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PLANT DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK AND DEEP LEARNING BASED STRATEGIES

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Abstract: One of the main farming industries where the process of automating plants based on illnesses may be carried out is the agricultural industry. It's important to maintain track of healthy and diseased plant leaves in such an agricultural setting so that they may be further separated to produce exponential crop yields and returns. Utilizing picture categorization techniques, a variety of cutting-edge technologies have been combined for this goal, including machine learning, deep learning, and artificial intelligence. To accurately identify the presence of illness in plant leaves, deep learning-based models' working theories have been continually improving**.** We suggest using Convolutional Neural Network, ResNet-50, Efficient-B2, and VGG-16 for this purpose in order to identify and confirm the existence of plant illnesses in the relevant leaves. Gathering a dataset of 87k plant photos from the Kaggle library is how the paper is put into action. This library runs on 38 different categories and includes photographs of both healthy and sick plants. However, 250 photos from each class are used in the final implementation. For the same, the complete dataset is trained, tested, and verified. We are expecting that the suggested models will ultimately assessed optimal accuracy of 94%.

Index Terms **- CNN, Efficient-B2, machine learning, deep learning, ResNet-50, VGG-16.**

I. INTRODUCTION

The agricultural industry has traditionally been the principal resource and the source of food, serving the human race's acquisition of fundamental needs. As a result, it has been acknowledged that this industry serves as the world's centre for human survival [1]. This brings up a crucial point: the agriculture industry may be further regarded as the most significant and central foundation of any economy. It is clear that the agriculture sector is essential to the livelihood of 70% of the world's population. Thus, it can be said that the agricultural sector has a significant impact on people's life, particularly their health [2]. As a result, this area must be carefully considered and not disregarded. Forests and whatever plants theyy produce play a significant role in the agriculture economy. In order to prevent the degradation of these plants, it is crucial that their quality be verified and maintained on a regular basis. To quickly identify the presence of illnesses in plants so that the health of the plants and crops is preserved and not jeopardised becomes one of the major difficulties in the agricultural industry. The prevalence of illnesses in plants may be caused by a variety of variables, including unsuitable soil, infertile land, water and sunshine availability, the use of pesticides, etc. All of these elements are in some manner accountable for influencing plant growth and may provide a barrier to it, which might result in illnesses that influence seedling and plant growth [3]. When a disease of this kind affects a plant, it has a significant negative influence on its growth and may alter its biological and morphological alterations. Abiotic stress and biotic stress are the main causes of the general plant illnesses that result in these modifications. Stress brought on by soil-dwelling organisms like bacteria and viruses is known as biotic stress. Such a critter frequently comes into touch with the plant and adversely affects the development of the seedling as a whole [4]. Abiotic stress, on the other hand, is brought on by non-living things like man-made or environmental elements [5]. A diagrammatic representation of biotic and abiotic stress is shown in Figure 1 below.

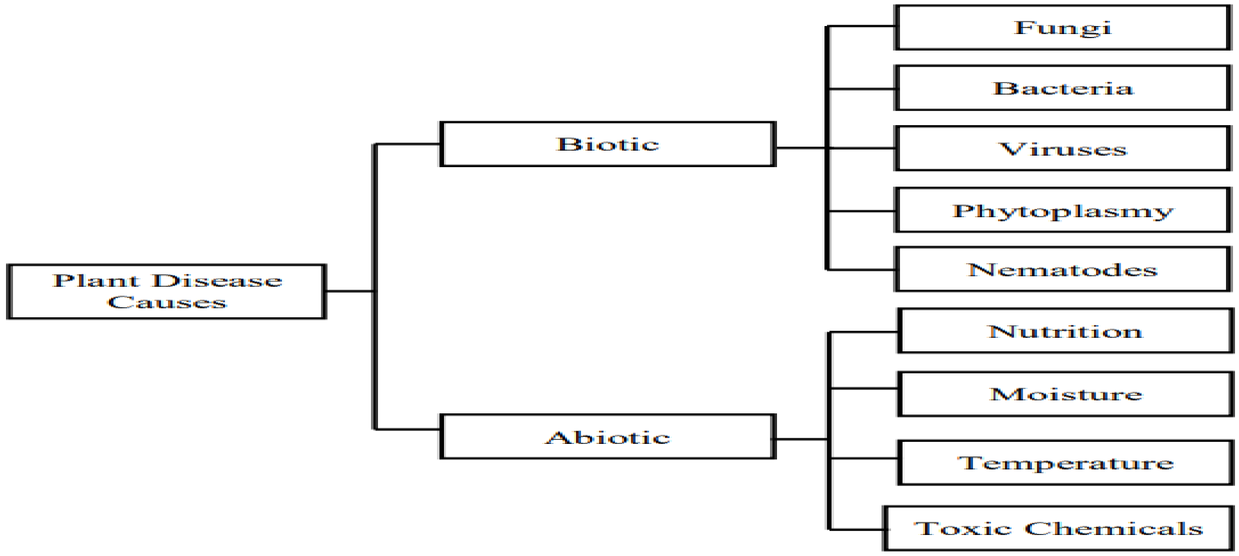

Figure 1: Schematic representation of diseases in plants [5]

Abiotic stress and biotic stress are the main causes of the general plant illnesses that result in these modifications. Stress brought on by soil-dwelling organisms like bacteria and viruses is known as biotic stress. However, physical inspection to check for illness in the plants is still a common practice among farmers. In order to diagnose the illness, a manual examination is conducted once information has been gathered from sources with relevant expertise. A significant drawback of this method is essentially the time commitment required to manually find the same. Because the crops are dispersed throughout broad areas, manually inspecting and spotting them becomes a tiresome chore [6]. Various strategies, including machine learning, deep learning, transfer learning, and artificial intelligence techniques, have been developed for this aim. The presence of illnesses in plants may now be detected with the maximum degree of accuracy and in the shortest amount of time thanks to advancements in such techniques and algorithms. As a result, these methods may be applied to image processing ideas where a certain portion of the picture is taken into account and algorithms are applied to them in order to observe a specific section of the leaf [7]. In addition to this, the depth of the plant leaf is also used which can help to detect the presence of diseases within itself. Using machine learning based algorithms of random forest, support vector machine; k-nearest-neighbour etc. this process of detection can be carried out effectively. Such algorithms tend to focus on specific features of the plant leaf such as it's; saturation colour, gradient orientation, RGB features etc. [8] hence, it can be concluded that machine learning, transfer learning and deep learning algorithms play a significant role in detecting the same and further classifying the plant leaf as healthy or diseased [9]. Deploying and automating the process of disease detection among plant leaves using CNN and deep learning-based models like Efficient-B2, ResNet-50, and VGG-16 is the main goal of the research article. The procedure is often automated with less computing complexity and in a shorter amount of time because to the additional layers of deep learning models and the hidden CNN layers. High degrees of accuracy are also produced through the process of precise tuning and application of assessment factors like confusion matrix, accuracy, precision, loss graph, etc. We have gathered the plant disease dataset for this purpose from the Kaggle repository, which includes 250 photos of both healthy and sick plants from each of 38 distinct classes.
The contributions of the proposed study can be summarised as follows:
Working with photos of diverse healthy and sick plant leaves after uploading a dataset on plant diseases from the Kaggle repository.
Using labelling to implement CNN and deep learning-based algorithms, compare the results to define the method with the highest degree of accuracy.

II. LITERATURE REVIEW

The conceptual notion of diagnosing plant illness through the leaves has been studied by several researchers. The use of machine learning techniques to identify the same has been the subject of extensive research. The study conducted by several writers in the same field is described in this portion of the thesis.

Author Ashwin et al. presented the detection of soybean plants in a study they did in [10], using both the physical and physiological characteristics of the leaf. This method assisted in identifying and separating healthy from sick plant leaves. The author utilised a dataset of 2500 photos and took several attributes from it that could be applied to further classify the images. The author used 21 characteristics from the gathered dataset to create the model. These characteristics included assessing the length of the stem, the length of the root, the number of pods present in each plant, and the quantity of seeds sown for it.

A hybrid model built on the ideas of CNN and CAE was portrayed in a related research study by Bedi et al. in [11]. (convolutional auto encoder). The model was applied to the leaves of peach plants, and it was then utilised to identify a specific location on each leaf in order to determine whether or not the disease was present. The dataset, which included 2160 infected leaves and 2267 healthy leaves, was obtained by the author via a GitHub repository. Thirty percent of the collected dataset was utilised for training, while the remaining seventy percent was used for testing. The dataset was pre-processed once it had been obtained. The tasks of labelling, categorising, and further dividing the data were completed at this level. However, the following phase involved using the appropriate CNN and CAE algorithms. Leaf photos were provided as input to the algorithm during the testing phase, and a ten-fold cross validation was carried out. 14 hidden layers of the neural network and 17 layers of the CAE were employed in the CNN implementation phase. Additionally, Adam was employed as the optimizer, and the rmse values were assessed. Upon execution, it was discovered that the CNN produced reduced error loss (0.607), and as a result, it was deemed to be the most optimal model.

In [12], Jeyalakshmi et al. suggested using the picture taken from the repository to identify illnesses in potato leaves. The author worked with the Plant Village dataset, which included 3270 healthy leaves and 1000 sick leaves. Grape plant photos were also included in the collection. Additionally, there were other subcategories and types of grape and potato plant leaves. Each RGB picture from the dataset was first captured, and each backdrop was then subtracted using the Grab Cut method during the filtering stage. Following that, different leaf aspects were chosen based on how intensely the RGB photos represented the colours red, blue, and green. Its contrast, entropy, and gradients, among other characteristics, were also identified. The system model was evaluated using three machine learning classifiers, which comprised the use of KNN, SVM, and Naive Bayes. From each subgroup, 13 characteristics were chosen to represent the grape and potato plant leaves. During execution, it was found that KNN produced accuracy of 91% and was the most effective model.

Extreme Learning Machine, a machine learning algorithm, was presented for implementation by author Xian et al. in [13]. (ELM). The algorithm was applied to determine whether a tomato plant had a disease. The full dataset was downloaded from the Kaggle repository, which included a dataset from Plant Village. 1000 photos of healthy plants and 1245 images of infected plants were included in the collection. CNN was also included to the ELM implementation. The CNN's neural networks had a number of hidden layers that made it possible to link internal nodes and helped enlarge a picture of a tomato plant. The image's segmentation, colour, and saturation of the leaf were taken into account in addition to its resizing. Later, a scatter plot was created that only highlighted the essential elements of the plant picture. Thirty percent of the dataset was utilized for testing, while seventy percent of it was used for training. Evaluation revealed that the ELM model yielded findings that were superior to those of the CNN model and had an accuracy of 93.65 percent.

The literature review reveals that many writers concentrated on identifying the presence of illness in plant leaves. A comparison of the literature review used for the research article is shown in Table 1 below. The fact that this detection was grouped by the categorization of only one form of a disease in only one type of plant leaf is clearly a significant drawback. In the agriculture industry, farmers frequently produce many crops, making it difficult to adjust to this detection. Therefore, one of the main objectives of the proposed research project is to develop a model that can be applied by several farmers who often cultivate and produce different crops. For this reason, we have suggested a research project in which different plants are combined and then trained to identify certain diseases. The implementation of multiple deep learning-based models alongside CNN occurs in the next stage. The models for deep learning features includes the implementation of VGG-16, ResNet-50 and Efficent-B2.

Table1: Comparison of surveys

Research Author	**Year**	**Crop**	**Dataset**	**Technique**
Ashwin et al. [10]	2021	Soybean	Real samples	random forest, gradient boosting, logistic regression, SVM, KNN and naïve Bayes
Xian et al. [13]	2021	Tomato	Plant village	ELM, CNN
Bedi et al. [11]	2021	Peach	Plant village	CAE, CNN
Jeyalakshmi et al. [12]	2020	Potato and grape	Plant village	KNN, SVM and Naïve Bayes

III. RESEARCH METHODOLOGY

The methods utilised to accomplish the detection of illness in plant leaves are highlighted in this portion of the research paper. For this, deep learning-based CNN, ResNet-50, VGG-16, and Efficient-B2 are employed, in addition to deep learning-based CNN.

The main conclusion from the definition of DL is that it involves extending the ML framework with a multilayer network for feature extraction. The term "deep" in DL architecture refers to the layer thickness. The categorization procedure for the notion is as follows: For the DL structure, the manually labelled dataset is divided into testing and training samples. The dataset is then normalized for quality improvement using image pre-processing techniques, and the pre-processed images are then fed into the DL design for feature extraction and ultimately classification. In a DL architecture, each layer uses the output of the layer above as its input, sends it to the layer below, and continues the process. Contrarily, transfer learning is the idea that the information obtained and used on one dataset may be used to another dataset with a much smaller population to train, so long as both datasets serve the same CNN design aim. By training the initial parameters on enormous datasets, this approach is applied in a conventional CNN. Based on a CNN's capacity to extract features, a particular model is selected for deep learning. Feature extraction is the name of this procedure. The primary objective of this strategy is to maintain both the neuron weights and the architectural framework of a CNN model.

The approaches employed for the purpose of putting the stated theory into practice are as follows:

CNN: The actual CNN software classifies incoming photos based on specified criteria after extracting features from them. These networks fall within the category of neural networks, therefore they have every attribute that makes a neural network distinct. Its execution is divided into two blocks: the first is in charge of feature extraction, while the second employs ML methods to categories data. To complete these blocks, CNN applies two operations—pooling and convolution—across a number of layers [14]. The first two layers of the network design handle the first block, or feature extraction, while the fully connected layer generates the output by mapping the features that have been extracted from the lower levels. This final result often constitutes the second block of execution, or categorization. Since all of the mathematical operations in the network are carried out by the convolutional layer, the first layer in the network, it is crucial to the complete implementation of the work. Additionally, a grid pattern is used to execute the full CNN process. The pixels of pictures are kept in the grid parameters of this grid pattern, which are two-dimensional arrays referred as as kernels. The initial block, also known as feature extraction, is completed by the initial These kernels carry out the actual feature extractors for the model, which is what gives CNNs their high degree of image processing efficiency. Since the output from one layer serves as the yield input to the next layer, all the layers in this network have a propensity to steadily increase in complexity. Training is the process of parameter optimization applied to kernels to reduce the discrepancy between output values and input labels. In this process, back-propagation optimization algorithms are used.

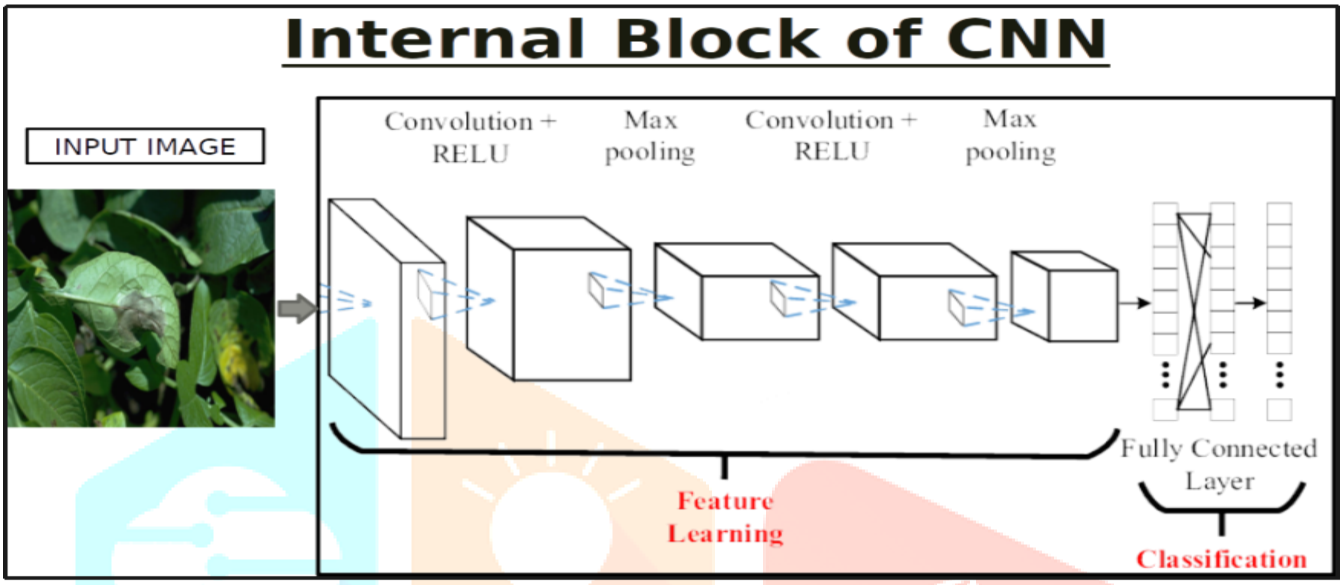

Figure 2: Architecture of CNN

ResNet-50: ResNet50 is one of the frequently utilised CNN models built on deep learning. 50-layer convolutional models are layered on top of one another. The method ResNet50 uses to circumvent the vanishing gradient issue is a key aspect of the network. Additionally, while iterating the model with necessary and needed execution stages, the design has short links, or "skips," that regularly avoid different execution steps.

Efficient-B2: The deep learning architecture includes an expanded and improved version of Efficient-B2. The model often employs a scaling approach that calls for uniformity across all sizes of its dimensional components, such as depth and breadth. They combine dimensional variables and a compound coefficient to alter the resolution of the input dimensional picture. EfficientB2's implementation uses scaling coefficients as opposed to a typical CNN, which uses scaling factors to prevent distortion in the image's ultimate resolution. For instance, the network's total depth rises by N while its overall breadth expands by N if the computing resource to be used is magnified to 2N times.

VGG-16: The VGG-16 is an open-source model based on deep learning. The VGG-16 design's 13 levels are divided into five groups, with a max-pooling layer coming after. The three linked layers, which have the same configurations, are then subjected to this feature vector. The Softmax layer is then used to generate and categorise the information.

IV. IMPLEMENTATION OF THE MODEL

By gathering data from the Kaggle repository, the research's main goal is to identify the presence of illness in plant leaves. A dataset is first gathered and pre-processed utilising labelling and resizing as part of the implementation. The model then goes through data visualisation, where all the chosen classes from the repository are utilised to represent the same. 38 classes in all are selected from the repository. Following this step, the dataset is further divided into training, testing, and validation phases, each of which uses a total of 60%, 20%, and 20% of the dataset, respectively. After the data has been divided, the model is tested using four algorithms: CNN, Efficeint-B2, ResNet-50, and VGG-16. Figure 4.1 shows the proposed model's whole process. To identify characteristics in plant leaves, we employ three deep learning-based algorithms and CNN.

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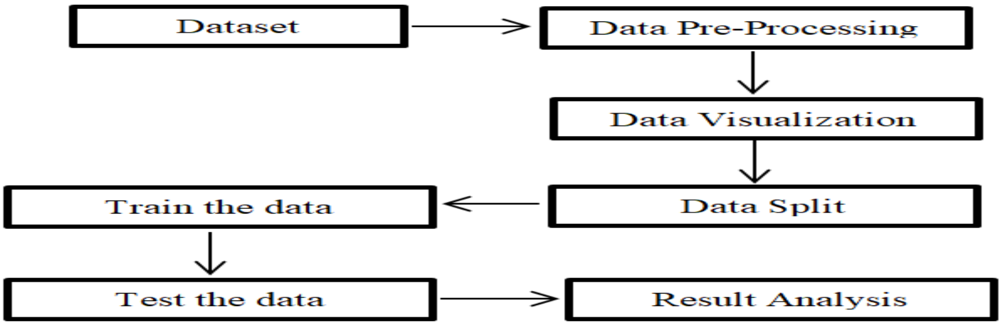

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Figure 3: Workflow of the Proposed Methodology

4.1 Dataset Used

The system model is put into practise by obtaining the dataset from the Kaggle repository. This library includes 87k RGB-based photographs as well as pictures of plant leaves from 38 distinct classes, each of which resembles a disease. The various plant leaf classes and graphics, nevertheless, do not cross over. These photos of plant leaves are utilised by many algorithms to carry out the process of training and testing phase. They include 250 photographs of different plants, including both healthy and damaged images.

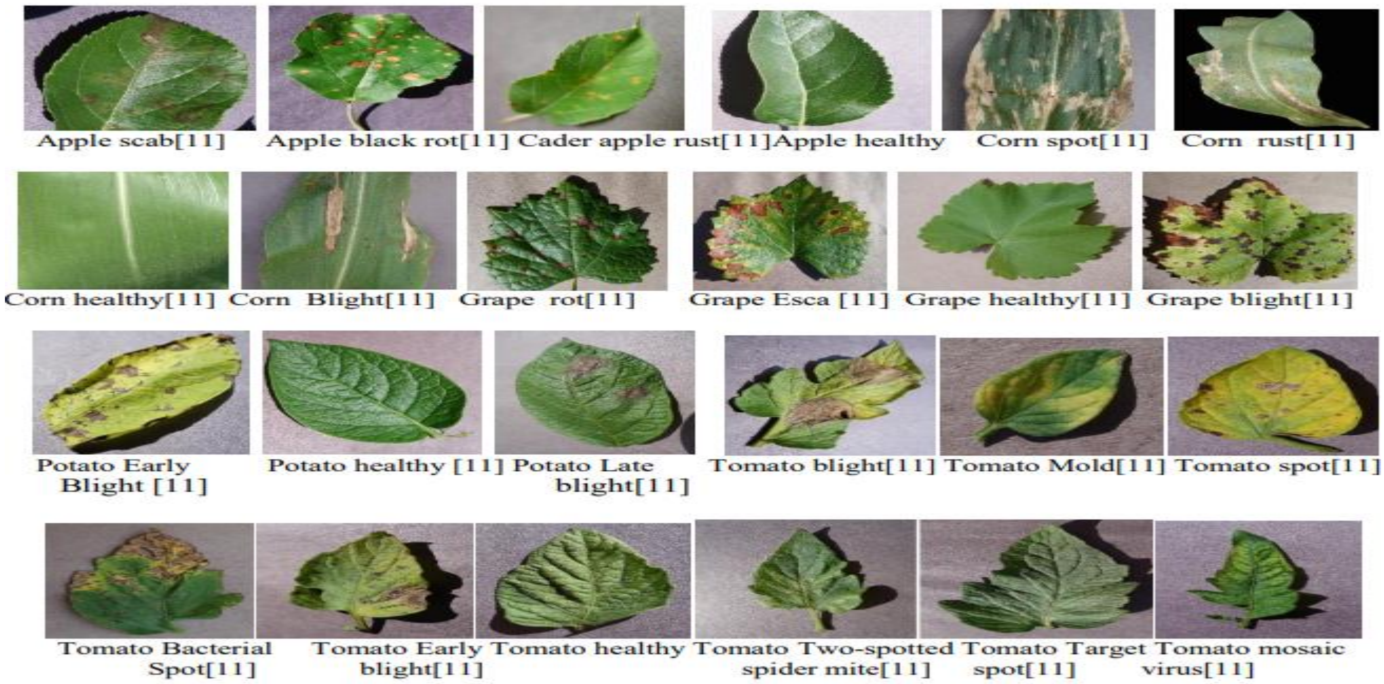

Figure 4: Sample dataset with multiple plant diseases

4.2 Data Pre-Processing

This step of the system model is crucial because it involves filtering out redundant data from the dataset so that the final implementation can work with accurate data. This is done to improve the model's overall effectiveness while consuming less time and providing high accuracy. Labeling the data and resizing the image are the two main components of the data pre-processing stage.

4.3 Data Visualization

By deleting previous data from the dataset, the data visualisation technique aids in the comprehension of trends. Bar graphs, pie charts, and other visual representations of this data are routinely used to show more information about each feature of the dataset. The data for the proposed research is graphically represented using photographs of the leaves from 38 different species of plants.

4.3 Data Split

The system model then goes through the process of data splitting, where the dataset is divided into ratios of the training, testing, and validation phases, after the process of displaying the dataset has been seen. The ratio is split into three equal parts for the sake of applying the suggested thesis: 60%, 20%, and 20%.

V. CONCLUSIONS AND FUTURE SCOPE

The main goal of the study is to find any signs of illness in plant leaves. In order to do this, we collected a collection of plant photos from the Kaggle repository and used data pre-processing techniques to label and resize the image. The dataset is anticipated to be divided in the following step into ratios of 60, 20, and 20 for training, testing, and validating, respectively. Four deep learning-based algorithms, including CNN, are used to deploy the trained dataset in its final form. The remaining three algorithms are ResNet-50, Efficeint-B2, and VGG-16.

In our next work we will evaluation parameters such as confusion matrix, accuracy vs loss graph, sensitivity values, specificity values, precision, f1 score and recall factors into consideration. Hence, this can be concluded to be as the extended study for future scope.

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