Detection of Plant Diseases Using CNN Architectures

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Abstract - *The agriculture industry is a significant sector in farming, and it is possible to automate plant processes based on diseases. In order to monitor the agricultural environment effectively, it is important to track both healthy and diseased plant leaves. This will help to separate them and generate higher crop yields and returns. Modern technologies such as machine learning, deep learning, and artificial intelligence have been used to classify healthy and diseased plants using image classification techniques. Transfer learning based models are continuously evolving to identify the presence of disease in plant leaves accurately, adding efficiency to the detection process and increasing the chances of identifying diseases at the right stage. The author recommends the use of Convolutional Neural Network, ResNet-50, Efficient-B2, and VGG-16 to detect and validate the presence of plant diseases in leaves. The dataset used in this paper includes 87,000 plant images from Kaggle repository, consisting of healthy and diseased plant images from 38 different categories. However, the final implementation of the models is tested on 250 healthy and 250 diseased plant images. The dataset is trained, tested, and validated using performance metrics such as accuracy and recall factors. Efficient-B2 was found to be the most accurate model, generating an accuracy of 94%.*

Key Words: CNN, Efficient-B2, machine learning, deep learning, ResNet-50, VGG-16

1.INTRODUCTION

The agricultural sector has always been the primary source and origin of food and serves the purpose of providing basic necessities for humans. Therefore, it has been recognized as the survival center of the world responsible for human lives [1]. As a result, the agricultural sector can be declared as the most important and central pillar of any economy. About 70% of the world's population depends on this sector for their livelihood, so the lives and health of individuals are a reflection of the agricultural sector [2]. Hence, this sector must be given due attention and not neglected. The forests and plants that they produce are an important aspect of the agricultural sector. The quality of such plants must be checked and monitored regularly to avoid decay. Detecting the presence of diseases in plants on time becomes a significant challenge in the agricultural sector to maintain the health of the plants and crops. Diseases in plants may occur due to various factors, such as improper or infertile land, inadequate water and sunlight, or an excessive number of pesticides [3]. All such factors are responsible for affecting the growth of the plant and creating a hurdle in its development and seedling growth, leading to diseases in plant growth. When a disease occurs in a plant, its growth is significantly impacted, and it may result in morphological and biological changes. The overall diseases in plants that cause such changes are mainly caused due to biotic and abiotic stress. Biotic stress is caused by living creatures in the soil, such as bacteria and viruses, that come in direct contact with the plant and negatively affect its growth [4]. On the other hand, abiotic stress is caused by non-living creatures, such as man-made or environmental factors [5]. Figure 1 below shows a diagrammatic representation of biotic and abiotic stress.

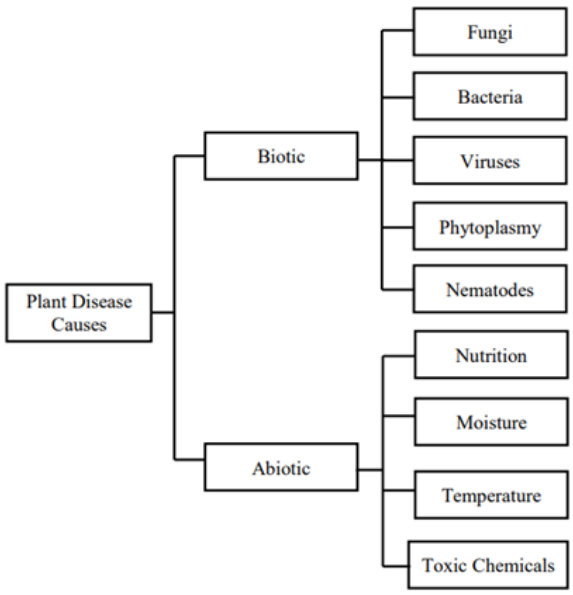


Figure 1: Schematic representation of diseases in plant[5]

The traditional method used by farmers to detect diseases in plants involves manual inspection, which is a time-consuming process due to the large fields of crops. Therefore, it is feasible to use machine learning techniques such as deep learning, transfer learning, and artificial intelligence for more precise and efficient detection. These algorithms can focus on specific features of the plant leaf, such as its saturation color, gradient orientation, and RGB features, to classify the plant leaf as healthy or diseased. The proposed research paper aims to automate the disease detection process using CNN and deep learning models like Efficient-B2, ResNet-50, and VGG-16. The study involves collecting a dataset of 250 images of healthy and diseased plant leaves from Kaggle repository and comparing the results obtained from the different algorithms to identify the one with the highest accuracy. The contributions of the study include uploading the plant disease dataset, implementing CNN and deep learning algorithms, and comparing the results to identify the most accurate algorithm.

2. LITERATURE SURVE

Numerous researchers have worked on the conceptual theory of using machine learning algorithms to detect plant diseases through their leaves. This section of the thesis discusses the research work conducted by various authors in this domain.

In one study, Ashwin et al. [10] proposed a method for detecting Soybean plant diseases by incorporating physiological and morphological features of leaves. The author used a dataset of 2500 images and implemented the model using six machine learning algorithms. The gradient boosting model yielded the highest accuracy of 92.56 percent.

Pushkara Sharma; Pankaj Hans; Subhash Chand Gupta, et al.[11]" Classification Of Plant Leaf Diseases Using Machine Learning And Image Preprocessing Techniques," The authors developed a model using Support Vector Machine (SVM) and Random Forest (RF) algorithms to classify the diseases based on their symptoms. The results showed that the RF algorithm performed better than the SVM algorithm in terms of accuracy. The study only evaluated the performance of two machine learning algorithms, SVM and RF, without comparing them to other existing models or methods for disease prediction in soybean.

Chohan, Murk, et al.[12] 'Plant disease detection using deep learning.' proposes a new method for detecting plant diseases using deep learning techniques. However, the authors also note that further research is needed to improve the efficiency and accuracy of their proposed method and to extend it to a wider range of plant diseases and crop types.

Finally, Shrivastava, Vimal K., et al.[13] "Rice plant disease classification using transfer learning of deep convolution neural network.". The proposed model is able to classify rice diseases with classification accuracy of 91.37% for 80%-20% training-testing partition. One potential limitation of the proposed method is that it requires a large dataset of labeled natural images for pre-training the CNN model.

The literature review shows that many researchers have focused on detecting plant diseases through leaves. However, few drawback of these studies are that they only classify one type of disease in one type of plant leaf and accuracy of their methods are not so high. This makes it difficult for farmers who grow multiple crops to adapt to these methods. Therefore, the proposed research aims to develop a model that can be used by farmers who grow various crops and tried to achieve maximum accuracy. To achieve this, the research will focus on training models on various plants for disease detection. The next step will be to implement deep learning-based models, including VGG-16, ResNet-50, and Efficient-B2, along with CNN.

3. METHODOLOGY USED

This part of the research paper focuses on the methods and techniques employed to execute the identification of plant leaf diseases. The central idea behind DL is that it involves adding a multi-layer network for feature extraction to the ML framework. The term "deep" in DL architecture refers to the thickness of the layers. The classification process in DL involves splitting a manually labelled dataset into testing and training samples, normalizing the dataset for quality improvement using image pre-processing techniques, and feeding the pre-processed images into the DL design for feature extraction and classification. Each layer in DL architecture operates on the output of the layer below as its input, passes it to the layer above, and repeats this process. Transfer learning refers to the process of applying the data gathered and used on one dataset to another dataset with a smaller population to train, provided that both datasets function on a similar CNN architecture objective. This approach is typically used to offset the computational expense associated with creating a neural network from scratch. The methodologies used for the implementation of the proposed thesis include choosing a specific model for deep learning based on a CNN's ability to extract features, which is termed as feature extraction. This process involves training the initial parameters on large datasets in a traditional CNN. The second tactic involves choosing from among several transfer learning-based variation models such as Alexnet, Densenet, Mobilenet, Inception, and VGG-16, and modifying the model's parameters to achieve the best results.

CNN: The CNN implementation works by taking input images, extracting features, and classifying them based on predetermined criteria. CNNs are a type of neural network and have all the characteristics that define neural networks. The implementation is divided into two blocks: feature extraction and classification, and employs two operations - convolution and pooling - across multiple layers to perform these blocks [14]. The first two layers of the network architecture perform feature extraction, and the final output is generated by the fully connected layer by mapping the extracted features from the earlier layers. This output is typically used for the second block, or classification. The convolutional layer, which is the first layer in the network, is critical to the entire implementation of the work as it carries out all the mathematical operations in the network. Furthermore, the CNN procedure is conducted in a grid pattern. In the parameters of this grid pattern, two-dimensional arrays known as kernels store the pixels of images. These kernels perform the actual feature extraction, which is what gives CNNs their high image processing effectiveness. Since the output from one layer is supplied as the input to the next layer, all levels in this network have a tendency to gradually increase their level of complexity. The process of parameter optimization used in kernels to reduce the difference between output values and input labels is referred to as training. The back-propagation optimization algorithm is employed in this process.

ResNet-50: ResNet50 is a CNN model that is commonly used in deep learning. It consists of 50 convolutional layers stacked on top of each other. One of the key features of ResNet50 is its ability to overcome the problem of vanishing gradients. The architecture also includes "short links" or "skips" that often bypass certain execution steps while traversing the model through important and necessary execution stages.

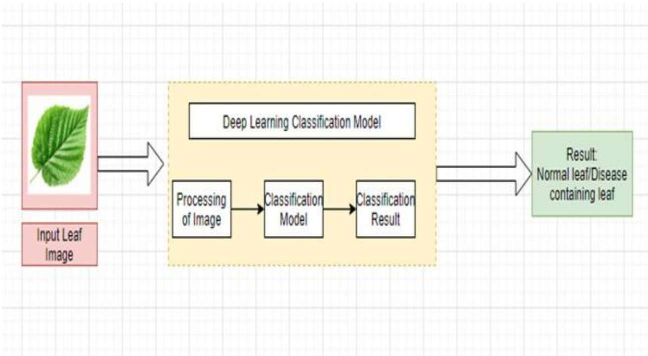
Efficient-B2:The deep learning architecture includes an improved and expanded version of EfficientB2. This model utilizes a scaling technique that maintains consistency in its dimensional components, such as depth and width, across all sizes. Additionally, a compound coefficient is employed in conjunction with dimensional variables to adjust the resolution of the input dimensional image. Unlike a standard CNN that uses scaling factors to avoid distortion in the final resolution of an image, EfficientB2's implementation uses scaling coefficients. For example, if the computational resource to be used is increased by 2N times, the overall depth of the network increases by N, and the width increases by N.

VGG-16: is an open-source deep learning model that consists of 13 levels grouped into five sets followed by a max-pooling layer. The feature vector obtained from this is passed on to three fully connected layers that have the same configuration. The information is then generated and classified using the Softmax layer.

4. IMPLEMENTATION OF THE MODEL

The primary objective of the study is to identify disease in plant leaves by gathering a dataset from the Kaggle repository. The implementation procedure includes collecting and pre-processing the dataset through labeling and resizing. Data visualization is performed to represent all the chosen classes from the repository, which totals to 38 classes. The dataset is then split into three phases, namely training, testing, and validation, in which 60%, 20%, and 20% of the data are used, respectively. Four algorithms, including CNN, Efficient-B2, ResNet-50, and VGG-16, are used to test the dataset. After testing, the models undergo evaluation based on parameters such as accuracy and precision to determine the optimal model. The models are compared based on the generated accuracy, and the entire workflow is depicted in Figure 4.1. The proposed model utilizes CNN and three deep learning-based algorithms to detect features in plant leaves.

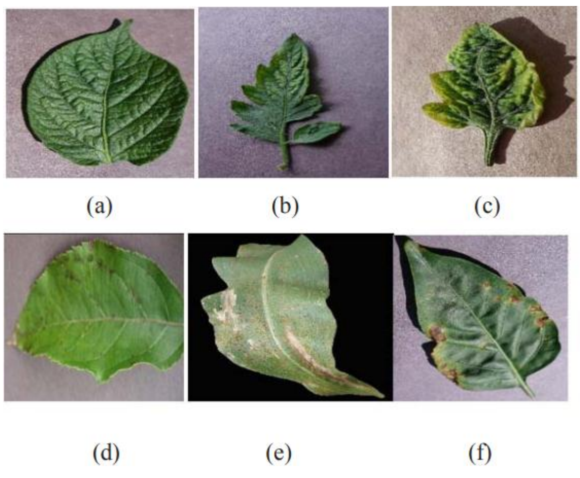
Figure 4.1: Workflow of the Proposed Methodology



4.1 Dataset Used

The system model is developed by collecting data from the Kaggle repository, which includes pictures of plant leaves from 38 distinct categories, each representing a disease, and a total of 87,000 RGB images. The plant leaf categories and images are distinct and do not overlap. The dataset contains 250 images of various plants, including both healthy and diseased ones, which are utilized by several algorithms during the training and testing stages. The diagram in Figure 4.2 illustrates this.

Figure 4.2: (a) Apple scab (b) Raspberry (c) Tomato (d) Soybean (e) Blueberry (f) Cherry



4.2 Data Preprocessing

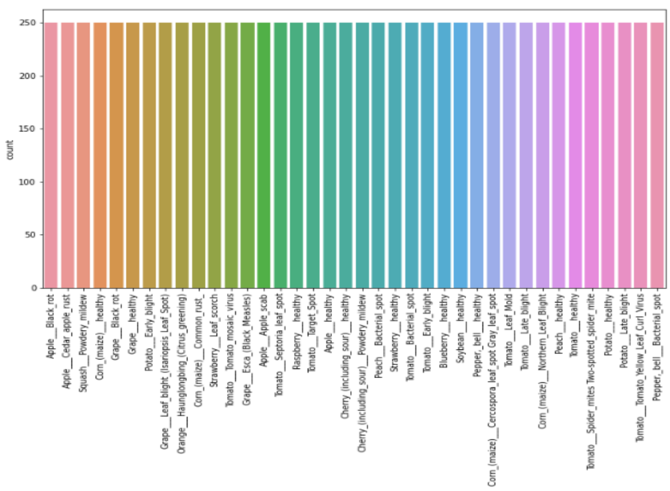
The stage of preparing the dataset is crucial in the system model as it involves filtering out redundant data to ensure that the final implementation operates on relevant data, resulting in higher efficiency, less time consumption, and greater accuracy. The data pre-processing stage involves labeling the data and resizing the images to increase their resolution, which is necessary for efficient image classification. In the context of implementing the proposed thesis, the images of plant leaves in the dataset are reduced to a pixel size of 128*128 to maintain the resolution of all images.

4.3 Data Visualization

The technique of data visualization is useful in identifying patterns by excluding past data from the dataset. It often involves using bar graphs, pie charts, and other visual representations to provide further insight into each attribute of the data. In the proposed research, images of plant leaves from 38 different types of plants are utilized as a visual representation of the data.

The data visualization process can also be represented by a count plot, which displays all 38 categories of classes in a bar graph. This implementation helps in identifying the various categories by depicting them visually. The bar graph in Figure 4.4 shows the 38 classes of plant leaves obtained from the dataset.

Figure 4.4: Data Visualization of 38 classes using count plot



4.4 Data Split

After completing the data visualization process, the system model proceeds to the data split stage, where the dataset is divided into separate portions for training, testing, and validation. In the proposed thesis, the split ratio is set at 60 percent, 20 percent, and 20 percent, respectively. Once the data is split, the system model is tested on four pre-determined algorithms: CNN, Efficient-B2, ResNet-50, and VGG-16.

5. EXPERIMENTAL ANALYSIS AND RESULTS

To evaluate the performance of the system model, several parameters such as the confusion matrix, classification table, sensitivity, and specificity are used. These parameters are applied to the four deep learning-based algorithms being employed.

Confusion matrix: It is a graphical representation of the obtained values and can be depicted by comparing the predicted values with the actual values.

Classification Table: A classification table contains information about the accuracy achieved, as well as values obtained from precision, recall, and F1-score. The various terms associated with a classification table can be calculated using the following methods.

Accuracy	$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)}$
Precision	$Precision = \frac{TP}{TP+FP}$
Recall	$Re\,call = \frac{TP}{TP+FN}$
F1 Score	$\frac{2*precision*recall}{precision+recall}$

Sensitivity: Sensitivity is a ratio that informs the user of the positive values that have been obtained in relation to all instances of negative occurrence in the fraction at hand. It can be calculated using the formula below:

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

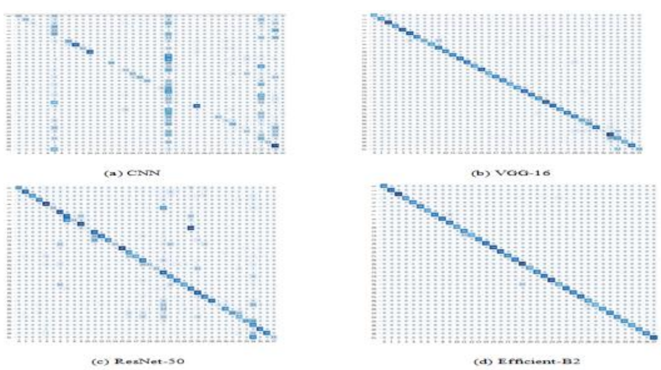
Specificity: A ratio called specificity tells us how often there are negative values compared to positive values in the fraction that is now present. It can be calculated using the formula below:

$$\text{Specificity} = \frac{TN}{TN+FP}$$

5.1 Results of algorithms using Confusion Matrix

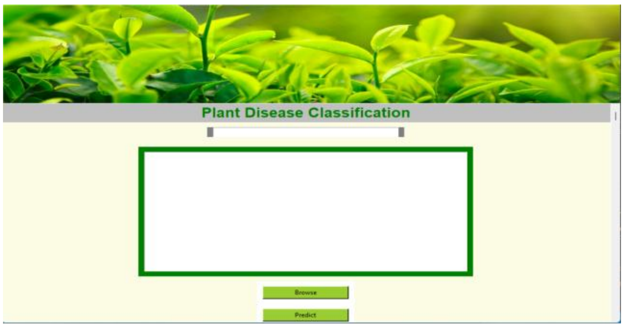
The confusion matrix generated by all four algorithms is depicted in figure 5.1 below

Figure 5.1: Confusion Matrix

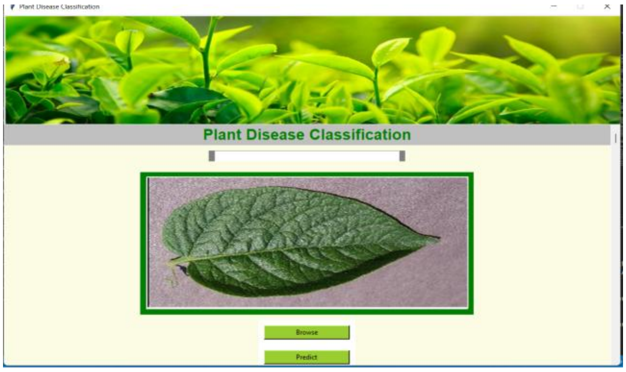


5.2: EXPERIMENTAL RESULTS

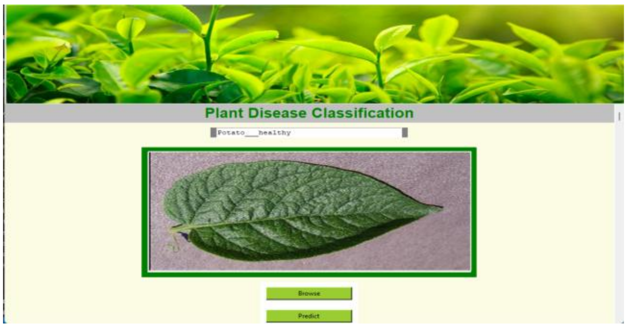
Step 1: Model Deployment



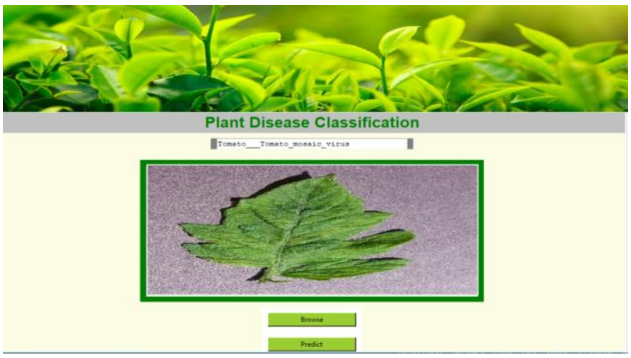
Step 2: Image Classification



Step 3: Healthy Leaf detection



Step 4: Diseased Leaf Detection



5.3 Results obtained using Classification Table

Table2: Classification Table

CNN	
Validation_Accuracy	61.78
Validation_Loss	1.7432
VGG-16	
Validation_Accuracy	82.70
Validation_Loss	1.4811
ResNet-50	
Validation_Accuracy	70.99
Validation_Loss	1.0110
Efficient-B2	
Validation_Accuracy	**94.14**
Validation_Loss	0.1954

As evident from the classification table presented earlier, it can be concluded that Efficient-B2 algorithm achieves the highest accuracy of 94 percent as compared to other algorithms that were tested. The table also provides information on the validation accuracy and loss error obtained from different algorithms. Additionally, the precision values given in the table are used to determine the final accuracy of the model.

6. CONCLUSIONS

The main objective of this research is to identify the presence of diseases in plant leaves. To achieve this goal, a dataset of plant images was obtained from Kaggle repository and pre-processing techniques were applied to label and resize the images. The dataset was then split into a training, testing, and validation ratio of 60:20:20. Four deep learning based algorithms, including CNN, VGG-16, ResNet-50, and Efficient-B2 were used for implementation, with Efficient-B2 generating the highest accuracy of 94%. The research was divided into two parts, comparing the models and determining which model produced the highest efficiency. Evaluation parameters such as confusion matrix, accuracy vs loss graph, sensitivity, specificity, precision, F1 score, and recall were used for analysis. The research concluded that Efficient-B2 was the most optimized model for identifying and categorizing plant infections as normal or infected.

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