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Incorporating MobileNet models into the classification of bean leaf diseases

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Abstract

In the past few years, the prevalence of plant leaf diseases has emerged as a significant issue, necessitating the need for precise investigation and prompt use of deep learning techniques in the categorization of plant diseases. Beans are considered to be one of the most significant plants and seeds that are widely used globally for culinary purposes, whether in their dried or fresh state. Beans are considered to be a very valuable protein source that confers several health advantages. However, the cultivation of beans is sometimes impeded by various illnesses, including angular leaf spot disease and bean rust disease. Therefore, it is essential to establish a precise categorization system for bean leaf diseases in order to effectively address the issue in its initial stages. The objective of this study is to use a deep learning approach for the precise identification and categorization of bean leaf disease. There are several illnesses that are often linked with bean leaves, including angular leaf spot disease and bean rust disease, which have a detrimental impact on bean yield. Therefore, in order to address these issues in their initial stages, a suggested solution involves the use of a deep learning technique. This strategy aims to accurately detect and classify bean leaf diseases by using a publicly available collection of leaf images and employing the MobileNet model, which is implemented using the open source library TensorFlow. The MobileNetV2 architecture was used to train the model under controlled settings, aiming to assess the potential benefits of quicker training times, improved accuracy, and simplified retraining compared to the MobileNet design. The algorithm was evaluated using the bean leaf dataset, and the findings indicate that our approach exhibits a higher level of accuracy in detecting faults.

Keywords: Beans Leaf, CNN, Dataset, Deep Learning, Disease Classification, MobileNet, Plant Disease, Transfer Learning,Tensorflow.

1. Introduction

This research presents a novel approach for the classification of bean leaf illnesses into distinct groups. The suggested technique leverages MobileNet, a convolutional neural network(CNN) renowned for its effectiveness in generating efficient models suitable for a wide range of mobile applications[1-3]. The approach described in this study used the MobileNet architecture, which was implemented using the open source library TensorFlow. The present study involves a comprehensive analysis and assessment of MobileNet architectures, specifically focusing on hyperparameters and optimization methods. The primary objective is to develop a compact and highly efficient MobileNet model that can accurately classify diseases into their respective classes. Various architectures were compared and evaluated to determine their effectiveness in achieving this goal. In the present investigation, public datasets including two categories of

ISSN PRINT 2319 1775 Online 2320 7876
 Volume 11, Iss 12, 2022

beans leaf disease and one category of healthy leaves were used. The dataset included in this study comprises a collection of leaf photographs captured in various geographical locations by the AI lab in collaboration with the National Crops Resources Institute (NaCRRI) [4].
Beans are a highly prevalent seed in global consumption and hold significant agricultural importance on a global scale. Small-scale farmers in Latin America and Africa contribute to approximately 30% of the worldwide bean crop production [5]. Beans serve as a valuable protein source and offer numerous health benefits. However, despite their significance, beans plants are susceptible to a range of diseases, including those caused by fungal and bacterial organisms [6]. Therefore, the production of beans is significantly impacted by diseases such as angular leaf spot disease and bean rust disease. To combat these pathogens, a variety of pesticides are employed. For instance, fungicides, biological control methods, and cultural practises such as intercropping, optimal plant spacing, and the use of soil amendments that enhance soil health and plant nutrition can effectively manage angular leaf spot disease and bean rust disease [7].
Nevertheless, the extensive and pervasive use of these compounds may have detrimental effects on both human health and the environment. Consequently, the detection and categorization of plant leaf diseases continue to play a crucial role in the field of agriculture. Hence, the development of an automated system is necessary for the early control of crop diseases. The utilisation of automatic techniques for the identification of crop diseases proves advantageous, particularly in large-scale agricultural production where supervision can be challenging. One such technique involves the application of deep learning models for the automatic classification of bean leaf diseases. This research topic holds significance as it aims to provide benefits to farmers by enabling the effective management of crop diseases in large fields at an early stage and with high efficiency. Consequently, this work will address the issue of disease identification in plants, enabling prompt treatment and ultimately enhancing the quality and quantity of crops. As a result, farmers will experience increased profitability.

2. Related works

In the field of precision agriculture, the development of a precise disease classification model is crucial for the effective detection and diagnosis of various plant diseases.Classification approaches have the potential to effectively discern and differentiate various forms of plant diseases by analyzing the symptoms shown in leaf images during the first stages. Numerous authors have undertaken the development, testing, and validation of diverse classification algorithms in order to achieve precise diagnosis of various plant illnesses, including but not limited to fruit classification [8], disease classification [9], and species classification [10]. In a previous study, [11] conducted a classification of rice plant diseases by using a pre-trained Convolutional Neural Network (CNN) model in conjunction with Support Vector Machine (SVM). [12] developed an automated system for diagnosing wheat diseases, utilizing the VGG-FCN-VD16 and VGG-FCN-S architectures. The authors of this research used the Beans leaf image collection for the purpose of disease classification.

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The field of automated illness categorization using image analysis has garnered significant attention from scholars in recent years.Nevertheless, despite the extensive measures implemented, these diseases continue to pose a significant obstacle to the achievement of sustainable agriculture. Furthermore, there exists a significant requirement for a rigorous protocol carried out by a substantial group of experts to consistently monitor these diseases in their early stages. This is due to the fact that the prevailing methodology for classifying and detecting plant diseases primarily relies on visual observations made by specialists. However, it has become increasingly apparent in recent years that deep learning models employing various techniques have proven to be highly efficient in disease classification. MobileNet is a convolutional neural network architecture that has been trained on the ImageNet datasets for the purposes of object recognition and classification. This training has been conducted using the TensorFlow library. In comparison to standard neural networks, MobileNet has the ability to achieve high accuracy in its predictions while using a very little amount of training data. Additionally, MobileNet exhibits the advantage of requiring a shorter training period. TensorFlow, developed by Google, is a specialized platform designed for machine learning applications [13]. It offers extensive educational resources for beginners to gain proficiency in various classification techniques via the process of transmitting knowledge. TensorFlow has garnered significant interest in the field of machine learning[15] globally because to its notable attributes of high flexibility, accessibility, and exceptional performance. MobileNets is a set of pre-trained models available on the TensorFlow platform. These models have been specifically designed to enhance the efficiency and usability for researchers across multiple domains. Over time, MobileNets have undergone several enhancements and modifications, building upon the foundations laid by previous models such as Inception-v1, Inception-v2, and Inception-v3. In this work, the researchers have used MobileNet, a well-established model for picture classification, to examine its performance in the context of classifying Beans leaf illnesses. The analysis reveals a very satisfying outcome in terms of classification accuracy.

3. Materials and Methods

3.1 Datasets

The Beans Leaf Dataset has a total of 1295 photos of beans that were obtained using mobile phone cameras in agricultural areas. The classification consists of three distinct groups, namely two illness categories and one category representing a state of health. The disease categories include Angular Leaf Spot and Bean Rust. The data, obtained by the Makerere AI research group, was analysed by experts from Uganda's National Crops Resources Research Institute (NaCRRI). In this experiment, the dataset was divided into three distinct classes: Angular leaf spot class, Healthy bean class, and Bean rust class. The dataset was then allocated with 80% for training, 10% for testing, and 10% for validation purposes. Figure 2 shows samples of leaf pictures classified according to the classifications used. The picture in this public dataset was captured using a smartphone camera on the farm, thus in order to give an appropriate trainer model to enhance illness prediction, we converted every image in this dataset into 128-by-128

ISSN PRINT 2319 1775 Online 2320 7876
Research paper **Volume 11, Iss 12, 2022**

pixels in accordance with MobileNet's input requirement. Each picture in this public dataset was related with (NaCRRI) specialists who decided which illness was exhibited and associated with precisely one condition (healthy, angular leaf spot disease, or bean rust disease). As illustrated in figure 2, some leaf picture backgrounds consist mostly of other overlapping leaves of the same plants, and the diameter of images varies between groups of photographs within the same category. The dataset will be trained in the CNN model utilizingMobileNet topologies, and the results will be assessed using four distinct performance assessment criteria. F1-score, recall, precision, and accuracy.

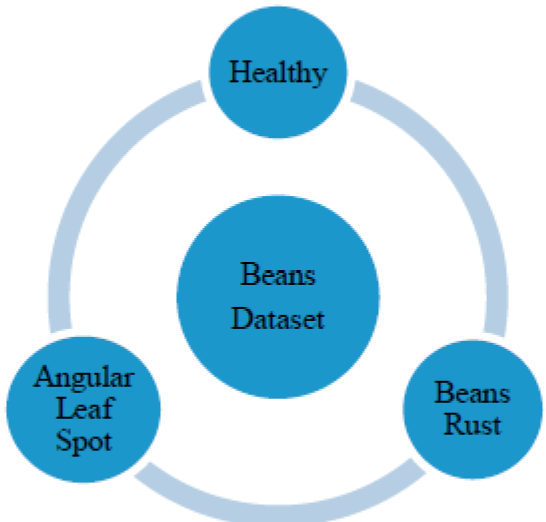

Figure 1. Beans Leaf Image Dataset

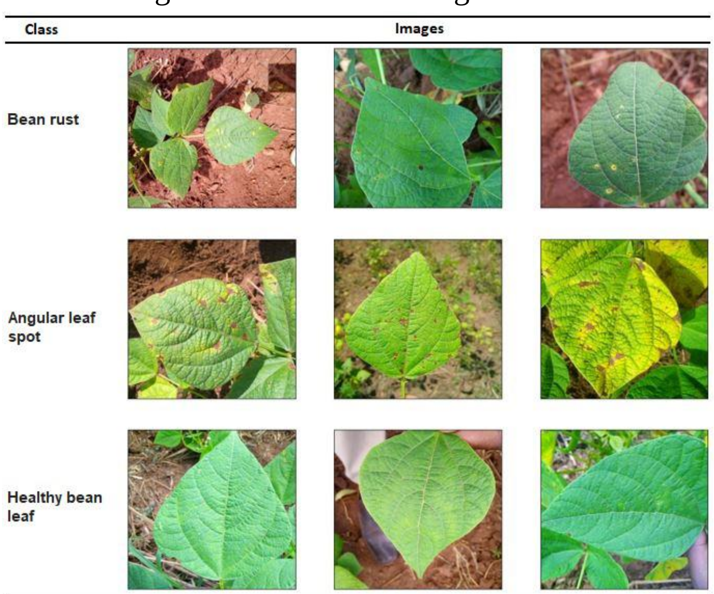

Figure 2. Some examples of bean leaf diseases classifications

3.2 Implementation

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This section discusses the experimental setup of a bean disease model using the MobileNet architecture with the TensorFlow framework. To implement deep learning architectures, several steps are required, starting from dataset collection to performance analysis and classification. In this case, the classification model is divided into different stages, including data examination and building an input pipeline. The goal is to develop a classifier that can predict whether a bean leaf has been affect. In a similar manner, we constructed a validation and test pipeline that employed comparable transformations. It is advisable to assess the imbalance in disease classes and determine if there exists a class with a notably lower number of samples compared to the other disease classes. However, in the present study, we utilized a publicly available dataset that initially exhibited a nearly balanced distribution of classes. This dataset was subsequently divided into three distinct classes, namely Angular Leaf Spot, Healthy class, and Bean Rust. This study examines the architecture of MobileNet, which consists of 8 convolution layers specifically designed for image classification. The training process involves the repeated use of each image, and the learning algorithm experiences each training batch exactly once per epoch. At the end of each epoch, the algorithm evaluates its performance on the validation set. In this particular study, the training set consists of 1034 images, and each batch comprises 32 examples, resulting in a total of 33 batches in each stage.

3.3 Transfer Learning

The MobileNetV2 model has an inverted residual structure, which is characterized by the presence of residual connections between bottleneck layers. The use of light-weight depth-wise convolutions in the intermediate expansion layer filters serves as a means to introduce non-linearity. MobileNetV2's architectural design includes a fully convolutional layer including 32 filters, which is then succeeded by 19 residual bottleneck layers. EfficientNetB6 is a CNN that use a compound coefficient to systematically modify the network's depth, breadth, and resolution, resulting in enhanced performance. In contrast to the conventional approach, which randomly modifies these parameters, the EfficientNet scaling technique employs a predetermined set of scaling coefficients to enhance the breadth, depth, and resolution of the network. NasNet, a kind of deep neural network architecture known as Neural Search Architecture (NAS), has been used in several applications where the selection of an appropriate design is critical to achieve optimal performance. The first investigation in this domain was conducted by NASNet, which entails the formulation of a CNN[14] as a sequential decision-making task that can be effectively addressed using deep learning techniques.

3.4 Training Process

This work included the training of MobileNet models in TensorFlow, using several MobileNet architectures and five distinct optimizers: adagrad, nadam, SGD, RMSprop, and adam optimizer. The training process used asynchronous gradient descent. However, when comparing MobileNets to other models like Inception, it is seen that MobileNets use less regularisation and rely on depthwise separable convolution. In contrast, Inception V3 utilises ordinary convolution.

IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
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Research paper Volume 11, Iss 12, 2022

As a consequence, MobileNet has a lower parameter count. Nevertheless, this phenomenon leads to a marginal decline in performance. Therefore, it is crucial to apply little or no weight decay to the depthwise filters due to their limited parameter count. In essence, while training big models, we use data-organizing methods such as geometric transformations to a lesser extent, since smaller models have less challenges in this regard. In fact, the dimensions of the input data fed into the neural network are quite modest. Consequently, the output of the neural network consists of three class labels, each corresponding to a certain crop [16].

4. Results

This research conducted an experiment on three distinct CNN models, namely MobileNetV2, EfficientNetB6, and NasNet. The experiment used open source frameworks TensorFlow and Keras, and was executed on the Google Colab deep learning server. The dataset of Beans had a total of 1295 photos, which were allocated into three distinct subsets: training, testing, and validation. The training subset contained 1034 images, the testing subset contained 128 images, and the validation subset contained 133 images. The dataset consists of three distinct classes: the healthy class, the angular leaf spot disease class, and the bean rust disease class, containing 427, 432, and 436 photos respectively. In this experiment, all the convolutional neural network (CNN) models were trained using consistent learning rates, epochs, and batch sizes. Various optimisation strategies, including Adam, SGD, and Nadam, were used, and the resulting outcomes were then compared. The study revealed that the use of EfficientNet in conjunction with the Adam optimizer yielded the most notable validation accuracy, reaching 93.47%. Furthermore, the MobileNetV2 model trained with the Nadam optimizer achieved a validation accuracy of 94.25%, whereas the MobileNetV2 model trained with the RMSprop optimizer achieved a little lower validation accuracy of 93.58%.

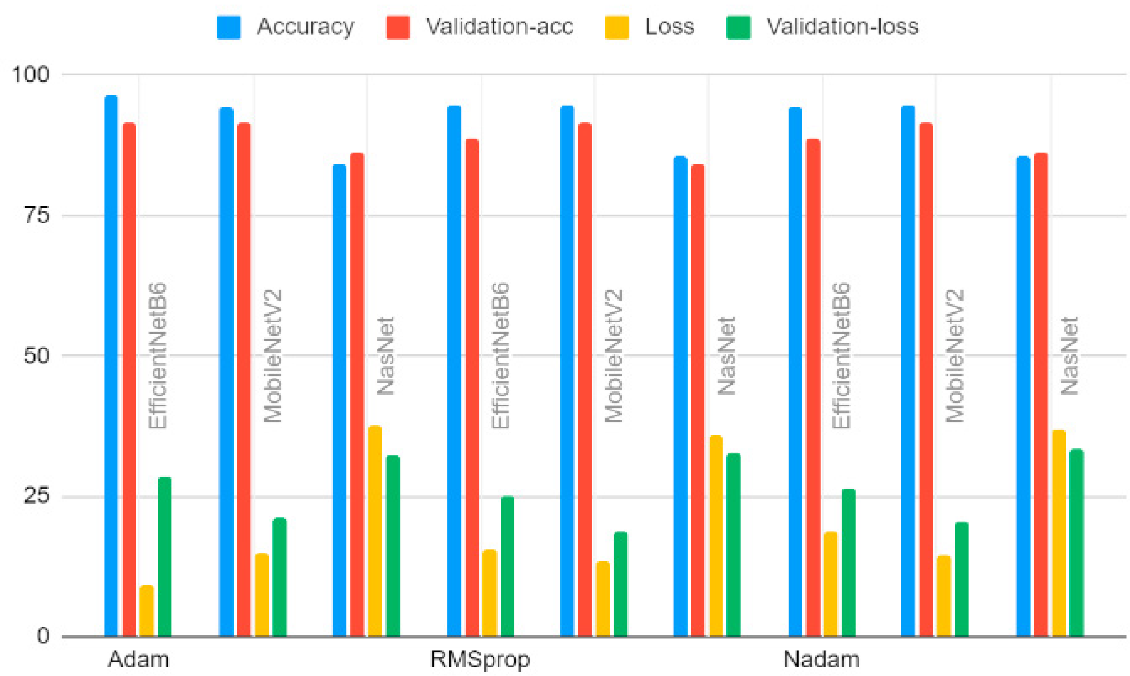

Figure 3. Comparative analysis of CNN models using a variety of optimizers

ISSN PRINT 2319 1775 Online 2320 7876
Research paper **Volume 11, Iss 12, 2022**

The findings are shown in the form of a bar chart in Figure 3 for training accuracy and loss, as well as validation accuracy and loss, in the comparison charts for all variants. It has been noted that EfficientNetB6 with the Adam optimizer got the maximum validation accuracy, which came in at 92.35%. In addition to this, the validation accuracy of MobileNetV2 with the Nadam optimizer was determined to be 93.54%, while the validation accuracy of NasNet with the Adam optimizer was determined to be 87.51%.

As the model evolves, the previously chosen hyperparameters may no longer be optimal; yet, it is impossible to manually conduct fresh searches on an ongoing basis. Selecting hyperparameters manually is laborious, time-consuming, and prone to making mistakes. As a result, we used our Mobilenet model to undertake an automated comparison of the effectiveness of various learning rates for the purpose of bean leaf disease classification. As can be seen in Figure 4, the purpose of this comparison was to effectively assist disease categorization within their respective classes.

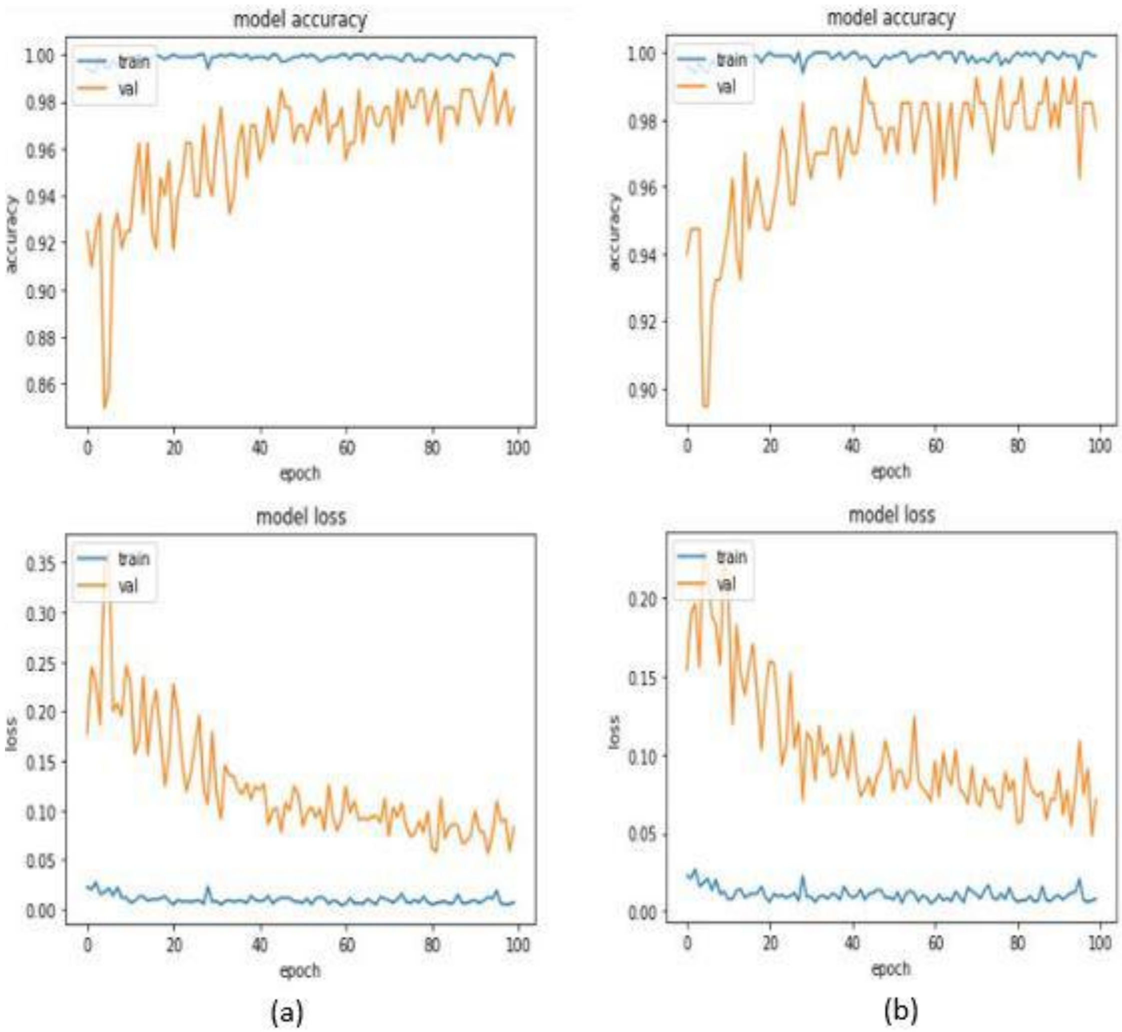

Figure 4. Accurate and lost for different learning values : 0.01, 0.001

Figure 5 illustrates that the Adam optimizer achieves the highest accuracy of 100% in diagnosing bean leaf illnesses. Following closely is the SGD optimizer, which achieves the second highest accuracy of 91%. Figure 6 displays the training accuracy and validation accuracy.

ISSN PRINT 2319 1775 Online 2320 7876
 Volume 11, Iss 12, 2022

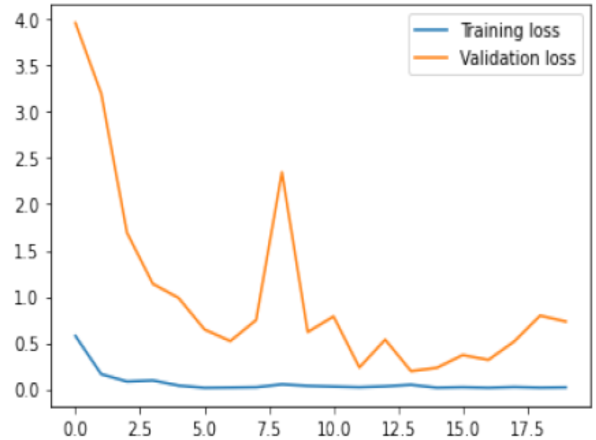

Figure 5. Model Accuracy and Model Loss

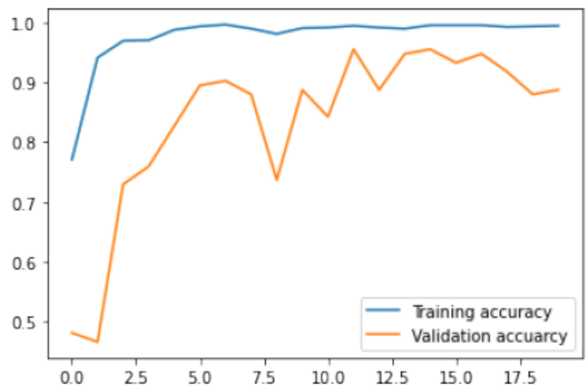

Figure 6. Training Accuracy and Validation Accuracy

According to the findings shown in Figure 7, the MobileNetV2 model achieved a validation accuracy of 91.73% when trained with the Nadam optimizer, resulting in a validation loss of 0.2055. Additionally, when the same model was trained with the Adam and RMSprop optimizers, it achieved validation accuracies of 91.72% and 91.72% respectively, accompanied by validation losses of 0.2055 and 0.1888 respectively.

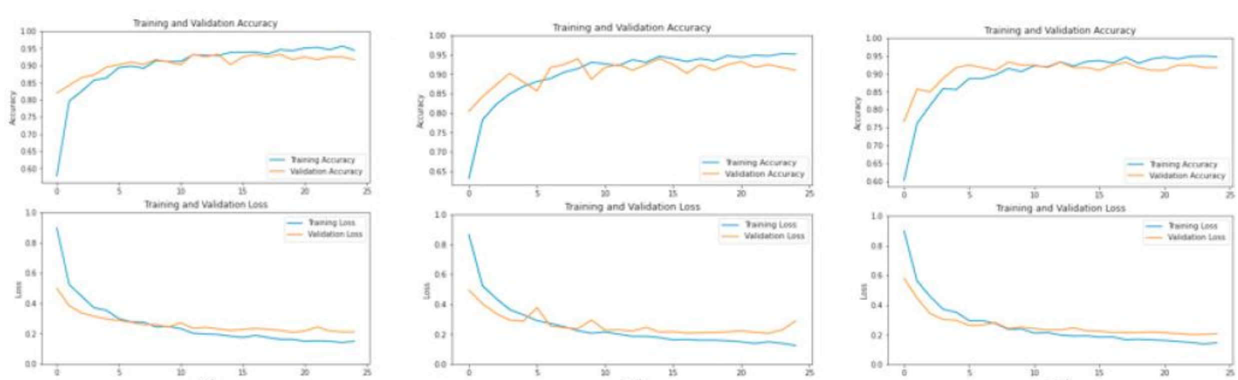

Figure 7. Accuracy and loss graph of MobileNetV2 with Adam; RMSprop; Nadam

5. Conclusion

The issue of plant disease has been a significant and longstanding problem within the field of agriculture. The use of smart agricultural techniques has facilitated the timely detection of diseases and the reduction of losses by using decision-making processes informed by deep learning outcomes. In this study, the researchers use a dataset consisting of 1295 photos of Beans leaves. These images were acquired using smartphone cameras in the field. Beans may be susceptible to many illnesses, including angular leaf spot disease and bean rust disease, which have the potential to inflict harm onto bean foliage, resulting in significant damage to bean harvests and a subsequent reduction in bean output. In order to enhance both the quality and quantity of the product, it is essential to identify diseases at an early stage.This study presents the development of an automated model using MobileNet, a CNN architecture, for the purpose of classifying and identifying the kind of illness present in bean leaf images. The objective is to construct precise models capable of effectively categorizing the diseases into their respective classes. This research introduces a methodology for the classification of bean leaf disease. Additionally, many architectures were used, assessed, and compared to determine the most effective approach for categorizing bean leaf disease. The classification outcome is very acceptable, demonstrating that the suggested methodology exhibits superior performance in the categorization of plant leaf diseases. The optimal experimental outcome is achieved by training our model using the Adam optimizer, using a learning rate of 0.01 and 0.001.The model also attained a precision rate of 91.4%. Moreover, empirical evidence suggests that the accuracy of classification training diminishes with an increase in batch size and a reduction in learning rate.

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