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Deep Learning-Based Disease Identification and Classification in Potato Leaves

Sobia Sadiq[1], Kaleem Razzaq Malik[1], Wasif Ali[2], Muhammad Munwar Iqbal[2]

[1]Department of Computer Science, Air University Multan Campus, 60000, Pakistan
[2]Department of Computer Science, University of Engineering and Technology, Taxila.
[*]Corresponding Author: Muhammad Munwar Iqbal. Email: munwariq@gmail.com.

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Abstract: This research endeavored to deploy deep learning models for accurate illness detection within potato crops, a crop of global economic significance. Four specific deep learning models, namely VGG16, EfficientNet B4, InceptionV3, and Inception ResNetV2 were trained using a comprehensive dataset constituted of images of both healthy and diseased potatoes. The performance of these models far surpassed traditional methods of visual inspection. Among the models evaluated, the EfficientNet B4 model demonstrated the highest level of accuracy, achieving a perfect score of 100%. VGG16 followed with an accuracy of 99%, Inception V3 at 98%, and Inception ResNet V2 at 94%. The results yield significant potential for enhanced crop management methodologies, facilitating a considerable reduction in economic losses linked to potato diseases. The study's findings corroborate the transformative capacity of artificial intelligence, particularly deep learning models, for the innovation of agricultural practices. This is pertinent for upholding food security in light of the increasing challenges posed by plant diseases.

Keywords: Deep Learning, Disease Detection, Classification, EfficientNet B4, Potato Crop

1. Introduction

Most people in the world must rely on farming for their livelihood, and the agricultural sector has a notable impact on the economy. Crop infections can cause a substantial reduction in crop yields and quality, making early detection, prevention, and management of diseases crucial. Researchers have proposed a plethora of automatic disease detection methods based on computer vision to help with this problem [1]. Pakistan ranks 19th in potato production and 16th in the area cultivated for potato production globally. However, Pakistan's per hectare yield for potatoes is significantly lower compared to other regions, with a ranking of 54th. In addition, Pakistan's potato harvest has been on the rise. Khan, Ullah, and Murtaza argue that despite this, potatoes are Pakistan's fourth most significant crop after wheat, rice, and corn. [2]. Potato is one of the primary staples in the country, contributing significantly to national domestic consumption and food requirements, as noted by Majeed and Zia [3]. In addition, Pakistan's potato harvest has been on the rise. Potatoes, scientifically known as Solanum tuberosum L., are a crucial vegetable crop that China cultivates, having recently obtained the highest gross yield in the globe. Unfortunately, potato crops globally experience significant yield losses from the two most harmful foliage diseases: Phytophthora infestans, often known as late blight, and early blight (Alternaria solani) [4]. Late blight manifests on potato leaves, there are pale green or olive green spots that quickly turn into brown-black, dripping, oily-looking sores, while early blight shows up as dark brown to black patches, both round and irregular ones. Early blight and late blight can affect a plant at any stage of development.[5]. It is critical to quickly diagnose these illnesses and assess the level of infection on potato leaves to effectively control and prevent them in a timely manner.

Expanding on the study's aims and methods, this study has devised innovative deep learning models, specifically VGG16, EfficientNet B4, Inception V3, and Inception Resnet V2. These models undergo rigorous training and evaluation to ascertain their proficiency in discerning diseases within a broad database of potato crop images. As part of our analysis, we scrutinize each model's unique strengths, comparative performance, and potential areas for refinement to ensure optimal disease detection efficacy. The utility of this approach extends beyond mere disease identification. By offering an early detection mechanism, the models can provide timely data for pre-emptive measures, which can significantly mitigate potential crop losses. Furthermore, these insights can be leveraged to devise targeted disease control strategies, thereby optimizing the resource allocation in pest management practices. The study also aims to contribute to the broader academic discourse on applying artificial intelligence in agriculture, exploring its potential to revolutionize conventional farming practices. By leveraging these advanced technologies, we aspire to improve the efficiency of potato farming in regions like Pakistan and China, enhancing their crop yield and food security measures. Ultimately, we envision our findings will serve as a foundation for future investigations and technological advancements in sustainable agriculture.

The research is structured as follows: The introduction and significance of the study problem constitute the first section. It highlights the application of computer-aided design in agriculture, the obstacles of automatically identifying diseases in leaves, and how they are overcome. The second section examines appropriate methodologies proposed by the research community. The third section describes the pre-processing stage for quality enhancement and estimating prospective disease by training the different deep learning models. The results section discusses the experimental design and a deep model that employs assessment criteria. The fifth section is the conclusion and includes considerations for the future.

2. Related Literature

Many strategies have been used in the study of plant disease classification. Nevertheless, it remains inadequate and remains an area of active investigation owing to the intricacies involved [6]. This fact highlights the novelty and contemporary nature of this technique in the agricultural sector.

A strategy predicated on deep learning can be designed to learn an efficient feature representation. In their study, Prajwala and colleagues [7] detection of tomato leaf diseases, such as Septoria Leaf Spot and Yellow Leaf Curl, can be detected and classified using a CNN model and LeNet architecture. The dataset used in the study was sourced from PlantVillage, an Open Access image database. The proposed methodology yielded an accuracy level of 94% to 95%. Meanwhile, Srdjan Sladojevic and his team [8] used a novel strategy based on convolutional neural CNNs) to identify diseases in thirteen disease classes and five plant species. Experimental results demonstrated an average accuracy of 96.3% on the developed model. Erika Fujita et al. [9] combining the Convolutional Neural Network technique and the AlexNet architecture, created a system to detect plant diseases in cucumbers. By applying this method, they achieved an average accuracy of 82.3%. Meanwhile, Raja P et al. [10] collected 2000 images of corn leaves from PlantVillage, an open-access image database, to perform an object classification of 3 types of diseases in maize leaves. With findings compared to the histogram and feature-based grey-level co-occurrence, images were categorised using a multi-feature bag and the Multiclass SVM method. The results showed that the SVM Multiclass method was completely accurate. In their study, Pranjali B. Padol and Prof. Anjali A. Yadav [11] employed K-mean clustering for segmentation to identify the disease area, followed by the process of removing colour and texture information from an image. The authors utilized the SVM classifier technique to classify potato leaf diseases and obtained an accuracy of 88.89%. Eftekhar Hossain et al. [12] applied the same method to classify several diseases, including Anthracnose Alternaria Alternata, , Leaf Spot, Bacterial Rot, and Plant Leaf Cancer. The KNN disease detection system achieved 96.76% accuracy in their experiment. Aakanksha Rastogi et al. [13] have focused on investigating disease detection in plants by analyzing leaf conditions through the utilization of fuzzy logic methods and artificial neural networks. Diseases on hydrangea and maple leaves were the primary focus of their research. The diseased leaves were categorized into two types: scorch leaf and leaf spot. Leaf spots were characterized by specific points of disease on the leaves, while scorched leaves had a more even spread of disease across the leaves. In 2020, V. Suresh and colleagues [14] presented a technological methodology for image processing and machine learning using a website. The framework involves collecting images and feeding them to a trained classifier through the website. Once the disease has been identified by picture processing and feature extraction, the website will take the user to a new page that details the best pesticides and chemicals to use, along with instructions for application and suggested retail prices. This proposed methodology stands out as it not only detects and classifies diseases but also recommends appropriate pesticides, making it a significant contribution to the field.

Yanli and colleagues [15] pointed out that lightweight models offer quicker disease detection and are less resource-demanding. They designed the HLNet, a deep learning model utilizing lightweight CNN, specifically for the rapid and efficient recognition of disease. Suleman and team [16] devised a model reliant on meta-deep learning for the detection of cotton leaf disease. The model was trained on a dataset comprising 2385 images of healthy and diseased leaves, managing to achieve an accuracy of 98.53%. The Backpropagation Neural Network technique was used by Jobin Francis et al. to categorize illnesses affecting pepper plants. For feature extraction, they employed GLCM (Gray Level Co-occurrence) technique. a fungal infection, Berry Spot Disease, and Rapid Disease, caused by mineral shortages including magnesium, nitrogen, and potassium, were among the illnesses picked up by their method. Deep learning techniques applied to plant image recognition based on leaf vein patterns were first introduced [17]. These techniques facilitated the classification of three different types of legumes (white bean, red bean, and soybean) using a CNN comprising 3-6 layers. Deep learning models were validated on the Plant Village dataset [18]. During this assessment, GoogleNet outperformed AlexNet, another renowned CNN architecture, under color, grey, and segmentation scenarios, resulting in an accuracy rate of 99.35% on the test set. For the symptom-wise identification of four cucumber diseases, Ma et al. [19] employed a deep CNN, attaining a recognition precision of 93.4%. Kawasaki et al. [20] introduced a CNN-based system for cucumber leaf disease detection, reaching an accuracy rate of 94.9%. Muammer et al. [21] used nine deep learning architectures for feature extraction, proceeded by classification using SVM, ELM, and the k-nearest neighbour algorithm, to implement deep learning techniques for the detection of plant leaf disease and pests. Despite the limitation of a relatively small dataset of 1965 images representing eight different plant leaf diseases, the approach achieved an impressive accuracy of 97.86% with the ResNet 50 model and SVM classifier. Ghosal et al. [22] a deep CNN framework was created to identify and classify eight distinct forms of soybean stress, and it provided an explanation mechanism and forecasts using top-K high-resolution feature maps that isolate visual symptoms. For unsupervised recognition of visual symptoms, Barbedo [23] and Lee et al. [24] proposed the examination of lesions and spots instead of the entire leaf. This method made it possible to identify and categorise foliar stress and to provide a numerical indicator of the severity of the stress. The occurrence of multiple diseases on the same leaf could be determined by focusing on lesions and spots, and data could be improved by segmenting the leaf picture into various sub-images using the GoogLeNet model.

Anim-Ayeko et al. use a convolutional neural network (CNN) architecture, specifically a modified version of ResNet, which was employed. The proposed deep learning model achieved an impressive accuracy of 95% for detecting blight disease in both potato and tomato plants, demonstrating its effectiveness in early disease detection. By effectively capturing complex patterns and features in the images, the CNN facilitated accurate disease classification, highlighting its potential for automated blight disease detection in these plant species [25]. Singh & Yogi conducted an extensive evaluation of deep learning models for detecting plant leaf diseases. They employed various popular architectures such as VGG16, ResNet50, and InceptionV3 to train and test their models. The results revealed that ResNet50 achieved the highest accuracy of 92% in accurately identifying plant leaf diseases, followed closely by InceptionV3 with an accuracy of 89%. The study demonstrated the efficacy of deep learning models in plant leaf disease detection and provided insights into the performance of different architectures [26]. Mahum et al. proposed a new approach for detecting potato leaf diseases. They employed an efficient deep learning model called EfficientNet, which has demonstrated superior performance in image classification tasks. The framework achieved impressive results, with an accuracy of 95% in distinguishing healthy potato leaves from diseased ones. The model's efficiency allowed for fast inference times, making it is appropriate for use in agricultural situations in real-time [27].

The primary objective of the research strategy is to utilize Deep Learning for classifying and identifying healthy and diseased and infected leaf conditions. Convolutional neural network architecture models are used in the study, including VGG16, inception v3, inception resnet v2, and efficient net b4, to achieve this objective. These models' architectural layer enables the identification of useful characteristics for accurately classifying leaf diseases. The study's focus on the use of Deep Learning and these advanced architecture models underscores the importance of machine learning in addressing complex problems in plant pathology. The research methodology presents a promising approach to diagnosing and classifying diseases through leaves using powerful machine learning techniques. This approach has the potential to significantly aid in the development of efficient and long-lasting disease management strategies for the agricultural industry.

3. Methodology

3.1. Dataset

In a deep learning-based paper, a dataset serves as the fundamental building block. It not only facilitates the training of the model but also enables us to derive a multitude of additional findings from it. For this particular study, the Plant Village Dataset [28] was utilized, which was sourced from Kaggle. Kaggle is an online hub for data scientists and ML engineers, providing them with opportunities to engage in ML competitions and work with diverse datasets and notebooks [29]. A few samples from the dataset are presented below in Figure 1.

Figure 1. Kaggle: Plant village potato dataset

The dataset comprises approximately 20,000 images showcasing diverse plant species in either jpg or png format. This collection contains both healthy and diseased plant leaves, with our focus solely on the Potato plant subset. The dataset used in this study is made up of a subset that includes 152 photos of potato leaves in good health, 1000 images of leaves affected by late blight, and 1000 images of leaves affected by early blight. The diseased leaves were classified into two distinct categories: early blight and late blight. Throughout the process of training and evaluating the model, a greater number of leaves will be utilized for training, with fewer leaves reserved for testing, to achieve optimal prediction and detection accuracy. The label count of the datasets is shown in Figure 2 as shown below:

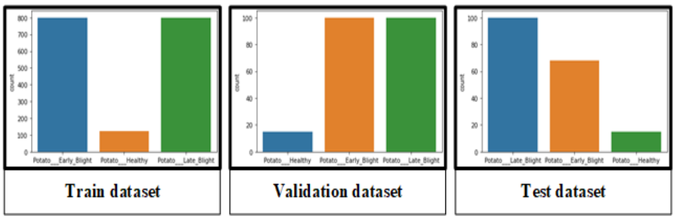

Figure 2. Label counts of datasets

3.2. Method

In this research, the primary objective is to create a deep learning model that can accurately identify diseases in potatoes. Four popular convolutional neural networks (CNN) architectures, namely VGG16, Inception ResNet V2, Inception V3, and Efficient Net B4 were utilized for this purpose. We have used the Plant Village Dataset, which includes numerous images of both healthy and damaged potato plants. The dataset was preprocessed and augmented to ensure sufficient variability in the training data. The preprocessed dataset was then separated into test, training, and validation sets. The CNN models were trained on the training set using transfer learning, incorporating pre-trained weights acquired from the ImageNet dataset. The best-performing model was determined based on the validation set's accuracy, and its performance was assessed using the test set. The evaluation metrics included recall, precision, accuracy, and F1 score. The four models' outputs were compared, and the most accurate model was identified for potato disease detection. The proposed model based on deep learning demonstrates the considerable potential to assist potato farmers in the early detection of diseases, allowing for timely intervention and minimizing yield losses.

3.3. Model architecture

A deep convolutional neural network called the VGG16 model has gained significant popularity and has been widely employed in diverse image classification tasks., including the identification of diseases in medical images. This model has 16 layers, including 3 fully connected layers and allowing it to effectively extract essential features from images at a high level. Studies have shown that the VGG16 model has achieved high accuracy in detecting diseases such as breast cancer, diabetic retinopathy, and lung cancer from medical images [30, 31]. The Inception v3 and Inception ResNet V2 models comprise various layers, such as convolutional layers, pooling layers, and inception modules. These components allow the models to extract significant features from images at multiple levels. Studies have shown that the Inception v3 model has achieved high accuracy in detecting diseases such as skin cancer, lung cancer, and diabetic retinopathy from medical images [32, 33]. The use of these models for disease detection has significant potential for enhancing the accuracy and efficiency of medical diagnosis. A deep neural network architecture called EfficientNet-B4 has attained cutting-edge performance on several computer vision applications, such as object detection and image categorization. It was introduced by Tan and Le in 2019 as an improvement over the previous EfficientNet models [34]. EfficientNet-B4 employs a fusion of convolutional neural networks (CNNs) and efficient scaling methods to achieve high accuracy while minimizing the computational cost. Specifically, the model employs a compound scaling method that optimizes the scaling of depth, width, and resolution dimensions of the network, resulting in a more efficient and accurate model. In a comparative study of various CNN architectures, including ResNet, Inception, and VGG19, EfficientNet-B4 was found to outperform them in terms of accuracy and efficiency of computation on the ImageNet dataset. With just 17M parameters, it managed to attain top-1 accuracy of 85,1%, which is significantly smaller than the other models with similar accuracy. EfficientNet-B4 has also been used in several applications in the real world, such as autonomous driving and medical image analysis, where high accuracy and efficiency are crucial. Its versatility and performance have made it a popular choice among researchers and practitioners in the computer vision community.

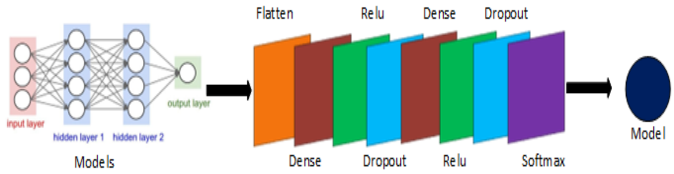

Figure 3. Model architecture

The model architecture shown in Figure 3 starts with a model (Vgg16, inception v3, and inception-resnet V2), then a layer that is flattened that converts the output of the previous output into a one-dimensional array. The next layer is a dense layer that connects every input to every output neuron. After the dense layers were rectified linear unit (ReLU) activation function was implemented to introduce non-linearity. The following layer is a dropout layer, which can aid in preventing overfitting, a technique called "dropout" is commonly employed, which involves randomly setting a fraction of input units to zero during each training iteration. Another dense layer follows the dropout layer, again with a ReLU activation function. The final layer is another dropout layer to further prevent overfitting. Overall, this model with a series of layers and activations is designed to effectively learn features from the input data and make accurate predictions.

3.4. Platform utilized

The hardware used in the paper is a laptop with the specification of 6 GB with Intel Core i5 CPU @ 2.50GHz and OS of 64-bit. To run the source code, we have utilized the Google colab. The Collaboratory, or simply "Colab," is a creation of Google Research. With Colab, anyone may write and run arbitrary Python code online. It is especially useful for teaching, data analysis, and machine learning. Colab is a distributed Jupyter Notebook solution that doesn't require installation and provides open access to hardware like GPUs [35]. For data visualization, we have used the matplotlib library to plot graphs related to the model's performance. An open-source Python package used for charting is called Matplotlib. For Machine learning, we have used TensorFlow and Keras library. TensorFlow and Keras are open-source software libraries for deep neural nets [36].

4. Results

4.1. VGG16

A well-known convolutional neural network design utilized in computer vision tasks is the VGG16 model. It has seen widespread application recently in several fields, including agriculture, for the detection of illness in crops. One such application is in detecting diseases in potatoes, where the VGG16 model has been used to achieve high accuracy rates. According to the results reported, the VGG16 model used for disease detection in potatoes achieved an accuracy rate of 99%. This indicates that in 99.9% of the potato photos it examined, the model correctly identified them, which is an impressive result. The high accuracy rate suggests that the model demonstrates efficacy in detecting the presence of diseases in potato crops. Figure 4 and Table 1 correspondingly display the results.

Vgg16 model results

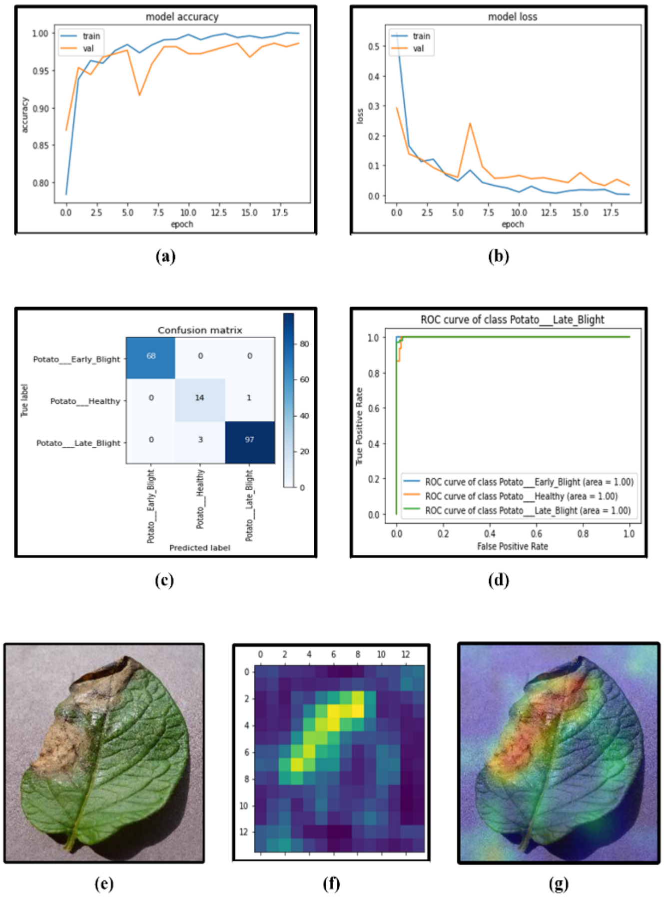

Figure 4. VGG16 model results. (a) Model accuracy (b) Model loss (c) Confusion matrix (d) ROC curve (e) Diseased leaf (f) Heatmap (g) Grad Cam

Table 1. Classification report of VGG16

Categories	Precision	Recall	F1-Score	Support
Potato__Early_Blight	100	100	100	68
Potato_Healthy	82	93	87	15
Potato_Late_Blight	99	97	98	100

4.2. InceptionV3

Another convolutional neural network design that has been used to handle the problem of disease detection in potato crops is the Inception model. The results indicated that the Inception model accomplished an accuracy rate of 98%, an AUC score of 99%, a Cohen's Kappa coefficient of 97%, a recall of 97%, and a precision of 98%. These outcomes show how well the Inception model works in accurately identifying diseased potato crops, with high levels of agreement between the model's predictions. This model shows comparatively fewer results than VGG16. Overall, the reported results suggest that the Inception model can be a reliable and effective tool for detecting diseases in potato crops. Figure 5 and Table 2 correspondingly display the results.

InceptionV3 model results

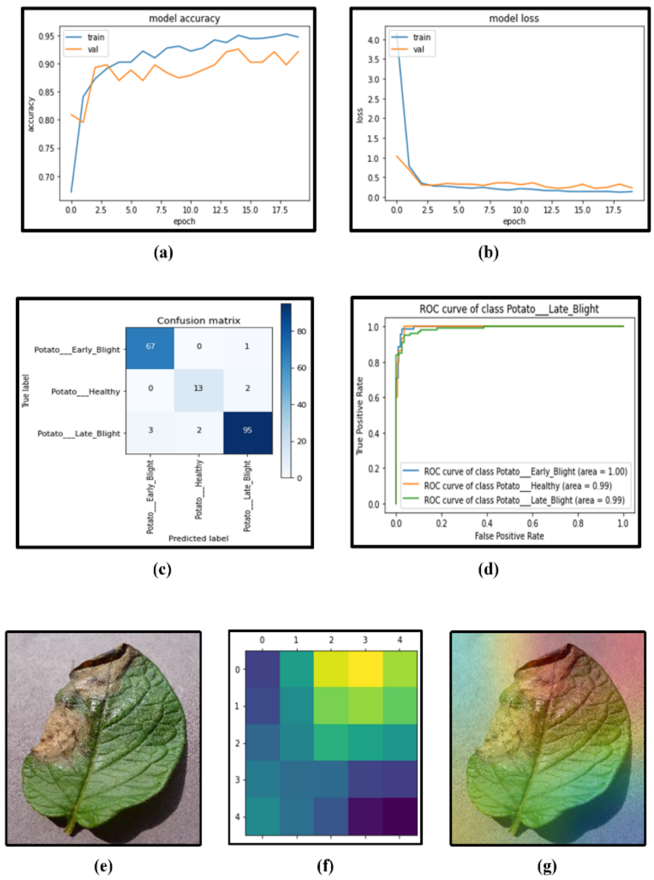

Figure 5. InceptionV3 model results. (a) Model accuracy (b) Model loss (c) Confusion matrix (d) ROC curve (e) Diseased leaf (f) Heatmap (g) Grad Cam

Table 2. Classification report of Inception V3 model

Categories	Precision	Recall	F1-Score	Support
Potato__Early_Blight	96	99	97	68
Potato_Healthy	87	87	87	15
Potato_Late_Blight	97	95	96	100

4.3. Inception resnetV2

The inception resnet v2 model is a unique deep learning architecture that integrates the features of both Inception and ResNet models, enabling it to excel in image classification tasks with remarkable performance. When applied to disease detection in potato crops, the reported results showed an accuracy rate of 94%, an AUC score of 99%, a Cohen's Kappa coefficient of 90%, a recall of 94%, and a precision of 94%. Although the accuracy rate is slightly lower compared to the other models discussed, the Inception ResNet v2 model still demonstrated high levels of performance in correctly identifying diseased potato crops, as indicated by the high AUC score, recall, and precision metrics. The lower Cohen's Kappa coefficient suggests that there may be some variability in the model's predictions. Overall, the results suggest that the Inception ResNet v2 model can be a useful tool for detecting diseases in potato crops, but further evaluation may be needed to improve the model's reliability. Figure 6 and Table 3 correspondingly display the results.

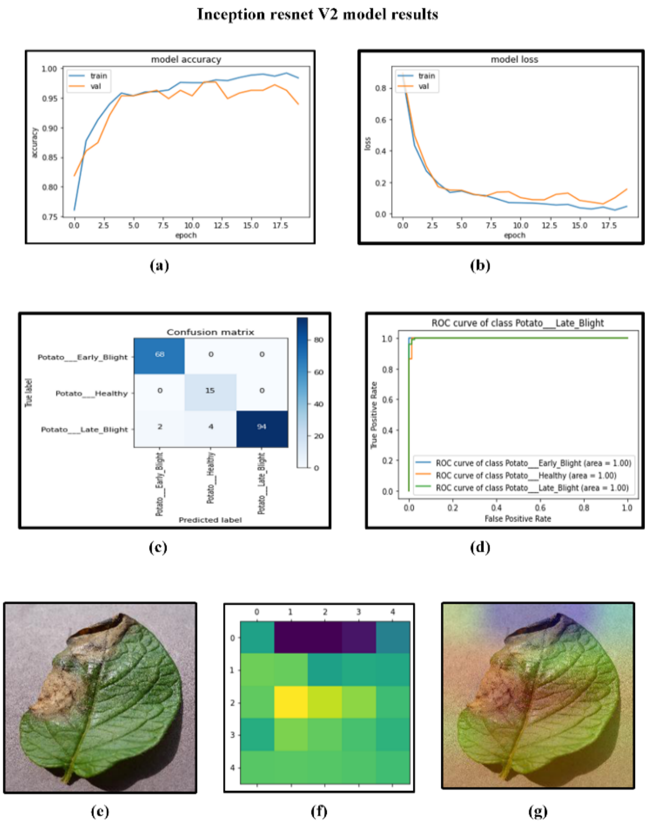

Figure 6. Inception Resnet V2 model results. (a) Model accuracy (b) Model loss (c) Confusion matrix (d) ROC curve (e) Diseased leaf (f) Heatmap (g) Grad Cam

Table 3. Classification report of Inception Resnet V2 model

Categories	Precision	Recall	F1-Score	Support
Potato__Early_Blight	100	100	99	68
Potato_Healthy	79	100	88	15
Potato_Late_Blight	100	94	97	100

4.4. EfficientNet B4

The results of using the EfficientNet B4 model for disease detection in potatoes are also very impressive, as it also achieved 100% accuracy, AUC, Cohen kappa, recall, and precision. This suggests that the model is very effective at identifying disease in potato plants, with no false positives or false negatives. The high level of performance of the EfficientNet B4 model indicates its potential for use in disease detection in other crops and could help in developing strategies for controlling plant diseases. The prediction results with respective confidence are given in Figure 7.

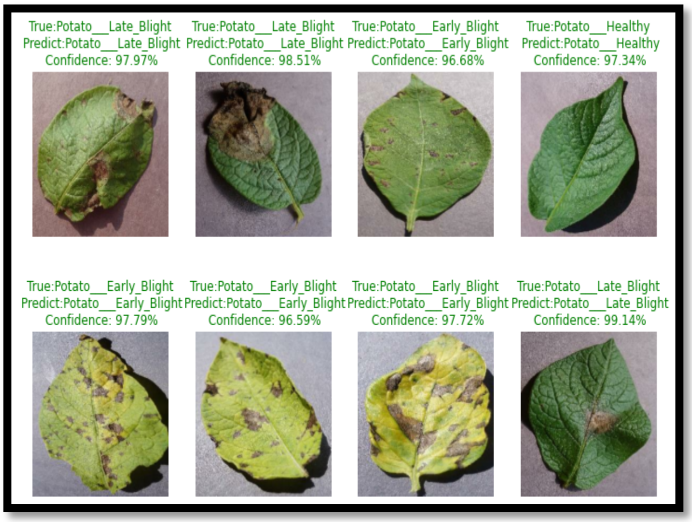

Figure 7. Efficient Net B4 predictions

The accuracy of a neural network is a crucial performance indicator, which measures the percentage of samples in the test dataset that were properly categorized. In the case of Efficient Net B4, if the accuracy is reported as 100%, it means that the network has correctly classified all the samples in the test dataset. This is an impressive achievement, as it indicates that the network can generalize well to unseen data and has learned the underlying patterns of the dataset. However, accuracy alone may not be enough to fully analyze the effectiveness of a neural network, as it can be biased towards the majority class or may not capture the subtle differences between classes. Therefore, the metric validation accuracy measures the proportion of correctly classified samples in an independent validation set from the training set. Having both accuracy and validation accuracy at 100% in Efficient Net B4 indicates that the network has learned a highly discriminative representation of the dataset, which can be attributed to its architecture that combines different scaling dimensions and efficient building blocks as shown in Figure 8:

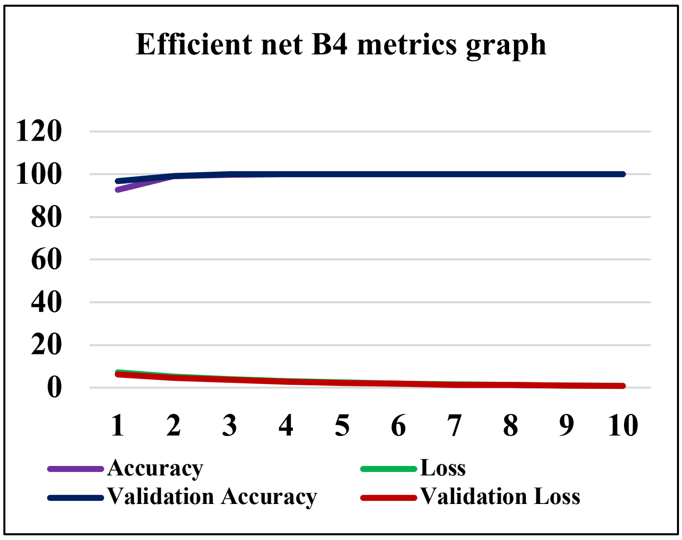

Figure 8. Efficient Net B4 metrics graph

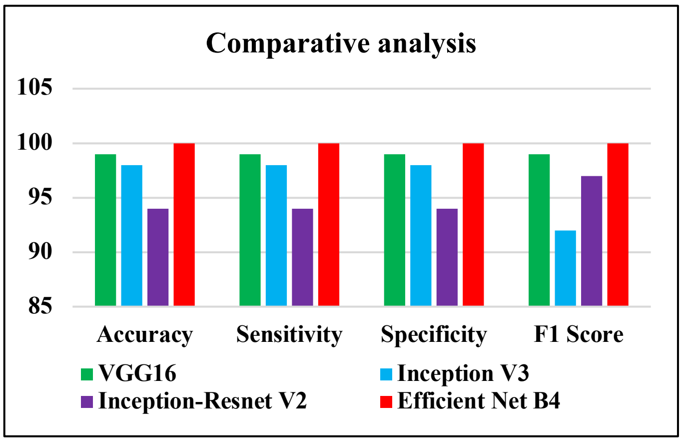

Figure 9. Comparative analysis

Figure 9 shows that the EfficientNet-B4 is a powerful deep neural network architecture that has accomplished cutting-edge performance on some computer vision tasks. Its efficient scaling methods and compound scaling approach make it a more accurate and efficient alternative to other CNN architectures.

5. Conclusion and Future Work

This study underscores the profound importance of the devised deep learning model for the precise detection of potato diseases. Our research illustrates the effectiveness of various CNN architectures such as VGG16, Inception V3, Inception ResNet V2, and Efficient Net B4, thereby demonstrating the compelling potential of deep learning algorithms for pragmatic applications in the agricultural sector. Our model, having demonstrated an impressive accuracy rate of 100% in identifying potato diseases, has significant implications for farmers, as it facilitates plant disease early detection, enables swift intervention, and consequently reduces the risk of significant yield losses. The development of such automated and effective disease detection systems can herald a new era in sustainable farming, encouraging less reliance on pesticides and fungicides, and promoting eco-friendly agricultural practices. In essence, the proposed deep learning model has the potential to significantly transform the agricultural sector, serving as a dependable and efficient tool for disease detection in potato crops. Looking towards prospects, it would be worthwhile for evaluating the performance of our model in detecting diseases across a broader variety of crops, leading to the creation of more comprehensive and versatile disease detection systems for extensive agricultural use. Recent years have seen a variety of promising approaches to disease treatment. Early detection can lead to less damage and easier management, whereas late detection can result in severely reduced yield and increased costs due to the need for pesticides and manure. However, disease detection alone is not sufficient for farmers; proactive measures are necessary to mitigate potential losses. One potential avenue for future research could be the development of an Artificial Intelligence (AI)-driven bot capable of initiating the required measures to treat diseased leaves, thus making farming more effective and less demanding.

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