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An Intelligent Approach towards Plant Leaf Disease Detection through Different Convolutional Neural Networks

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Abstract*:* Identification and diagnosis of plant leaf diseases at an advanced stage and with a high degree of accuracy are essential for ensuring plant production and minimizing losses in agricultural yields, both qualitatively and quantitatively. The millions of living organisms, including plants and animals, are kept in balance with one another by many ecological processes, such as plant diseases, which are a recurrent aspect of nature. The subfield of computer vision, object recognition, has made substantial progress in recent years. Convolutional neural networks are deep learning network architecture trains using data in a hands-on manner. Our primary emphasis was making minute adjustments to the hyperparameters of well-known pre-trained models, including DenseNet-121, ResNet-50, VGG-16, and Inception V4. This study presented a convolutional neural network model for detecting and identifying plant leaf diseases based on visual data to boost accuracy, generality, and the overall efficacy of training. The outcome of the suggested model evaluates next to the results of other models. Experiments demonstrated that the proposed convolutional neural network-based model worked better than other models and achieved a classification accuracy of 99.23% higher.

Keywords: *Machine Learning (ML), Deep Learning (DL), Convolutional Neural Networks (CNN), Features extraction, Image augmentation*.

1. Introduction

India's main source of income is agriculture, and more than 54 percent of the country's total land area uses for farming. India is one of the top agricultural producers in the world because it grows many vegetables, fruits, rice, wheat, cotton, and dairy products. Due to the rapid increase in population, the market for agricultural goods is expanding at a pace never seen before [1]. The best way for the body to work is to get all the nutrients, vitamins, and minerals it needs through a healthy diet. It is also crucial for optimal health to ensure enough minerals and vitamins. To keep a healthy food supply, avoiding and eyeing agricultural diseases is crucial. because they might hurt crops, which would cut down on the food supply chain and raise prices simultaneously. It is also possible for plant pests and diseases to make crops less tasty, which could cause people to change their traditional eating habits [2]. The technology known as machine learning is what makes it possible for computers to connect with people and comprehend their requirements [3]. In addition, it allows robots to mimic human behavior and decide things on people's behalf. It is one of the regions that has seen rapid expansion for the previous several years. The classification of plant diseases aids by ML [4]. Almost everyone agrees that using this technology is a big step forward and a success in the fight against plant diseases. Additionally, it has led to a rise in overall production in the agricultural sector. This technology also includes visualization methods, which have significantly developed during the last three years to achieve the degree of sophistication they are now operating [5]. In [6], researchers used a deep convolutional neural network (DCNN) architecture with nineteen convolutional layers to classify the two most common diseases that affect apple leaves. The algorithm used to classify test data to find apple disease was 99.2% accurate. Compared to k-nearest neighbor (KNN), support vector machine (SVM), logistic regression (LR), and random forest (RF) approaches, the performance of their model was superior. Utilizing SVM and principal component analysis (PCA), the authors of [7] proposed a method for identifying the pumpkin powdery mildew disease. With a 97.3% chance of being right, their model found the powdery mildew disease on the pumpkin leaf. It was able to classify the disease. [8] Researchers created a method for automatically detecting illnesses in soybean plants. They changed the image's color scheme from red, green, and blue (RGB) to hue saturation value (HSV). For segmentation, color, and cluster-based approaches use. The form of the leaf is a clue; the scale-invariant feature transform (SIFT) approach identifies the plant species. The authors of [9] chose to conduct their study on five distinct types of apple leaf diseases as their research objects: mottled evergreen disease, mosaic disease, xanthous leaf disease, circular spot disease, and rust disease. By extracting eight characteristics from the picture of the spot on the apple leaf, like color, texture, and form, the neural network model process of illness classification and identification, and the overall recognition accuracy was 92.6% on average. The CNN was used by the researchers so that they could identify the plant disease [10]. The authors correctly classified 12 different plant diseases with an accuracy of 88.80 percent. The experiments used a dataset of 3000 photos with a high resolution for each RGB color. The network is composed of three separate convolutional and pooling layers. Because of this, the network becomes more difficult to compute. In addition, the

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overall F1 score of such a system is 0.12, which is rather low because of the number of predictions that turn out to be incorrect. The study's authors cited in [11] constructed a disease detection model for tomato leaves using the DenseNet 121 transfer learning approach. They made the conditional generative adversarial network (C-GAN) to produce augmented data to balance training datasets, and the DenseNet121 model attained an accuracy of 97.11% on tomato disease classification. In [12], the writers presented a method that uses DL to identify illnesses that might affect plant leaves. They constructed a DCNN to categorize 54,306 photos from the PlantVillage dataset, which included 14 crop kinds and 26 illnesses. They compared CNN architectures based on domain adaptation and scratch training. When working with the colored version of a dataset, the models perform much better [35]. The categorization of single leaves that are upright in a consistent environment is presently difficult, which is one of the reasons for this constraint. With a refinement filter bank framework for tomato plant disease and pest recognition [13], this research aims to combat the issue of false positives and class unbalance. The three primary components comprise the system: First, a primary diagnosis unit, also known as a "bounding box generator," creates the bounding boxes that outline the region and class affected by the disease. The suggested technique has the potential to eliminate the issue of false positives caused by bounding box generators as well as class inequalities that occur in data sets that include only partial information. The approach suggested can achieve a recognition rate of roughly 96%. A method for detecting and classifying plant diseases by researchers in [14] and its domain adaptation with deep feature extraction. The authors conducted a study in which they compared the outcomes of using CNN architectures such as Visual Geometry Group (VGG16), GoogLeNet, and Residual Neural Network (ResNet50) to deep feature extraction using VGG16 and InceptionV3. The experiment results demonstrated that classification using DenseNet 121 and ResNet 50 provided the best results (98%) compared to the other possible combinations. The researchers also compared the outcomes of classic ML algorithms, such as ResNet50 and DenseNet121. The findings showed that the unified model had a higher accuracy rate (99.17%), but test accuracy had a lower accuracy rate (98.57%), and the suggested method had a higher rate overall. Also, the literature review shows how important it is for classification systems to add data and adjust hyperparameters. In this study, a new residual CNN uses to find plant diseases, and its performance was better than that of established residual networks and other transfer learning methods. Throughout this research, we conducted an in-depth analysis of the various transfer learning models suited to precisely categorizing 38 distinct types of plant diseases. Figure 3 is an illustration of our process architecture. Standardization and assessment of CNN employing transfer learning methods based on the classifier's precision, recall, and F1 score. The next part details the design of the suggested plant disease detection model and the training procedure.

2. Literature Review

In this literature review, we look for current research on ML-driven leaf disease detection systems that aid farmers in identifying and correcting such illnesses to boost crop yields, improve food quality, and protect plants from disease. It is a summarised version of the complete survey:

R. Sujatha, Jyotir Moy Chatterjee, NZ Jhanjhi, and Sarfaraz Nawaz Brohi use image processing and ML to identify healthy and unhealthy leaves [26]. This approach utilizes leaf data. Diseases may affect leaf chlorophyll, causing dark or black patches on the leaf surface. They are preprocessing, feature extraction, segmentation, and ML classification. A high-yield agricultural method relies on disease detection. Farmers may typically see early indicators of plant illnesses that require monitoring by regularly checking their crops. Diseases may kill plant leaves. Agriculture struggles to diagnose these illnesses. Digital plant leaf pictures and rapid image processing allow reliable disease identification. Plant disease diagnosis begins by photographing the diseased plants. Digital cameras, scanners, and drones can take high-quality plant photos. If accessible, a grey-level co-occurrence matrix (GLCM) may extract the diseased plant's color, shape, and texture. Any ML can categorize various plant diseases. Throughout classification, we need to choose healthy or unwell images. Diseased plant leaves identify by category. SVM accuracy is 80%.

Hatuwal, Bijaya, Shakya, Aman, Joshi, and Basanta [27] proposed a study that covers dataset preparation, feature extraction, classifier training, and classification. Because many countries lack basic infrastructure, agricultural diseases are still hard to identify. Crop diseases threaten global food security. This research uses RF to differentiate vacation and sick time from l sets. Diseases and pests reduce food output, worsening food poverty. Polymerase chain reaction, gas chromatography, spectrometry, thermography, and super spectral methods have effectively identified numerous illnesses. DL and ML have improved accuracy and precision. Recent ML research has focused on plant disease detection and diagnosis.

Umit Atila, Murat Ucar, Kemal Akyol, and Emine Ucar proposed EfficientNet DL for plant leaf disease categorization [28]. This model was tested against other cutting-edge DL algorithms. Plant village data taught the models. All algorithms were trained on the 55,448-photo original dataset and the 61,486-photo expanded dataset. Deep neural networks with several processing layers, including neurons, can perform complicated tasks like voice and image recognition by processing large input volumes. The study proposes EfficientNet, a DL architecture for plant disease classification. The suggested model is compared against the AlexNet, ResNet 50, VGG 16, and Inception V3 CNN models. EfficientNet and other DL models were trained via transfer learning. Each algorithm layer must be trainable during transfer learning. The test dataset showed that the EfficientNet B5 and B4 models outperformed other DL models in the original and supplemented datasets. These models achieved 99.91% and 99.97% accuracy and 98.42% and 99.39% precision. Shima Ramesh, Mr. Ramchandra Hebbar, Nivedita M., Pooja R., Prasad Bhat N., and Shashank N. categorize leaves accurately in [29]. We use preprocessing to reduce the image size and a feature extract to identify whether a leaf is diseased. It lets us identify diseased leaves. HOG's histogram of oriented gradients may remember a picture's characteristics. HOG uses the Haralick texture approach to distinguish damaged leaves from healthy ones and the color histogram to analyze the picture's color scheme. Hu moments emphasize the leaf, and color histograms examine color. After gathering features, learning the classifier and classifying data follow. The RF classification algorithm does this. A RF technique trains a HOG-based characteristic vector for the training dataset. These methods let us spot plant leaf abnormalities. This classification model has 70% accuracy.

[30] Guan Wang, Yu Sun, and Jianxin Wang deploy a DL method to accurately and automatically assess plant pathogens.

When managing plant diseases, guaranteeing food security, and projecting yield loss, severity matters. This trait determines the severity. To select the best DCNN architecture, researchers will compare: (i) building a shallow network with layers from scratch, and (ii) transfer learning, which uses a small amount of data points to correctly align the network parameters to build an effective classification network. Botanists use Plant Village's collection of healthy and apple black rot leaf photos. These grades reflect whether the leaf is healthy, early, intermediate, or late in development. Eighty percent of the images in each class are used as the training dataset for the beginning, middle, and end phases, while the remaining twenty percent are hold-out test sets for balance. A study using VGG16, VGG19, Inception-V3, and ResNet50 found that carefully adjusting pre-trained deep models improves network performance. With 90.4% dependability, the VGG16 model performs best. Flexible sensors like thermal imaging and multispectral cameras collect data for future studies.

Sharada P. Mohanty, David P. Hughes, and Marcel Salathé used 54,306 pictures and CNN to identify 26 illnesses in 14 crops [31]. These photos analyze illness signs. How accurately their algorithms predict which of the 38 crop-disease combinations will occur determines their accuracy. They tested DCNN for the classification challenge. They focused on popular frameworks like AlexNet and GoogleNet. The most excellent accuracy score of 99.35% achieves in the PlantVillage data set, which features 54,306 pictures and 38 classes comprising 14 agronomic characteristics and 26 illnesses.

RehanUllah Khan, Khalil Khan, Waleed Albattah, and Ali Mustafa Qamar describe how ML and DL have helped identify plant diseases [32]. If the infections aren't found, they'll lower food yields and cause climate change and famine. They also discussed database searches, size, feature extraction approaches, and classification module issues.

Kshyanaprava Panda Panigrahi, Himansu Das, Abhaya Kumar Sahoo, and Suresh Chandra Moharana examined maize plants for leaf diseases [33]. ML may categorize using the KNN Decision Tree, Naive Bayes, SVM, and RF. Disease classification uses picture acquisition, preprocessing, segmentation, and edge detection—3,823 pictures of maize plant diseases. The RF approach improved accuracy to 79.23 percent.

Kawcher Ahmed, Tasmia Rahman Shahidi, Syed Md. Irfanul Alam and Sifat Men have collaborated to develop a ML-based algorithm for rice leaf disease detection. This model aims to assist in identifying diseases affecting rice plants. [34] We trained our model using WEKA, an open-source ML platform. This work used ML Repository data. This research uses K-means, logistic regression, naive bayes, and decision trees. Based on test findings, the decision tree had a maximum accuracy of 97.9167%.

Table 1. Detailed Descriptions of Datasets

Class	Sub Class	Number of Images	
		Taken From GitHub	Collected
Apple	Apple_scab	2016	63
	Black_rot	1987	58
	Cedar_apple_rust	1760	28
	Apple___healthy	2008	102
Blueberry	Blueberry___healthy	1816	12
Cherry	Including_sour___Powdery_mildew	1683	17
	Including_sour___healthy	1826	25
Corn_(maize)	Cercospora_leaf_spot Gray_leaf_spot	1642	137
	Common_rust	1907	65
	Northern_Leaf_Blight	1908	34
	healthy	1859	103
Grape	Black_rot	1888	55
	Esca_(Black_Measles)	1920	79
	Leaf_blight_(Isariopsis_Leaf_Spot	1722	64
	healthy	1692	116
Orange	Haunglongbing_(Citrus_greening)	2010	210
Peach	Bacterial_spot	1838	66
	healthy	1728	98
Pepper	bell___Bacterial_spot	1913	13
	bell___healthy	1988	29
Potato	Early_blight	1939	1103
	Late_blight	1939	1095
	healthy	1824	1232
Raspberry	healthy	1781	45
Soybean	healthy	2022	208
Squash	Powdery_mildew	1736	1078
Strawberry	Leaf_scorch	1774	35
	healthy	1824	113
Tomato	Bacterial_spot	1702	452
	Early_blight	1920	378
	Late_blight	1851	407
	Leaf_Mold	1882	699
	Septoria_leaf_spot	1745	302
	Spider_mitesTwo_potted_spider_mite	1741	208
	Target_Spot	1827	189
	Tomato_Yellow_Leaf_Curl_Virus	1961	540
	Tomato_mosaic_virus	1790	600
	healthy	1926	1005

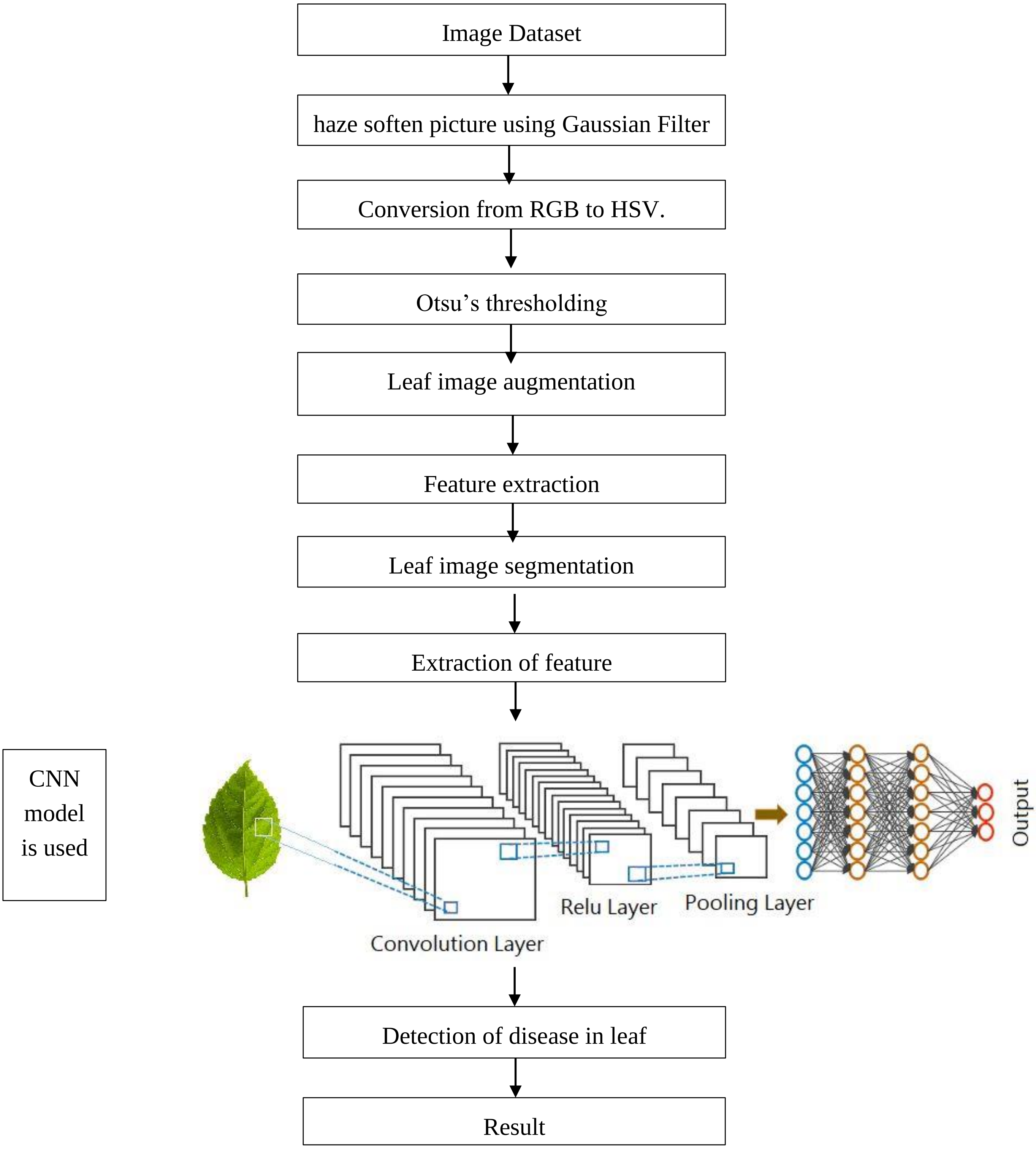

Fig. 1. The proposed model's overall workflow is being presented.

3. Methodology

Recent years have seen rapid development in image classification, and the introduction of transfer learning has further accelerated the pace of progress. To rephrase, "transfer learning" allows us to use a model previously trained on a massive dataset for our objectives [15]. Since the datasets review, the cost of developing new DL algorithms and accuracy has decreased [16]. This study will concentrate on four widely used pre-trained image classification methods, including VGG-16, Inception V4, ResNet-50, and DenseNet-121. While other models may get less attention in this publication, our suggested system and its performance on a leaf dataset discuss in depth. We have also provided some outcomes from our deployment of the design. CNN models are very effective at finding and classifying objects in image datasets. There are several disadvantages to using CNNs, despite their many advantages. For example, training a CNN takes a long time and requires enormous datasets. DCNN models are necessary to extract basic and complicated information from images. It adds complexity and increases training time for the models. Transfer learning-based methods provide a solution to the issues we have discussed. Pre-trained networks utilize transfer learning, with the model parameters learned on one dataset being used to solve a new problem type. Here, we will discuss the approaches used in doing the research for this study.

Fig. 2. Images taken from the dataset as examples

A. Model technique method

1. VGG-16

The network takes in images with dimensions of 224 by 224 by 3, and the first two layers each have 64 channels, with filters measuring 3 by 3, and a stride of 2. After a layer with a maximum pooling capacity and a stride of 2, the VGG-16's two layers each include 256 channels and 33 filters. Two 256-channel, 3-by-3-filter-size convolution layers follow the pooling layer. After the first two convolution layers, a pooling layer with 33 filters comes next, followed by two sets of three convolution layers. The network consists of two dense layers, one flattens layer and a maximum of five pool layers.

2. Inception V4

Inception's V4 block may break into two distinct sections.: the first is used for feature extraction, while the second uses ultimately linked layers. With Inception V4, there is a stem block, A, B, and C blocks for inception, A and B blocks for reduction, and an auxiliary classifier block.

3. ResNet-50

The first layer of this residual CNN network is a convolutional layer, and its parameters are as follows: kernel size 77, stride 2, and 64 channels. Convolution layers with 64, 64, and 256 channels follow the first layer. Their filter widths are 1, 1, and 1. It's said three times. Then, four iterations of a convolution layer perform, followed by six iterations of a convolutional block.

4. DenseNet-121

DenseNet -21 addresses vanishing gradient problems, allowing the CNN to function at a deeper level. There are four solid sections. Convolution is done six times on the first dense block, with 1 x 1 and 3 x 3 filter sizes. Convolution is performed 12 times inside the second dense block, using the exact filter sizes as in the first: 3×3, and 1×1. Within the third dense block, convolution procedures repeat 24 times while maintaining the same filter size, while repeating the steps 16 times occurs in the fourth dense block. The dense block separates by transition blocks, which include convolution and pooling repeated 16 times. There are convolution and pooling layers in the transition blocks that lie between the dense blocks.

B. Proposed method

1. Dataset

The original dataset uses to build this new dataset using offline augmentation. Table 1 shows the classes of the dataset, which contains approximately 97K RGB images of healthy and diseased plant leaves, which we classified into 38 categories, of which 87K takes from a GitHub repository [17]. The remaining 11K are from various districts in West Bengal and other states in India. Here we are creating a dataset using 11K images of diseased and normal leaves collected from various places with the help of mobile cameras. These images can also be collected using DSLRs and mobile phones. Here are some of the pictures collected from Bankura using the Realme 6i in the sunlight using the default settings, i.e., HDR (auto), Filter (original), and Chroma Boost (off). Indas used an Asus Zenfone Max Pro M2 to take pictures outside in the sunlight. Moreover, some images were collected from Burdwan, Hooghly, using the Samsung F41 with default settings in the sunlight. Furthermore, various pictures from several websites use in our research as datasets. Each class represents a plant type, and each subclass represents a leaf disease. The whole thing is split in two, with the training set accounting for 80% and the validation set for 20%. Fig. 2. displays a few of the photographs included in the dataset.

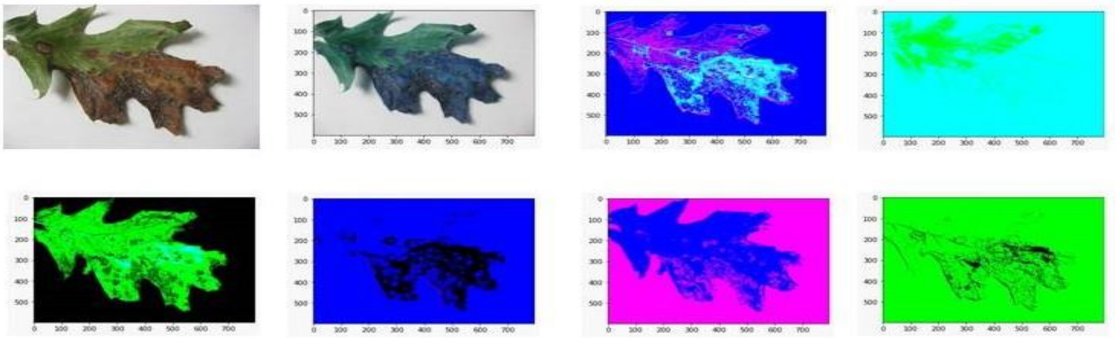

Fig. 3. The Proposed System's Produced Images and Results

2. Feature extraction

"Image processing" is the process of putting a picture into a digital format like this to make it easier to get information from it. Converting an image to grayscale is known as grayscale conversion and is used in image processing [18]. This approach converts every color in an idea into a different tone of grey. The lightest shade, white, is produced, while the deepest dye, black, results from the conversion. Most of the time, the brightness of the intermediate hues is comparable to that of the red, blue, and green primary colors [19]. The grey scale's three components are the dye, saturation, and brightness. Hue is a technique that involves changing the color shades and focusing on the edges and shapes of an item rather than the colors themselves [20]. Adjusting the saturation consists in changing the vibration of pixels in the image. The range is from 0 to 100 on the brightness scale. The farther down the scale, the deeper the color [21]. The shade will seem more brilliant when the scale increases. The color is always somewhere between white and black. Each pixel's red, green, and blue values average and blend to create the primary color. A reasonable approximation of the value of the grey scale creates by combining the luminous intensities of each color band. Therefore, the picture is changed so that it is grayscale.

Grayscale is essential in image processing because it helps simplify algorithms, eliminate complications, improve simple visualization, and minimize the complexity of colors. The images are subject to the Gaussian filter treatment following the grayscale conversion. The sections of an image are blurred using a low-pass filter known as a Gaussian filter. This filter uses to minimize high-frequency components or noise in a snap. The filter applies as an asymmetric kernel of an odd size to the pixels that make up the chosen regions of the picture. An approximation of the Gaussian function refers to as a Gaussian filter. In the Gaussian filter's first step, the matrix's length has an odd number of elements, so the output of the matrix calculates to the middle pixel.

Furthermore, the matrix is symmetric since there is the same number of rows and columns. The Gaussian function uses to calculate the values here. A smaller region of the picture is blurred instead of the whole image. It accomplishes first cropping and filtering the relevant portion. The results superimpose on the source picture. Therefore, output occurred. Thresholding is complete after this. In this study, we use Otsu's thresholding technique. By applying threshold values to the pixel values of an image, the thresholding image processing technique transforms a grayscale or colored picture into a binary image. In image processing, thresholding uses to identify and isolate objects within a picture or to distinguish between foreground and background pixels. Data augmentation use to improve existing images and give more information for more complicated models. The term "data augmentation" refers to adding more information to a dataset made up of computers. Methods include scaling, rotation, cropping, padding, and many more. It makes the model more resilient and improves performance by addressing problems like overfitting and lacking data. Modifications, such as blurring, flipping, shifting, noise reduction, and rotation, are required for the same purpose. As computer vision focuses on pictures, image segmentation is a crucial first step. The visual input is segmented to highlight the importance of image processing. Pixels organize into groups or segments. With image segmentation, we can forget about treating individual pixels as independent entities. It is the method of cutting a big picture into smaller, more manageable pieces called "tiles." Segmenting a picture begins with identifying areas that should be kept intact. Seeds are defined areas whose locations determine the layout of the tiles.

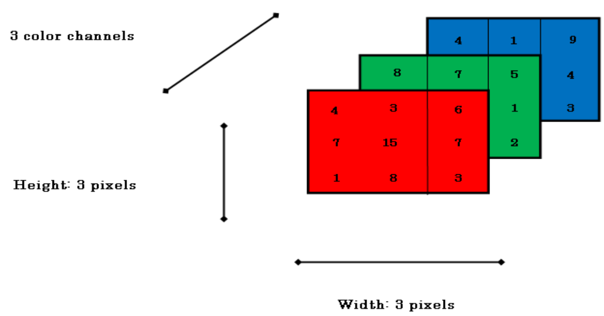

Fig. 4. CNN workflow

3. CNN

A CNN may include dozens or even hundreds of layers, and each of those layers trains to recognize distinct aspects of an image. The network recognizes different aspects of an image. After each layer's completion, the images are passed through a strainer or

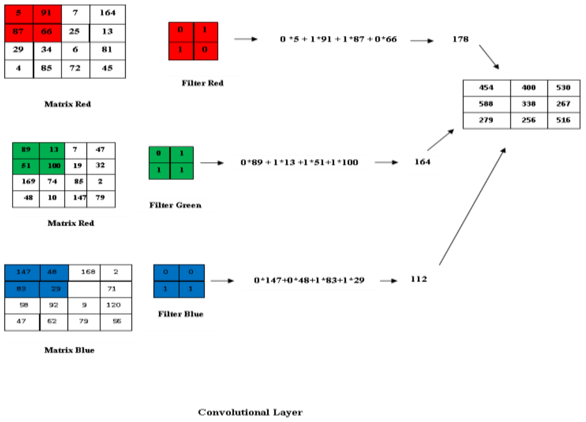

Fig. 5. Convolution Layer

kernel to produce an output that is superior in quality and level of detail to that produced by the one that came before it. The convolutional, activation (ReLU), and pooling layers are the three kinds of layers used most often. During the convolution process, the photo route through several convolutional filters in sequence. Each filter draws attention to a distinct set of qualities in the photographs. Because it converts negative numbers to zero and displays positive values, the rectified linear unit, more often referred to as the ReLU, makes it feasible to finish training in a more timely and effective way. Pooling cuts down on the number of parameters that a network has to be able to understand while at the same time enabling non-linear downsampling to be carried out to make output simpler. The convolutional network makes use of a one-of-a-kind strategy that is comparable to how our eyes assist us in gaining an understanding of our surroundings. As soon as we take in an image, our brains quickly begin to break it down into a variety of smaller images, each of which we analyze in turn.

We can analyze and better understand the bigger picture after stitching together these individual photographs. To implement a convolutional network, one must follow the steps outlined below. The convolutional layer is a pivotal component responsible for executing essential operations, deriving its name from its distinctive structural characteristics. In order to accomplish this, we design a filter that determines the size of the incomplete pictures that we will be analyzing, as well as a step length that determines the number of pixels that we accompany after each computation, or, to put it another way, how close the incomplete pictures should be to one another. Together, these two components determine the size of the incomplete pictures we will analyze. When used together, these two aspects define the appropriate proximity of the individual partial images to one another. The three-dimensionality of the picture has undergone significant transformation as a direct consequence of this action. Following that is the layer that sinks to the very bottom of the container. The identical procedure within the convolutional layer also occurs in this layer, except that, for the sake of this particular application, we extract the mean or highest value from the output. The two layers are indistinguishable from one another from the perspective of purely computational analysis. It ensures that the unimportant details essential to completing the task recover within the allotted amount of pixels. The most superficial layer is completely connected to each of the layers that lie underneath it. We can now utilize layers with a very thick mesh since the image's dimensions reduce, allowing us to do so. In this specific instance, the multiple sub-images reconnect to make it possible to see the relationships between them and conclude the categorization. A picture is nothing more than a matrix consisting of the values of its pixels. An RGB picture depicts three independent matrices, again for computers. These matrices are red, green, and blue. It provides a summary of the color that every pixel in the picture has. In order to accomplish this, the red element is specified first in the initial matrix. The

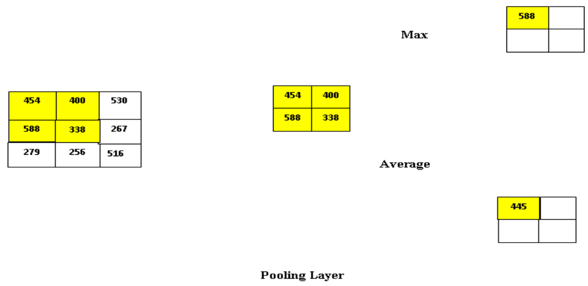

Fig. 6. Pooling Layer

green component is defined in the second matrix, while the blue component is in the third and final matrix.

To put it another way, when we take a photo with a resolution of 3 on 3, we have three distinct matrices, each 3 x 3. Once the photographs reach sizes such as 8K (7680 x 4320), we might begin to conceptualize how much more computationally tricky things will become. It is the responsibility of ConvNet to reduce the complexity of the pictures without omitting any of the components necessary for producing reliable forecasts. We can scrutinize the categorization process in great depth. In order to achieve this goal, we will endeavor to recognize a leaf picture that is 4 by 4 by 3. Step 1 (Convolution Layer): At this point, we want to begin by reducing the size of the 4x4x3 picture using the Convolution Layer. To achieve this goal, we create filters that are 2 by 2 in size for each color.

On the other hand, we want the filter to have a step size of 1, indicating that it should advance by precisely one pixel after every calculation step. The dimensions will not change significantly, and the image's details will remain intact. For our convolutional layer to create a 3x3 matrix, we must first convert a 4x4 matrix into a 2x2 matrix and then shift either one column or row at a time throughout each step.

The matrix's component values may be calculated by applying a scalar product of both 2x2 matrices, as shown in the image below.

Table 2. Analyzing the efficacy of different network models

Model	Training data Accuracy	Testing data Accuracy	Training Loss	Testing Loss	Recall	Precision	F1-score
VGG-16	89.47	87.62	0.48	0.59	92.43	87.63	87.81
Inception V4	98.68	97.16	0.46	0.41	98.55	89.48	89.72
ResNet-50	99.11	97.84	0.78	0.52	99.36	92.58	92.77
DenseNet-121	99.23	97.34	0.34	0.21	99.42	99.21	99.27
Proposed Model	99.25	97.59	0.33	0.21	99.44	99.27	99.28

Step 2 (Pooling Layer): The Max Pooling layer uses the input matrix of the 3x3 convolutional layer and makes an extra attempt to reduce the picture's dimensionality while collecting its most essential parts. We begin by searching for the highest possible value in every field of the input matrix, which we then divide into all of the incomplete matrices of dimension 2x2 that are viable given that the result of such a layer is to be a 2x2 matrix. This value includes the element in the state matrix. If we were to use an average pooling layer rather than a max-pooling layer, we would be able to get the mean of the four fields. In addition, the noise in the picture is removed by the pooling layer, as are any image components that do not contribute to the categorization process.

Step 3 (Fully-Connected Layer): The initial objective of achieving the overall vision accomplishes the seamless integration of all layers involved. We construct a neuron to correspond to each element in the more compact 2x2 matrix, and then we connect that neuron to each of the other neurons inside the layer below it. It offers us a much-reduced number of dimensions and uses fewer training resources. Ultimately, this layer is responsible for determining which aspects of the picture are necessary for the categorization. Suppose we have pictures that are much larger than our example. In that case, we may need to repeat the steps of setting the convolution layer and the pooling layer several times before moving on to the fully connected layer. We can reduce the dimensionality to the point that it will take less training if we proceed in this manner.

MatPlot, Image Data Generator, Keras [22], Open CV, and TensorFlow [23] are some of the libraries used. While evaluating the suggested model's effectiveness, precision, recall, and F1 score are used as measuring sticks. The complete accuracy we achieved on the leaf image dataset diverse from 89.47% (in the case of VGG-16::Training From Scratch::Gray Scale::80–20) to 99.23% (in the case of DenseNet-121::Training Learning::Color::80), thereby indicating the rigid promise of the DL technique for analogous prediction problems. It was the case across all of our research procedures about accuracy and loss, which include graphical representations of the image data in Fig. 3 and the results of all of our experiments shown in Fig. 9., which includes the mean F1 score, the mean precision, the mean recall, and the total accuracy. When each experimental setup executes for thirty epochs, they virtually always converge following the first reduction in the learning rate. Fig. 7. illustrates how well the crop disease prediction system worked using the VGG-16, Inception V4, ResNet-50, and DenseNet-121 neural networks. The outcome of the suggested model evaluates next to the results of other models.

The proposed model exhibits a higher training accuracy of 99.25% in comparison to the accuracy of the other previously utilized models. Table 2 contains a tabulation of the precession, recall, and F1 scores of the VGG-16, Inception V4, ResNet-50, and DenseNet-121 models and the suggested model.

A. Assessment of the Leaf Ailment

Precision is an important metric that measures the accuracy of a forecast in predicting outcomes related to the number of people.

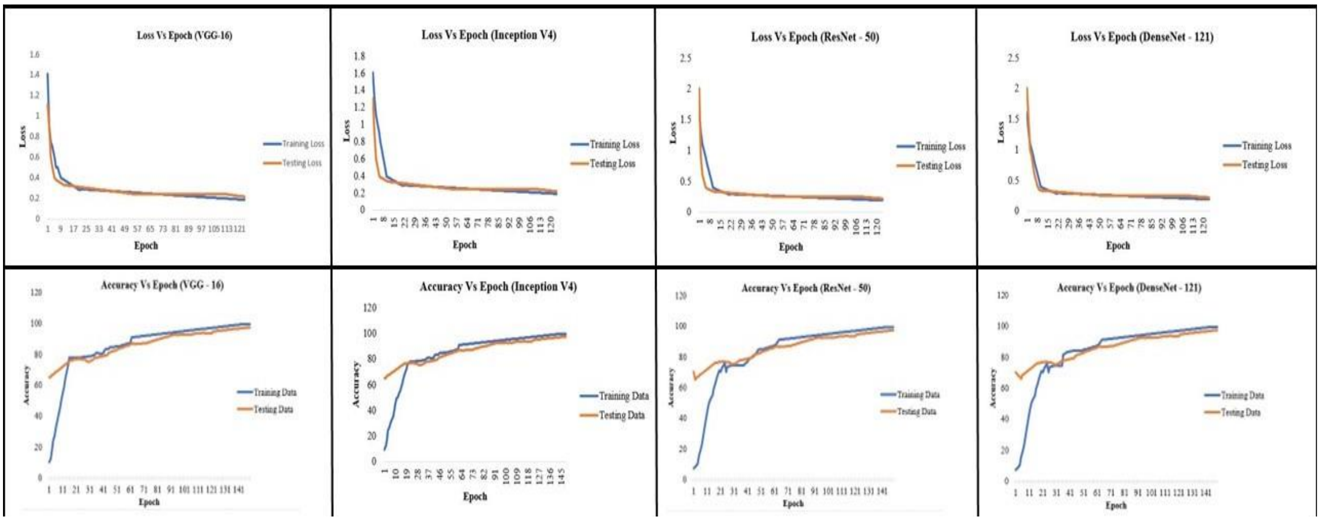

Fig. 7. Accuracy of four pretrained model

4. Results

The model's reliability is determined by training and testing the dataset samples. To do the job well, we should use the hardware and software requirements, i.e., the operating system is Windows 11, the core is GPU-NVIDIA, Python is the language, and NumPy,

Precision calculates by dividing the number of true positives by the sum of false positives and true negatives. Positive predictive value is another name for this concept. The proportion of accurately anticipated outcomes relative to the total number of predictions is called "recall." The percentage of true positives our model can identify and classify refers to as the "recall" for this model. When the cost of producing a false negative is higher than a false positive, we must choose the best model by utilizing the recall metric. We need to have an F1 score. As we have seen, accuracy refers to the proportion of adequately detected positives and negatives, which we have determined. Next, we are going to look at the "F1 Score," which is a method for determining the degree of accuracy that is available in the dataset. When making judgments, we tend not to concentrate on many diverse factors, yet false favorable rates and false negatives often have both actual and intangible costs for the company. Since it strikes a compromise between accuracy and recall, the F1 score might be a more appropriate metric to use in such circumstances [24, 25].

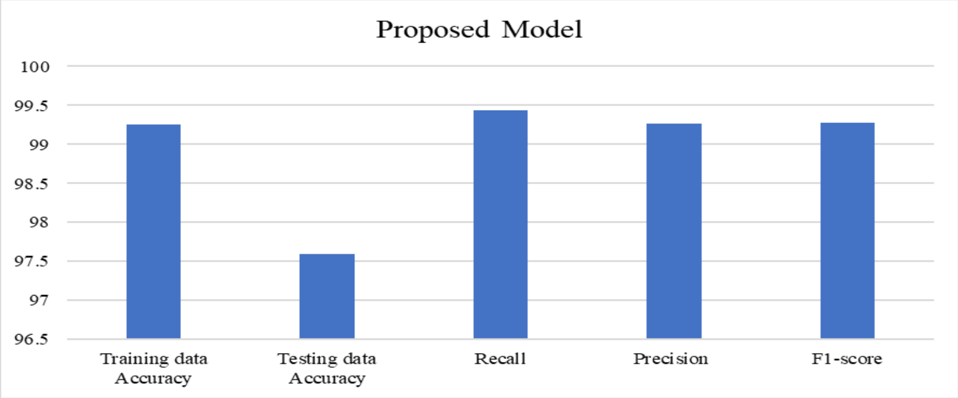

Fig. 8. Performance of Proposed Model

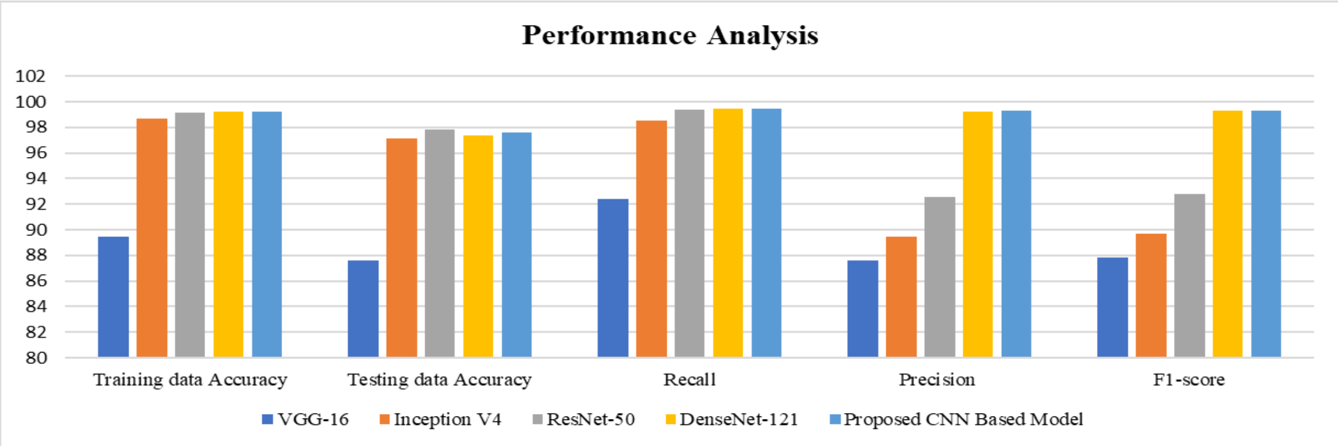

Fig. 9. Evaluating the efficacy of pre-trained models with the proposed model using a variety of criteria.

$$Precision = TP/(TP + FP) \times 100 \quad (1)$$

$$Recall = \frac{True\ Positives}{TP + FN} \times 100 \quad (2)$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \times 100 \quad (3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \times 100 \quad (4)$$

Here, TP is True Positives, FP is False Positives, TN is True Negative, and FN is a False Negative.

5. Conclusions

Finding plant diseases as soon as possible is significant to get high agricultural yields. If a high production rate is maintained, the most recent technological advances must find plant diseases as soon as possible. The literature review results show that DL algorithms are good at classifying images, but transfer learning-based models are better at eliminating the need for a large dataset and making training more straightforward. Because of this, throughout this research, we. We have analyzed four different pre-trained models, namely VGG-16, ResNet-50, Inception V4, and DenseNet-121, to identify which model most effectively categorizes different plant illnesses. The use of mobile phones contributed to a decrease in the costs and inefficiencies associated with the search for information, as well as an increase in market efficiency. Mobile phones could encourage low-income farmers to increase market participation and diversify their crop selection to include high-value products. For real-time prediction, an affordable system needs for the sake of farming. To fulfill these in the future, we will develop MobileNet. This CNN structure is much faster in addition to being a smaller model that employs an innovative sort of weird convolutional layer. Our future work will be a mobile-based model using sensor data from an IOT device and digital images.

Conflict Of Interest

The authors declare no conflict of interest.

Author Contributions

Mr. Saikat Banerjee was in charge of conducting the research as well as analysing the model's performance and writing the paper.
Dr. Abhoy Chand Mandol had directed the research work in the proper direction.
Both authors have approved the final version.

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