

Classification of Plant Diseases

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Abstract

This study focuses on the classification of potato plant diseases taken from the PlantVillage dataset. We use Simple CNN, Deep CNN, and pre-trained DenseNet 121. The models are trained and tested using the potato leave dataset. the classes are early blight, late blight, and healthy. Data augmentation techniques help improve model generalization. Accuracy, precision, recall, and F1-score were used to gauge the performance of the different models. The best result was the DenseNet121 which gave an accuracy of 99.77%, proving the effectiveness of potato plant disease classification.

Keywords: Potato plant diseases, Convolutional Neural Networks, PlantVillage dataset, Deep Learning, DenseNet121, Image Classification.

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1. Introduction

The identification and classification of diseases in plants are some of the key issues that go a long way toward increasing agricultural production and ensuring food security. The conventional disease detection approaches involve manual inspections by experts, which besides being time-consuming are also prone to various human mistakes. Recently, Artificial Intelligence has reached a point where Deep Learning Techniques can be applied to numerous tasks. Image classification, one of the most important fields where Convolutional Neural Networks have been gaining applicability includes plant disease detection.

The paper will study only early blight, late blight, and a healthy class. We designed three different CNN architectures based on the dataset used in the research: a simple CNN, a deep CNN, and a DenseNet121 model. The proposed architectures will be trained and then evaluated for their accuracy regarding correct disease classification.

2. Related Work

In [1] Grünig et al. applied Deep neural networks (DNN) to predict plant diseases. They created a dataset consisting of environmental data and historical plant disease data. The model is trained on multiple data sources, which gives strength to the model. The model is characterized by high accuracy in the prediction and integration of different data sources. The limitation of this model is historical data requirements. Finally, the model achieved an accuracy of 85%, which helped manage plant diseases.

In [2] Sharma et al. applied Convolutional Neural Networks (CNNs) to classify plant diseases. They used the PlantVillage dataset containing more than 50,000 diverse images of diseased and healthy plant leaves. That gives a large training set by the dataset. This model works with a layered structure to extract the classification. This model gives very accurate results and provides automated diagnosis which makes it practical to implement in the real world. The Limitations of this model are low-resolution images, and it requires a large dataset. This model achieved 98% accuracy which shows great results.

In [3], Akshai and Anitha used a deep learning (DL) model using (CNN) to classify plant diseases. They collected them from local agricultural sources. The dataset contained thousands of images. The model is adaptive to a variety of plant species, making it suitable for various crops. It is also compatible with a mobile application, which has enhanced its use in science. The model has an accurate performance. One of the limitations of this application is that it relies on high-quality images. However, the model achieved an accuracy of 94%, which gives it reliability in the real world.

In [4] Chen, Zhang, and Nanekaran applied Deep Learning with a lightweight neural network to identify plant diseases. They used the PlantVillage dataset, which contains more than 50,000 images and many types, to train the model. The computational efficiency of this model was improved by reducing the computational requirements, speeding up the inference time, and giving more accurate results. This model is considered good, but its limitations include not working with new types of diseases. However, it showed 96% accuracy results, which were effectively used to reduce computational resources.

In [5] Suresh et al. developed the DeepPlantNet model, which uses deep learning to classify diseases from plant leaf images. The plant dataset used to train the model was collected from different sources, which gave the possibility of scaling to different plants. One of the main limitations of this model is that training the data requires large computational resources and needs to be updated with new data to maintain a high level of accuracy. This model achieved an accuracy of up to 97%, which confirmed its effectiveness in classifying diseases.

In [6], Subasi, Gulam, and Sadikoglu use deep learning to build a model to detect maize leaf diseases. They collected a dataset from local sources consisting of maize leaf images and

trained the model on these images. The advantage of this model is that it is a mobile-based system and can be used in real-time. This makes it practical and easy to use for farmers. The model was limited to maize leaves and relied on the accuracy of the image quality. However, it achieved a performance of 92%.

In [7] Kaur et al. developed a mobile application to detect maize leaf diseases using deep learning algorithms. They used a dataset from agricultural research centres to train the model. The model can be used in real-time to give immediate results, so the model is practical for farmers. The model has accurate results of 93%, but the performance is affected by environmental factors such as lighting conditions.

Author	Methodology	Dataset	Advantages	Limitations	Results
<i>Grünig et al. (2021)</i>	DNN to predict disease incidence	consisting of environmental data and historical plant disease data.	High-accuracy data and analyzes of complex datasets	Data quality affects accuracy and historical data requirements	Successful predictions for disease with an accuracy of 85%
<i>Sharma et al. (2022)</i>	CNNs for image classification of plant diseases	PlantVillage dataset.	High accuracy, automates detection	Requires large datasets, low-resolution images	High classification accuracy 98% achieved
<i>Akshai & Anitha (2021)</i>	CNN models trained on leaf images	collected dataset from local agricultural sources	efficient classification	Sensitivity to overfitting and depend on high-quality images	classification accuracy of 94%
<i>Chen et al. (2023)</i>	Deep transfer learning with lightweight network	PlantVillage dataset and additional images from online sources.	Faster training, reduced resource needs	Performance dependent on base model so not working with new types of diseases	Effective disease identification showed 96% accuracy
<i>Suresh et al. (2023)</i>	DeepPlantNet for disease classification	collected from different sources	High accuracy and efficiency and the possibility of scaling to different plants	Requires substantial resources and large computational resources	classification performance achieved an accuracy of up to 97%
<i>Subasi et al. (2022)</i>	Mobile-based system using DL	Collected dataset for maize plant leaf diseases.	Practical application for farmers	Internet access required, light condition issues and image quality	Successful real-time disease detection 92% accuracy
<i>Kaur et al. (2023)</i>	Mobile-based system for disease detection	Custom dataset for maize plant leaf diseases.	Quick diagnosis, user-friendly	Accuracy may vary in diverse conditions	Effective classification with accurate results of 93%

3. Methodology

1.3. Data Collection

In this research potato datasets are used and taken from the PlantVillage Kaggle images dataset. We have focused on three categories of potato diseases: early blight, late blight, and healthy plants.

2.3. Data Preprocessing

The dataset is divided into 80:20 subsets and organized for training and validation purposes. where 80% of the images are used for training and 20% of the images are used for testing the potato dataset. The potato leaf dataset containing a total of 2152 images is used in the study. Some of the potato leaves are shown in Fig 1. Tab. 1 represents the number of training and testing images of the datasets.

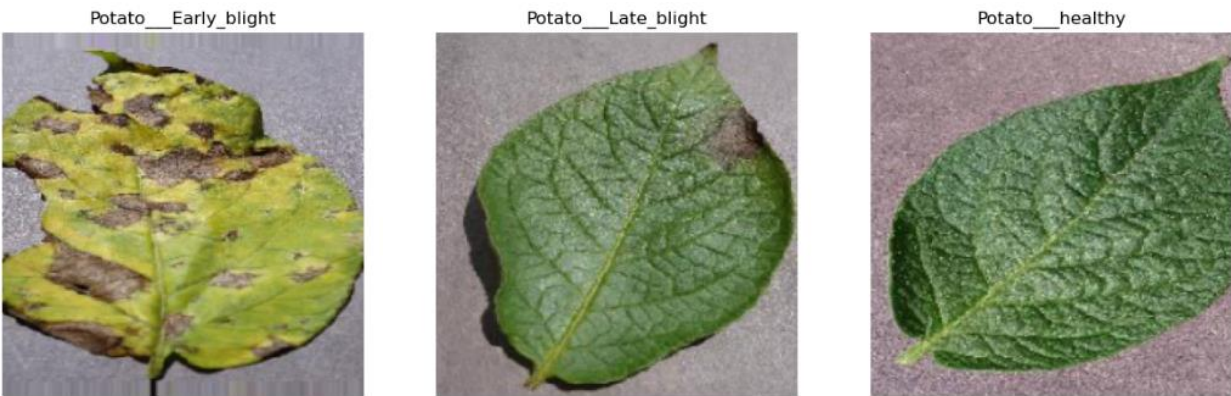


Figure 1: Sample image of potato leaf diseases, early blight, late blight and healthy

Image Dataset and class	Total Image Dataset	Training Image Dataset	Validation Image Dataset
Potato__Early_blight	1000	800	200
Potato__Late_blight	1000	800	200
Potato__healthy	152	122	30

Table 1: Potato leaf datasets

During the preprocessing stage, data augmentation techniques applied to this model included cropping, zooming, random rotation, horizontal flips, and frequent transformations due to diversity in training data to ensure the model is generalized and reduces overfitting. The input images were resized to a shape of 224x224 pixels. Images of the potato dataset after preprocessing are shown in Fig 2

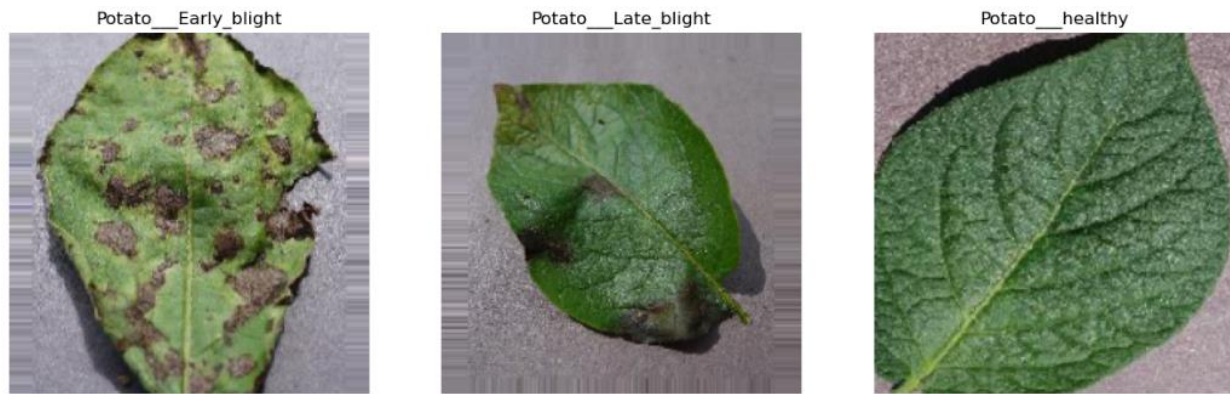


Figure 2: Resized potato leaf dataset

3.3. Model architecture

In this study, we build three different models to classify potato plant diseases working on three classes: Early Blight, Late Blight, and Healthy leaf.

The first model is a simple CNN structure that includes a few convolutional and pooling layers followed by some fully connected layers that capture some basic features to give a quick baseline in the performance.

The second model is a Deep CNN model, with more convolution and dense layers, but includes dropouts and learns more sophisticated features and relationships in the images. Finally, the DenseNet121 model is a pre-trained deep learning model effective in feature extraction. We pre-trained DenseNet121 for our task by freezing its base layers and then unfreezing them to train the model. This approach combines knowledge pre-learned from DenseNet121 with the one on our specific dataset to enhance capability and obtain higher accuracy.

We have used the Keras' Sequential API to build the models and compile each with an appropriate optimizer, loss, and metrics. In this manner, model building will be well-structured, not only for comparing and systematic experimentation but, also for obtaining high performance in classifying potato-plant diseases. See model architecture in Fig 3.



Figure 3: Model architecture

4. Implementation

4.1. Model Training

To build the models using ML for image plant disease classification, Python libraries have been used such as TensorFlow, Keras, NumPy, Matplotlib, and Seaborn. The models are trained on potato datasets. Tab.2 presents the hyper-parameter configurations of the CNN model architecture as given in Fig. 3. The Model was then compiled and optimized. Simple CNN and Deep CNN the learning rate was the default for the Adam optimizer (1e-3). DenseNet121 the learning rate was initially set at 1e-3 for the frozen layers and (1e-5) when fine-tuning after unfreezing the layers.

Parameter	Value
Optimizer	Adam the learning rate for Simple CNN, Deep CNN and frozen layers in DenseNet121 = (1e-3). The learning rate for unfreezing layers= (1e-5)
Loss	Categorical Crossentropy
Batch Size	32
Metrics	Accuracy
Activation Function	ReLU (Hidden layers of the Simple CNN and Deep CNN models. $f(x)=\max(0,x)$) Softmax (output layer of all models (Simple CNN, Deep CNN, and DenseNet121)) Sigmoid (Some Layers)

Table 2: CNN model training parameters

4.2 Training (Accuracy & Loss) Graphs of the CNN Model

The model for the designed CNN models to classify potato datasets was trained for 50 epochs. The validation accuracy in Simple CNN Accuracy: 97.91%, Deep CNN Accuracy: 96.51% and DenseNet121 Accuracy: 99.30%. Through monitoring performance metrics such as accuracy on training and validation datasets. The training graphs show model accuracy and loss in Figs 4 for the respective models. Visualization The accuracy and loss curves are used to assess the progress of the training. A heat map of the confusion matrix provided insights into the classification capabilities of the model.

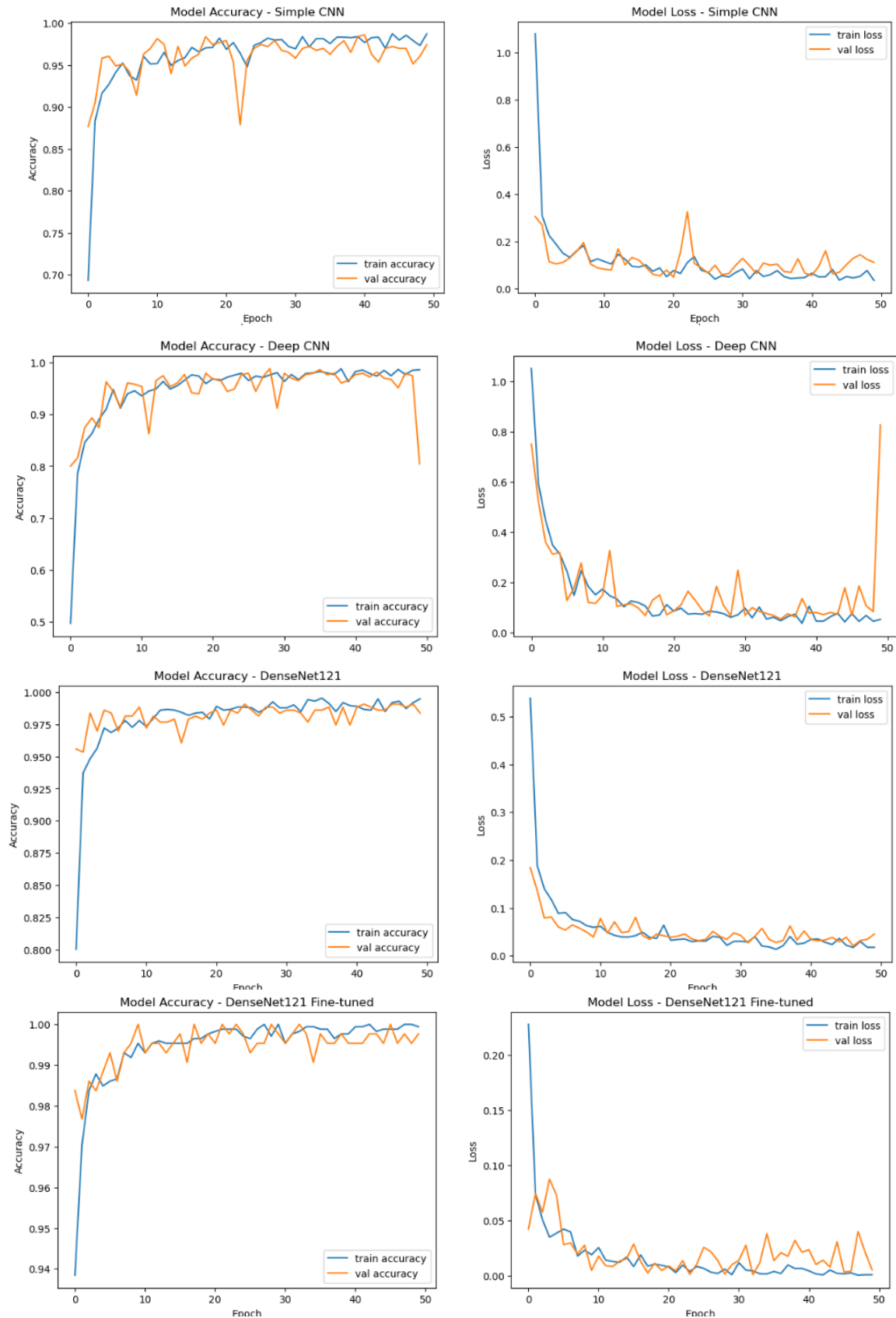


Figure 4: Training-progress graphs (Simple CNN model, Deep CNN, DenseNet121 trained with potato dataset)

5. Performance Evaluation

In this study, we use the Precision, accuracy, recall, and F1 scores to calculate and evaluate the model's performance as shown in Table 3. We create a confusion matrix to see the classification performance across different classes in Fig 5.

Model	Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Simple CNN Metrics	Potato__Early_blight	44.497608	46.500000	45.476773	20000
	Potato__Late_blight	44.210526	43.076923	43.076923	20000
	Potato__Healthy	3.225806	3.333333	3.276895	20000
	Accuracy	0.413953	0.413953	0.413953	43000
	Macro avg	30.445619	31.611111	30.610795	43000
	Weighted avg	41.484653	41.395349	41.416511	43000
Deep CNN Metrics	Potato__Early_blight	45.907473	64.500000	53.638254	20000
	Potato__Late_blight	47.863248	28.000000	35.313250	20000
	Potato__Healthy	0.000000	0.000000	0.000000	30000
	Accuracy	31.256097	30.833333	29.656495	43000
	Macro avg	33.614289	43.023256	41.381155	43000
	Weighted avg	43.614289	43.023256	41.381155	43000
DenseNet121 Metrics	Potato__Early_blight	44.000000	44.000000	44.000000	20000
	Potato__Late_blight	46.231155	46.000000	46.115288	20000
	Potato__Healthy	6.451613	6.666667	6.557377	30000
	Accuracy	6.423256	6.423256	6.423256	43000
	Macro avg	32.275990	32.222222	32.242422	43000
	Weighted avg	42.418992	42.325581	42.371579	43000

Table 3: Performance result of each class of Simple CNN, Depp CNN, and DensNET121 classifier on the potato dataset

The diagonal values of the confusion matrix represent the true positives of our model classification. To calculate correctly the false negatives, we will have to sum up all the values in the row with the corresponding class of interest, excluding the values from the true positives. In doing this, we will then have the total number of testing samples for any class computed as $TP + FN$. For FP, we would be able to calculate this as the sum of the values in the corresponding column, excluding, of course, the true positives for that class. Furthermore, to obtain the number of true negatives for a given class, we would sum all values in the two columns and rows, excluding of course the

respective row and column of the class in question. Accuracy is a strong indicator and is defined as the ratio of correct classification concerning the total number of classifications. It is the sum of all the diagonal elements divided by the total count of items in the confusion matrix. This metric provides the overall effectiveness and reliability of the predictive model. Using the confusion matrix in Fig. 4 we can infer several key performance measures using the following equations.

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

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{True negative rate or Specificity} = \frac{TN}{TN + FP}$$

$$\text{False Positive Rate} = \frac{FP}{FP + TN}$$

$$\text{Precision} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = 2 \times \frac{\text{sensitivity} \times \text{precision}}{\text{sensitivity} + \text{precision}}$$

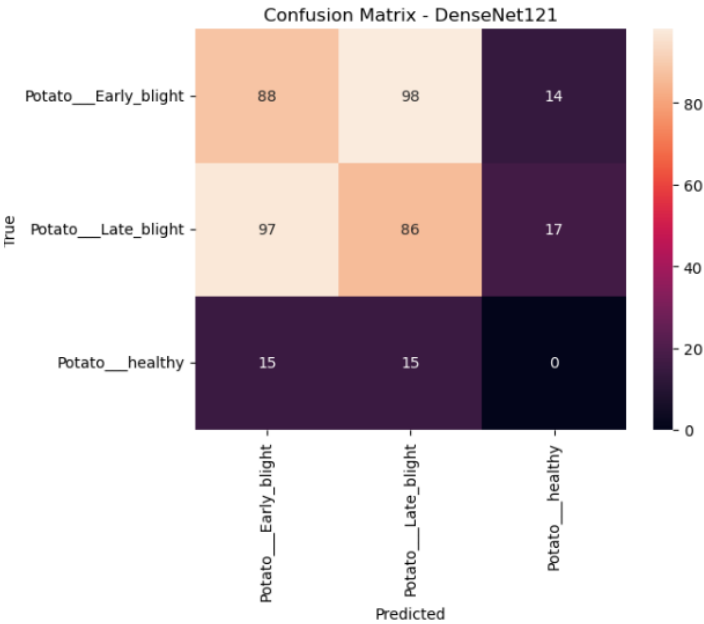
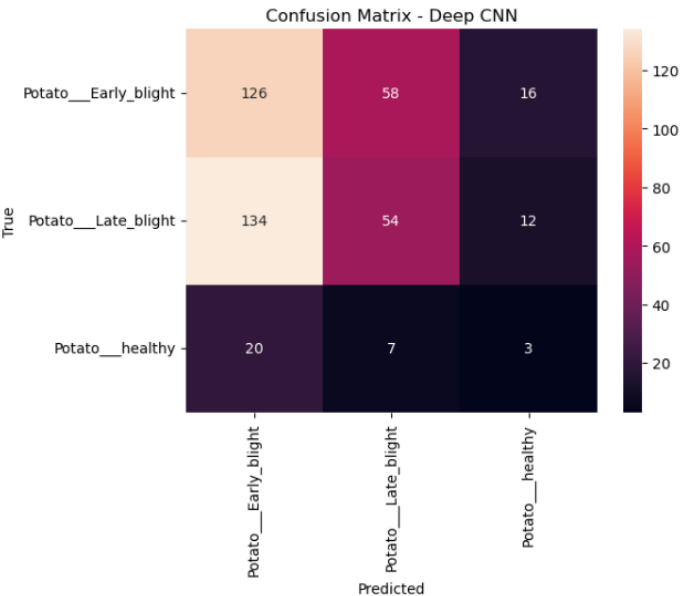
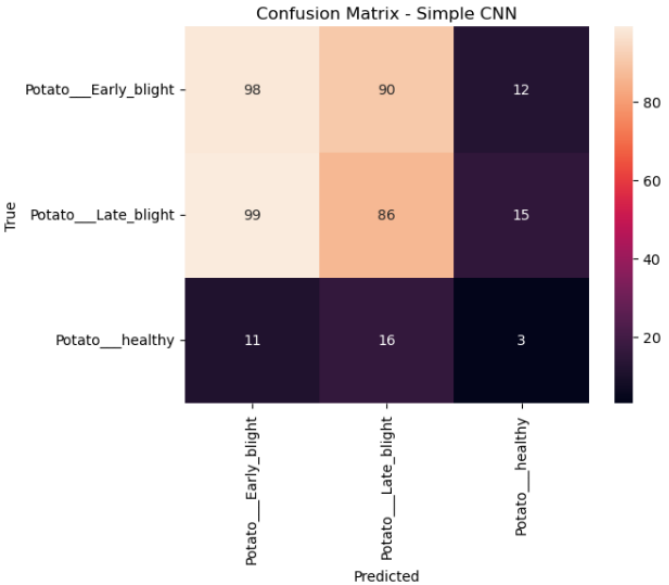


Figure 5: Confusion matrix obtained for the training of Simple CNN, Depp CNN, and DensNET121 using potato dataset

6. Result Analysis and Visualization

Performance analysis was performed with the results obtained using three convolutional neural network models Simple CNN, Deep CNN, and DenseNet121-with a dataset consisting of images of potato plants. Potato__Early_blight, Potato__Late_blight, and Potato__Healthy are the classes of the used dataset. Each model was further assessed based on precision, recall, and F1-score.

The Simple CNN model was reasonably balanced regarding precision and recall of the early blight and late blight classes but resulted in relative performance concerning the healthy state of potato plants. A general accuracy of about 96.98% was observed.

Deep CNN resulted in a general accuracy of about 96.51%, and this model performed concerning the healthy class, achieving zero precision, recall, and F1-score.

DenseNet121 reached an overall accuracy of about 98.60%, and the accuracy of the fine-tuned DenseNet121 model was approximately 99.77% in distinguishing between classes regarding healthy ones.

These results, with training graphs and metrics tables, present a good view of the strengths and weaknesses of these models. Training accuracy and loss graphs present how each model converged given epochs, whereas confusion matrices provide an idea of misclassifications. This is an essential analysis that shall help in understanding the models' performance and where their improvements should be made, such as increasing the dataset or tuning the hyperparameters for better accuracy see Fig 6.



Figure 5: Training and validation graphs

7. Conclusion

This study justifies the potential of deep learning models in the classification of potato plant diseases. The various models tested in this paper showed that the DenseNet121 model had the highest performance among them, with an accuracy as high as 99.77%. This proves that the pre-trained model with fine-tuning can improve the performance of the classification considerably. The results highlight that the advanced architecture of CNN and the augmentation of data play a crucial role in enhancing the accuracy of the plant disease detection system. Future studies may be directed toward the incorporation of more data from various sources and optimization of model parameters to make these models robust and applicable in real life.

8. References

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