predicted result, making it easier to understand the actual label of a particular class and what our proposed model predicted for each unseen data point. Our proposed model correctly predicted almost every image. Therefore, we can assert that our proposed model, trained using augmentation techniques, Adamax optimizer, a learning rate function, and the customization of our model with additional layers, achieved superior accuracy compared to other pre-trained models.

VI. CONCLUSION

This research aimed to develop a DL-based transfer learning strategy for multi-class plant disease classification. The study evaluated the performance of pre-trained deep CNN models (Xception, InceptionResNetV2, InceptionV3, and ResNet50) and compared them with the customized EfficientNetB3 AADL model for accurate disease classification. The results demonstrated that the EfficientNetB3-AADL architecture achieved the highest accuracy of 98.71% among the pre-trained models. The precision, recall, and F1 score of the proposed model were 98.85%, 98.71%, and 98.72%, respectively. The study highlighted the effectiveness of transfer learning, AADL techniques, and model customization in improving accuracy and performance. However, the model has certain limitations, including slow training time without a strong GPU, potential misclassification due to noise, and the need for real-time field testing. Future research can focus on testing the models on real-time environmental images to address these limitations and incorporate the latest advancements in DL to further enhance the model's accuracy and effectiveness.

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