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Early Blight and Late Blight Disease Detection in Potato Using Efficientnetb0

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Abstract: Potatoes are an important crop heavily consumed by Indian food products. It is produced on a massive scale, with China, India, Russia, Poland, and the USA being the main producers. Numerous leaf diseases harm the crop during its production. A typical Indian farmer lacks the tools necessary to detect Leaf Disease before damage is done. On a dataset of potato leaf images retrieved from Kaggle, we employed the EfficientNetB0 of Deep Learning to address this problem. This model uses width scaling and resolution scaling apart from depth scaling to perform the classification. Our work mainly focuses on the diseases Early Blight and Late Blight, two serious potato diseases. Early blight Spots start off as tiny, dry, dark, and papery specks that develop into brown to black, circular to oval-shaped regions. Veins that round the spots frequently give them an angular appearance. Late blight syntoms appear as small, light to dark green and round to irregularly shaped. Water-soaked patches are the first signs of late blight. The Data Collection has 2152 pictures in total, 2000 of which are diseased and 152 of which are healthy. The deep learning model provides a testing accuracy of 99.05%, which is higher than several widely used techniques available to provide farmers with knowledge about correct diseases well in time.

Introduction

Agriculture sustains approximately 70% of India's population, pivotal in its development. However, crop damage, particularly from leaf diseases, significantly threatens agricultural productivity and farmers' livelihoods. Leaf diseases, being the primary indicators of plant health, require vigilant monitoring throughout the crop lifecycle to minimize losses and ensure food security.

While traditional disease detection methods rely on expert visual inspection, recent advancements in automated and semi-automated systems offer promising alternatives (Bulawit et al., 2023). These technologies leverage various tools and methodologies, providing faster, more cost-effective, and precise solutions compared to manual inspection methods. For instance, diseases such as late blight (Phytophthora infestans) and early blight (*Alternaria solani*) are prevalent in potato crops across India, underscoring the importance of accurate disease detection systems tailored to specific regional contexts.

Despite the availability of such technologies, farmers often lack comprehensive knowledge about crop diseases, hindering effective disease management practices. Bridging this knowledge gap and empowering farmers with expert guidance and diverse knowledge sources are critical steps toward improving disease control measures and optimizing agricultural productivity (De and Dey, 2022).

In the realm of image recognition and classification, deep learning techniques, particularly convolutional neural networks (CNNs), have emerged as powerful tools for disease diagnosis and classification. These techniques leverage vast datasets to generate insights and predictions with unprecedented accuracy, revolutionizing agricultural practices. However, implementing deep learning models in agriculture presents its own challenges, including the need for substantial computational resources and the complexities of training with large datasets and intricate hyperparameters (Dawn et al., 2023).

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This study aims to address these challenges by developing and validating a deep learning-based disease detection model tailored to the specific context of potato cultivation in India. The dataset was divided into training and validation sets, with 20% of each class's images used for validation and 80% used for training. By leveraging state-of-the-art methodologies and insights from previous research, this study aims to enhance disease detection accuracy, streamline agricultural practices, and ultimately contribute to sustainable food production.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive literature review, highlighting previous research efforts in the field. Section 3 identifies research gaps and outlines the contributions of the present study. Section 4 elaborates on the methods and materials employed in the research, including the validation process. Section 5 offers a detailed discussion of experimental results and the performance of the proposed model. Finally, conclusions drawn from the study and avenues for future research are presented in the concluding section.

Literature Review

Machine Learning based Techniques

By using discriminant analysis and Bayesian discriminant principal component analysis (PCA) the author extracted 18 variables from the anthracnose images on tomato leaves, including colour, compactness, and configuration points. They investigated early and late blight, leaf spot, and other tomato illnesses. They used Fisher's discriminant to build the distribution model. The effectiveness of the Discriminant Analysis is 94.71% and PCA is 98.32%, respectively (ALi et al., 2010)

Five types of apple leaf diseases (mottled leaf, yellow leaf, round spot, mosaic, and rust diseases) were selected. The backpropagation method was employed to identify and detect the illness, with a mean accuracy of 92.6%, by deriving 8 apple leaf picture properties, hue, form, and structure (Liu et al., 2018).

In the article "Applying Image Processing Techniques to Detect Plant Diseases" depicts how to use Artificial neural networks (ANNs) and various imaging techniques to detect diseases early and accurately. The proposed method, built on the ANN model for categorization and the Gabor filter for extracting features, provides results with a detection rate of up to 90.5% (Kulkarni and K, 2012).

The authors presented a technique for diagnosing illnesses using recorded images of leaf diseases (Ranjan et al., 2015). An artificial neural network (ANN) is trained by selecting useful parameters to distinguish diseased plants from healthy specimens. An accuracy of roughly 80% is obtained using the neural network model (Ranjan et al., 2015)

Authors include four key steps in the disease diagnosis process: First, obtain the color conversion model for the RGB input (Arivazhagan et al., 2013). Then, decide to use some threshold to identify and ignore the green pixels. Then, segmentation is performed to calculate the tissue statistics and obtain the fragment. Finally, the classifier is used to classify organisms based on acquired characteristics. The achieved accuracy was 94% (Arivazhagan et al., 2013).

Deep Learning based Techniques

Authors of the research "Deep learning for image-based plant detection" suggested using deep learning-based algorithms to diagnose various plant diseases (Mohanty et al., 2016). To do this, they used 14 different plants and their 26 diseases to train their neural networks. The model achieved 99.35% accuracy on the given test data.

Authors detected and differentiated three diseases of citrus groves. They have used two different models based on machine learning to classify the disease. The authors have divided the collected features from citrus groves into four major categories of features (Pydipati et al., 2006). The first model used Mahalanobis minimum distance classification. The second model was created using back-propagation and Radial basis functions (RBF) neural networks. The former attained an accuracy of around 95%, while the latter reached an accuracy of over 90%.

Authors put forward a model for recognising plant illnesses using image processing and machine learning techniques to achieve it. The images used for detection were of five types of diseases. The authors pre-processed these (background removed) to gain a high-resolution image. K-means clustering algorithm was employed to obtain the area of the affected leaf imagery. The clusters here used are four, i.e., the value of k used here was 4. Various features of the cluster of the leaf, including its texture, colour, size, and shape, helped anticipate the disease. To extract those, the authors used the color co-occurrence method. Ultimately, MLP was employed to identify diseases (Al Bashish et al., 2010).

The authors recognised diseases in paddy crops. Authors used an SVM-based predictive model. They applied machine learning on pre-processed images (images with removed background) to make the model. The technique known as K-means clustering is employed to differentiate the affected part of the leaf from the total leaf for further processing. Various features of the leaf, including their texture, color, size, and shapes of the diseased parts of leaves, were helpful in exposing the paddy crop disease. The accuracy of over 73.33% was achieved on the test samples (Prajapati et al., 2017).

The authors created a network of convolutional neural networks to categorise cotton illnesses. A set of images of cotton leaves is used to train the classifier. The database contains 700 cotton leaf images, 500 of which are used for testing and around 200 leaf images are used for training. CNN is designed to recognize specific images using three hidden layers automatically. The earliest layer that identifies picture features is the convolutional layer. For reducing features, a second hidden layer called pooling layer is used. A fully connected layer, as a third hidden layer, flattens the network. It is recommended that the model's accuracy be between 80% and 90% of the training and test samples (Kumbhar et al., 2019).

The authors presented AlexNet and SqueezeNet-based methods for detecting diseases in tomato plants. Two well-known deep learning algorithms that are crucial for identifying images are Squeezenet and Alexnet. The PlantVillage dataset is used to collect images of tomato leaves. Ten disease groups were discovered through deep learning. AlexNet outperforms SqueezeNet on the given data. The results of this assessment show that SqueezeNet has a success rate of roughly 94%, while AlexNet has an accuracy rate of approximately 96% (Durmus et al., 2017).

The authors used neural networks to identify crop illnesses by employing pictures of healthy and damaged leaves in rice plants. They used a database of rice leaf images containing one healthy image class and three different diseased image classes. The three disease forms are brown spots, smut and leaf blight. A 34-layer neural network was created and approximately 96% accuracy was achieved (Patidar et al., 2020).

The author utilised a method called transfer learning that has been recognized to employ illnesses in soybean crops. They developed a virus detection method using two famous CNN architectures, GoogleNet and AlexNet. The models were made using photos of soybean leaflets. The training dataset contained approximately 650 diseased leaf photos plus 550 healthy leaf photos. The prepared models were evaluated on 80 sample images. According to the analysis of the results, The GoogleNet and AlexNet-based models' respective levels of correctness are 96% and 98% (Jadhav et al., 2021).

CNN-based concept is used the to detect diseases. They worked on infection categories that paddy crops are affected with, three of which are Brown spot, leaf blight and leaf smut. CNN models were trained using photos of healthy and diseased leaflets. The authors used the Inception-Resnet-V2, VGG-19, Xception and ResNet-101 CNN models. Inception-ResNet-V2 was determined to be the ideal model. Approximately 92% accuracy is achieved using Inception-ResNet-V2 (Islam et al., 2021).

Trained 19 CNN models, and then their findings to classify plant diseases are compared on the basis of the Plant Village Dataset. The finest model was chosen in order to increase productivity even further. It was discovered that the classification accuracy may be improved even further by using deep learning optimizers on the top model. Out of 19 trained CNN models, "Xception with Adam optimizer" emerged as the most accurate illness classification model after result analysis (Saleem et al., 2020).

The unique technique BLSNet is presented in order to identify and estimate the seriousness of the BLS (bacterial leaf streak) illness in rice. Semantic segmentation is a deep learning technique that BLSNet uses. Multi-scale extraction mechanisms were incorporated into the suggested model to improve the precision of illness segmentation. The authors trained the algorithm with photos of real rice fields. UNet and DeepLabv3+, two deep learning models based on semantic segmentation, were utilised to contrast how well the BLSNet model performed. According to the authors, the suggested model performed more accurately in terms of class and segmentation (Chen et al., 2021).

To categorise rice leaf illnesses, the author employed InceptionV3, which is a pre-trained Deep CNN Model. The collection of images comprised 2550 photographs in total and there were 5 different types of leaves. Contrast stretching was employed to improve the visual input of the images, while image augmentation contributed to a better and more comprehensive input. The precision was close to 100% (Upadhyay and Kumar, 2022b).

The author utilised denseNet201, a CNN architecture based on Transfer Learning, to identify rice leaf diseases such as Blast, Leaf Blight, and Tungro. The model's accuracy on the 240 images used for training was 96.09% as opposed to only 62.20% for a standard CNN. 4400 photos of rice leaves, including healthy leaves and those affected by Brown spots, bacteria-induced leaf blight, and leaf smut(Kumar and Upadhyay,2021). Working with factors including size, colour, and form of the leaf lesions, they used a fully linked CNN Architecture and Otsu's Global Thresholding Technique to reduce picture background noise to achieve an overall accuracy of 99.7% for disease identification (Rukhsar & Upadhyay, 2022a).

Using a CNN-based classification technique, the author identified Primary and Developed stage brown spot infections in rice leaves. Triangle Thresholding Segmentation was used to divide the dataset into primary and developed Brown Spots. This classification's overall accuracy was 99.20% (Upadhyay and Kumar, 2021).

The author used the Transfer Learning Technique to find illnesses in rice leaves. To obtain a 90.77% the overall precision the CNN architecture InceptionV3 based on Transfer Learning Approach was used (Rukhsar & Upadhyay, 2022b).

Figure 1. Sample Images (1. Early Blight leaf, 2. Late blight leaf, 3. Healthy leaf)

Table 1. Dataset Description.

Leaf Type	Images
Early Blight	1000
Late Blight	1000
Healthy	152

Research Gap and Contribution

During literature review, it has been observed that many plant disease detection methods fail to achieve an accuracy of 99% or greater. This paper puts forward a classification-based methodology to categorise late blight, early blight, and healthy leaf images of potato plants using the deep learning model *EfficientNetB0* to uniformly scale the network's width, depth, and resolution as opposed to the norm. This algorithm improves disease detection and classification accuracy to 99.05%.

Methods & Materials

This section details the methodology employed for classifying potato leaf diseases using convolutional neural networks (CNNs). It encompasses image pre-processing techniques, feature extraction methods, CNN architecture, hyperparameter tuning, training details, evaluation metrics, and dataset information.

Dataset

The dataset utilized in this study comprises potato leaf images sourced from Kaggle [https://www.kaggle.com/xabdallahali/plantvillage-dataset]. It contains 2152 photographs categorized into three classes: Early Blight, Late Blight, and Healthy leaves, as summarized in Table 1. Representative leaf samples are depicted in Figure 1.

Image Pre-Processing

Image pre-processing is vital for optimizing image data for CNN-based classification tasks. Techniques such as resizing and rescaling were employed to enhance the effectiveness and accuracy of the deep learning model. Specifically, image resizing ensures consistent input size, while image rescaling standardizes pixel values, reducing the impact of lighting variations and enhancing model robustness. These pre-processing steps are depicted in Figure 2.

Feature Extraction

CNNs can automatically extract relevant features from input images through convolutional and pooling layers. These features are essential for distinguishing between different leaf diseases. Convolutional layers apply filters to extract patterns while pooling layers reduce feature map dimensionality. Extracted features are then fed into fully connected layers for classification. The process of feature extraction and classification is depicted in Figure 3.

CNN Architecture

Two CNN architectures were employed in this study: ResNet50 V2 and EfficientNetB0. ResNet50 V2 consists of 50 layers and is pre-trained on a vast dataset, allowing it to classify images into 1000 distinct object types. EfficientNetB0 employs a scaling method to adjust depth, width, and resolution factors, enhancing model accuracy

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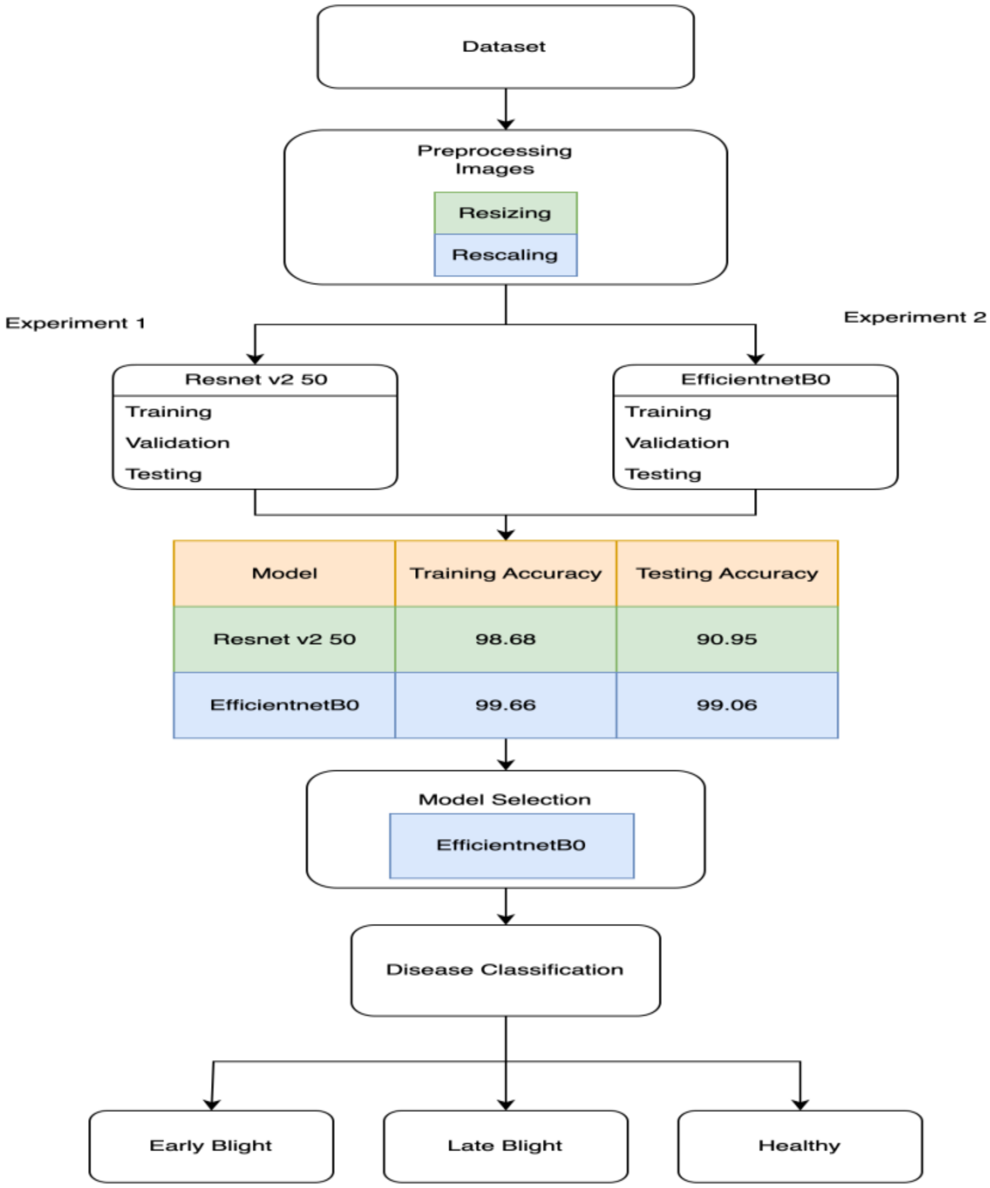

Figure 2. Image Pre-Processing Flow Diagram.

and performance. Architectural diagrams for ResNet50 V2 and EfficientNetB0 are presented in Figures 4 and 5, respectively.

The decision to choose EfficientNetB0 was based on its proven track record of achieving high accuracy with efficient use of computational resources, making it an ideal choice for our plant disease classification task.

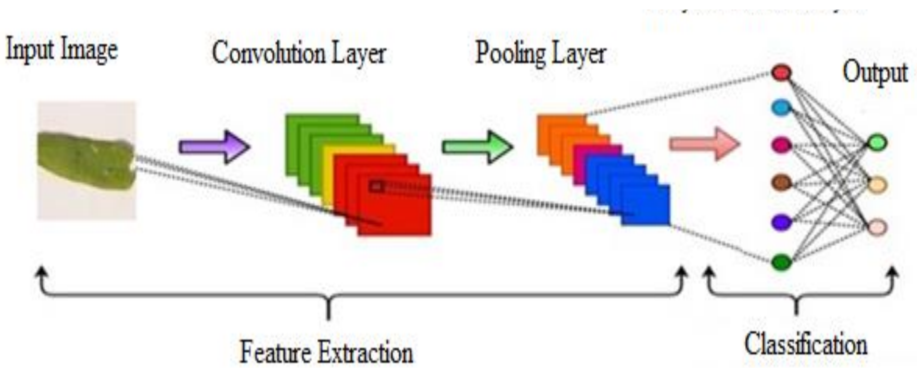

Figure 3. Feature Extraction and Classification (Upadhyay and Kumar, 2022a).

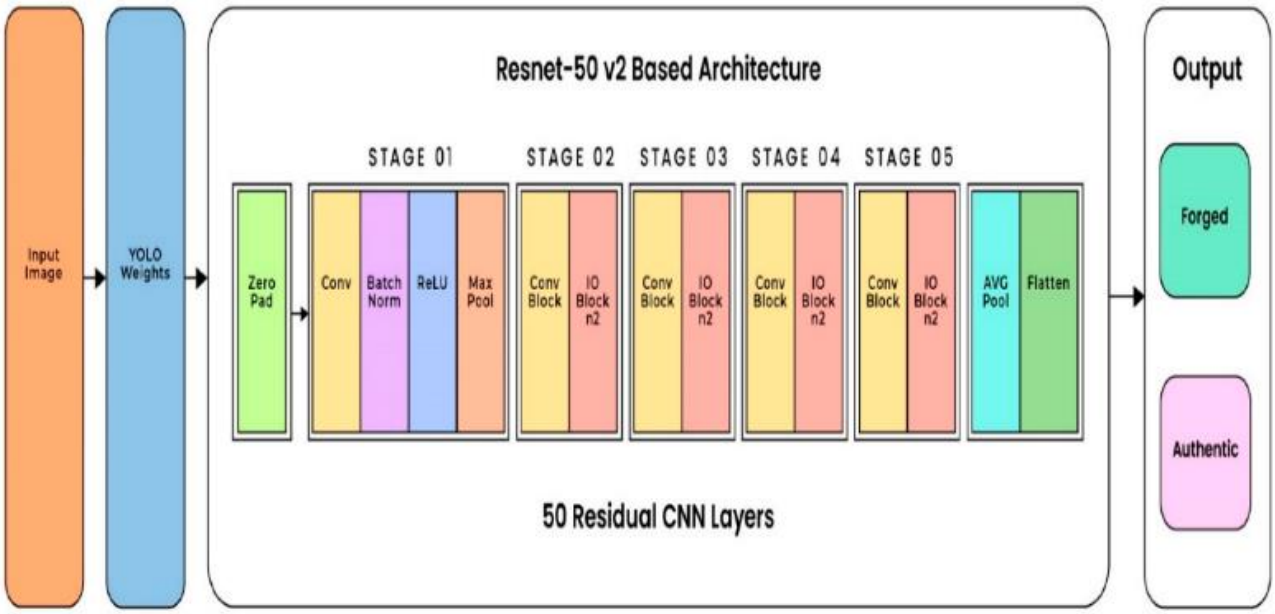

Figure 4. ResNet50 V2 Architecture [Source: Adapted from Qazi et al. (2022)].

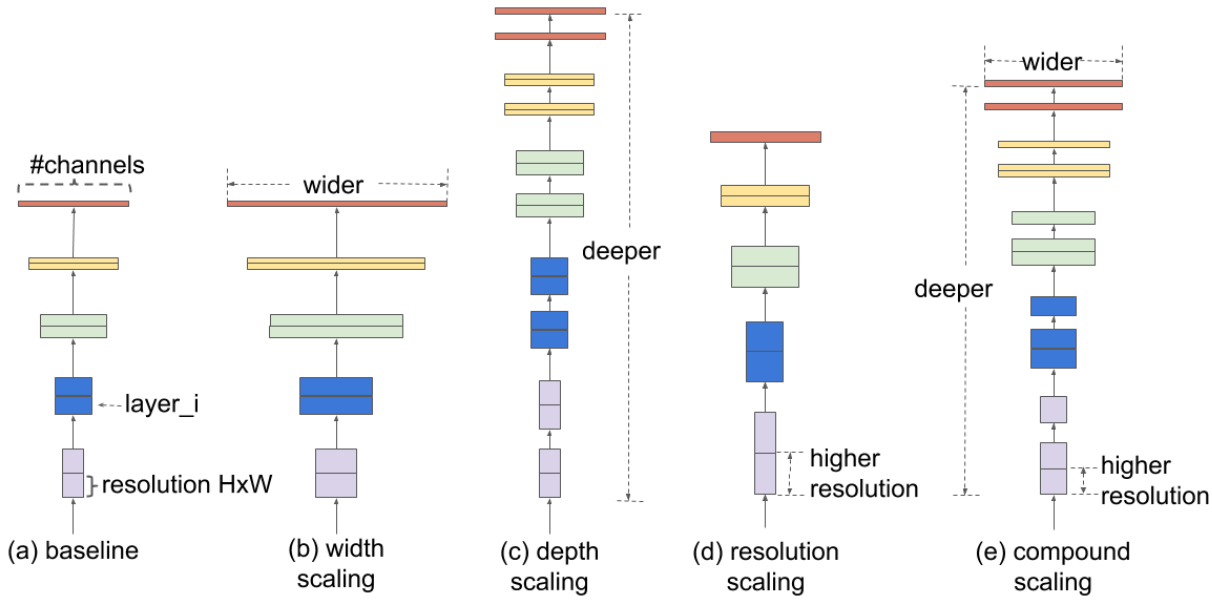

Figure 5. EfficientNetB0 Architecture [Source: Adapted from Tan and Le (2019)].

Hyperparameter Tuning

Optimal hyperparameters were selected through a systematic tuning process, including grid and random searches. Parameters such as learning rate, batch size, and regularization were fine-tuned to optimize model performance.

Training Details

The training was conducted using the specified hyperparameters, including Adam optimizer, learning rate schedule 0.001 and batch size of 32 samples. The proposed model's classification ability was evaluated using a training configuration of 10 epochs with 54 iterations between each epoch. Additionally, regularization techniques such as dropout were applied to prevent overfitting.

Evaluation Metrics

The performance of the trained models was evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix. These metrics provided insights into the classification performance and effectiveness of the proposed models.

Dataset Details

The dataset comprised 2152 potato leaf images, with each class appropriately balanced. Preprocessing steps included data cleaning and class balancing to ensure dataset representativeness. Potential biases were addressed to enhance the generalizability of the proposed model.

Discussion of Experiment

Section 4 presents the experimental configuration and performance evaluation of the suggested model. Here is the dataset that was used for validation and training

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purposes, along with information on the hardware and software needed to exercise and analyse findings.

Experimental Setup

The experiment utilized a dataset obtained from the Kaggle dataset on Potato leaf disease, comprising 152 images of healthy potato leaves, 1000 images of potato leaves with Early Blight disease, and 1000 images of potato leaves with Late Blight disease. The dataset was divided into training, validation, and testing sets, with 20% of each class's photos used for validation and testing and 80% used for training. The experiment was conducted on Google Colab using CPU Intel(R) Xeon(R) CPU @ 2.00GHz and Tesla 4 GPU, with Python as the programming language.

Performance Indicators Employed

Several evaluation metrics were employed to assess the model's performance, including accuracy, recall, and precision. Accuracy represents the percentage of correctly categorized specimens, while recall measures the percentage of correctly identified instances of a class relative to all actual instances of that class. Precision indicates the percentage of correct positive identifications among all positive identifications made by the model.

Many evaluation metrics are used to evaluate classification and the predictive model. These four-performance metrics are what we're using to judge how well our suggested technique is working.

Below is a brief explanation of these two measurements.

1-Accuracy: The percentage of specimens that are correctly categorised relative to all specimens employed in categorization is considered the accuracy of the classification or categorization model. Accuracy of classification model is calculated using Equation 1.

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

2-Recall: The percentage of data samples from a class of interest, or "positive class," that a machine learning model correctly identifies as being a part of the class as a whole is known as recall.Recall of classification model is calculated using Equation 2.

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

3-Precision: Precision indicates the percentage of affirmative identifications that were accurate. Precision of the classification model is calculated using Equation 3.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

Exploratory Model of System Assessment

The proposed model's classification ability was evaluated using a training configuration of 10 epochs with 54 iterations between each epoch, totalling 540 rounds of analysis. Figures 6 and 7 illustrate the loss fluctuation and accuracy versus epoch curves for Experiment 1 with the ResNet50 V2 model, while Figures 9 and 10 depict the same for Experiment 2 with the EfficientNetB0 model. Additionally, confusion matrices were generated to visualize the correct and incorrect classifications made by each model in Figure 8 and Figure 11.

Experiment 1 with ResNet50 V2 Model

The ResNet50 V2 model achieved an overall accuracy of 90.95%, with accuracies of 98.5% for early blight, 98.5% for late blight, and 75.7% for healthy leaf images. The precision, recall, and F1 score were all 0.9095.

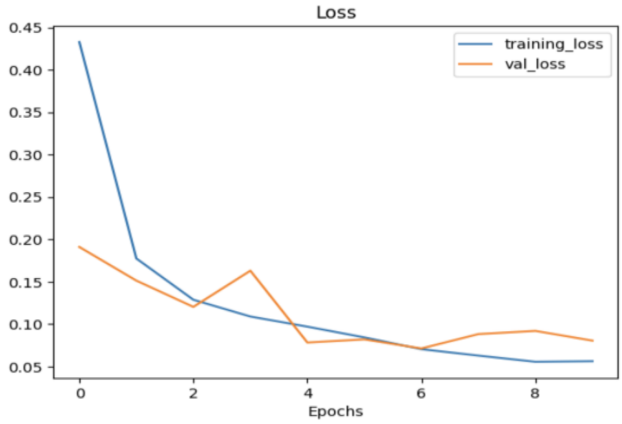

Figure 6. Loss vs Epoch curve of ResNet50 V2

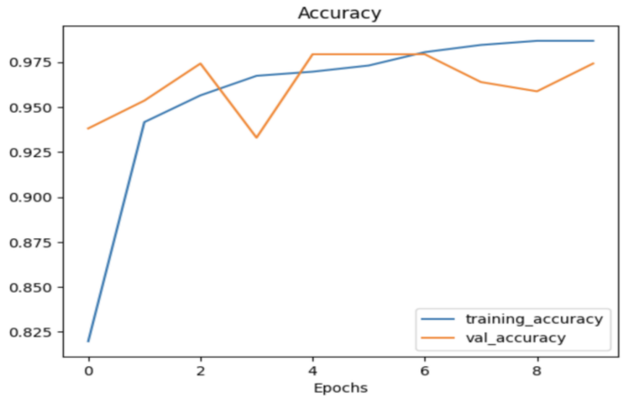

Figure 7. Accuracy vs Epoch Curve of ResNet50 V2

The EfficientNetB0 model outperformed the ResNet50 V2 model, achieving an overall detection accuracy of 99.05%. It exhibited accuracies of 98.5% for early blight, 98.5% for late blight, and 100% for healthy leaf images. The precision, recall, and F1 score were all 0.9905 as shown in Figure 12.

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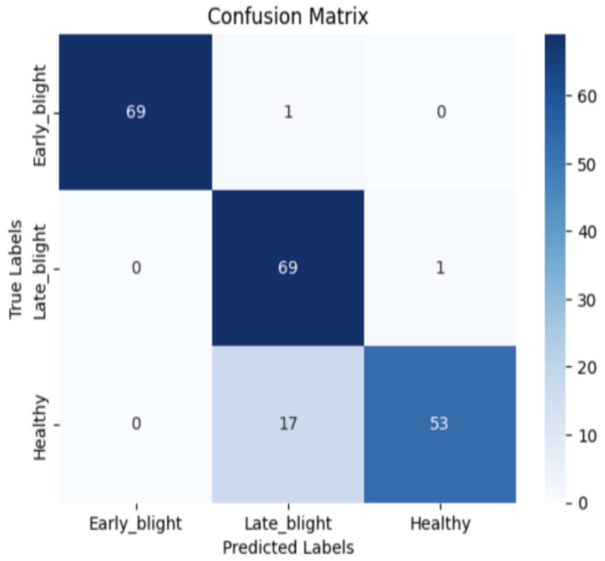

Figure 8. Confusion Matrix of ResNet50 V2.

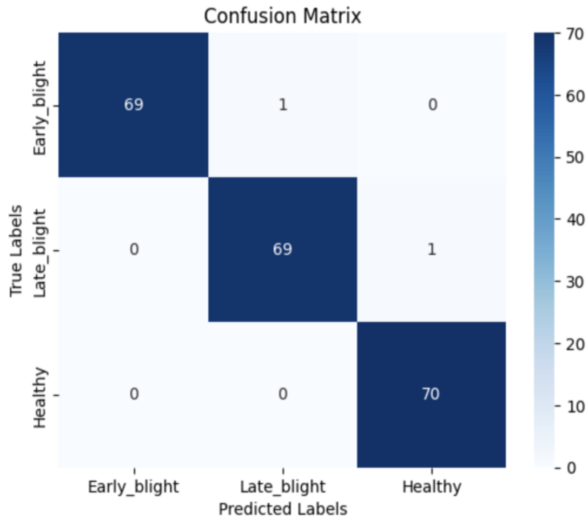

Figure 11. Confusion Matrix of EfficientNetB0.

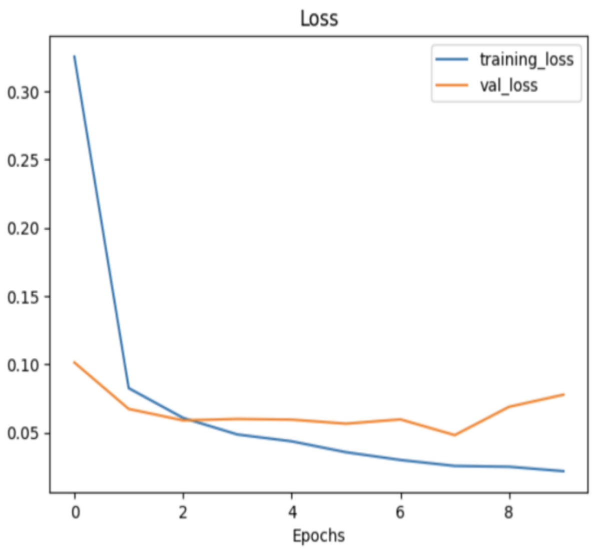

Figure 9. Loss vs Epoch Curve of EfficientNetB0.

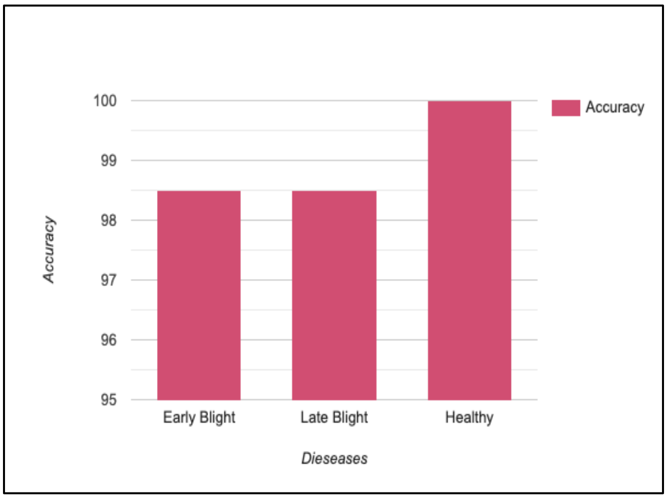

Figure 12. Accuracy Comparison for various Classes.

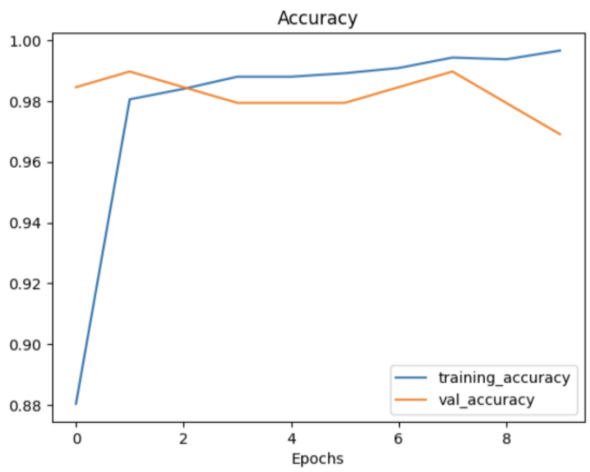

Figure 10. Accuracy vs Epoch Curve of EfficientNetB0.

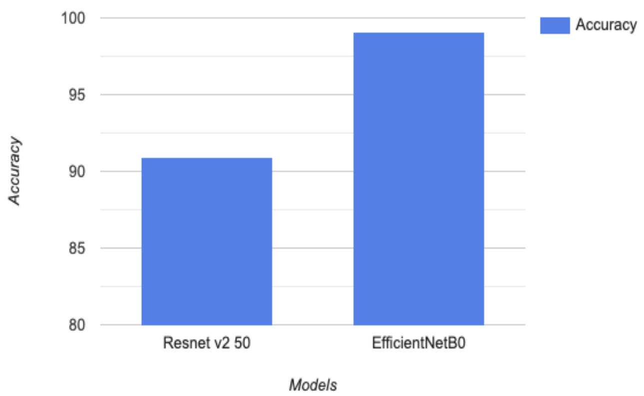

Figure 13. Accuracy Comparison between both the Models.

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Table 2. Accuracy comparison of experimented models.

Method Used	Accuracy
Resnet50 v2	90.95%
EfficientNetB0	99.05%

Table 3. Performance comparison with existing work

Sl. No.	Author	Method	Plant	Accuracy (%)
1	(Kumbhar et al., 2019)	Light Weight CNN Model	Cotton Plant	90
2	(Durmus et al., 2017)	AlexNet and SqueezeNet	Tomato Plant	SqueezeNet 94 AlexNet 96
3	(Jadhav et al., 2021)	GoogleNet and AlexNet	Soybean	GoogleNet 96 AlexNet 98
4	(Islam et al., 2021)	Inception-ResNet-V2	Paddy	92
5	(Rukhsar and Upadhyay, 2022b)	DenseNet-201	Paddy	96.09
6	Proposed Methodology (Experiment-1)	ResNet50V2	Potato	90.95
7	Proposed Methodology (Experiment-2)	EfficientNetB0	Potato	99.05

Comparison of Experiment 1 and Experiment 2

A comparison between Experiment 1 (ResNet50 V2) and Experiment 2 (EfficientNetB0) revealed a significant improvement in accuracy, from 90.95% to 99.05%, upon transitioning to the EfficientNetB0 model, as shown in Figure 13. This enhancement highlights the superiority of the EfficientNetB0 architecture for potato leaf disease detection as shown in Table 2.

Comparison with Existing Work

The proposed model was compared with existing disease categorization models, which utilized deep CNN architectures for automatic feature extraction and disease classification. The model demonstrated superior accuracy compared to many existing techniques while remaining competitive with other top-performing models in the field. The accuracy comparison of the proposed method against existing works is listed in Table 3.

Conclusion And Future Work

This paper presents a deep CNN-based methodology for categorizing healthy, early blight, and late blight leaves of potato crops, achieving an impressive accuracy of 99.05%. Our findings underscore the effectiveness of CNN as the optimal method for image categorization in agricultural contexts. We believe that initiatives like ours have the potential to significantly impact the agricultural sector, particularly in regions like rural India, where farmers may lack awareness of different plant diseases.

Moving forward, our future objective is to develop a user-friendly web application capable of recognizing a wide range of crop diseases and providing tailored recommendations for disease management. By expanding our dataset and continuously refining our model, we aim to enhance our classification system's accuracy and reliability. This initiative will empower farmers with timely and accurate information and facilitate prompt access to assistance and advice, ultimately improving agricultural productivity and livelihoods.

While our paper aims to highlight our methodology's potential benefits, we acknowledge certain limitations. These may include factors such as model generalization across different geographic regions or variations in environmental conditions. In our revised conclusion, we will briefly mention these known limitations and propose potential solutions or avenues for future research to address them.

In summary, our research represents a significant step towards leveraging deep learning technologies to address critical challenges in agriculture. We are committed to continuing our efforts to develop innovative solutions that have tangible benefits for farmers and contribute to the advancement of sustainable farming practices.

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Conflicts of Interest

The authors declare no conflict of interest, financial or otherwise.

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