A Multimodal Deep Learning Approach for Advanced Plant Disease Prediction

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***Abstract*—Excellent craftsmanship food is provided by the farming industry, which is also a major engine of GDP growth and demographic supports. Plants ailments, nevertheless, can seriously reduce the availability of food and endanger a variety of organisms. timely and precise. The use of computerized methods for identification for plant pathogen diagnostics is essential to improve Ensure high nutritional value while limiting monetary damages. Recently, deep learning was developed has demonstrated impressive progress, especially in enhancing categorized images along with precise identifying of objects. In the present investigation, we use models with prior training built on convolutional neural networks (CNN), which to correctly recognize crop illnesses. With DenseNet-121, ResNet50, which VGG-16, and Inception V4 as our primary targets, we concentrate on adjusting the extreme parameters of these well-known algorithms that were previously trained. We do trials using the frequently utilized Plant Villages information set, that includes 54,305 photos of diverse diseased plant types divided into 38classifications, to assess our methodology. Measurements such as categorization reliability, specificity, sensitivity, as well as the F1 score are employed to assess the efficacy of our methodology. We also perform a comparison against other cutting-edge work on deep learning-based plant sickness diagnosis. The outcomes suggest that DenseNet-121 outperforms pre-trained models as well as in terms of precision when classifying, solidifying its position as the most effective algorithm for identifying plant diseases. These results shed important light on how machine learning may be used to advance methods for environmentally friendly farming, guarantee nutrition, and protect the environment.**

Keywords— Image Processing, Deep Learning, Plant Disease, Neural Networks, Agriculture.

I. INTRODUCTION

Providing a major supplier of nourishment, revenue, and jobs, agricultural is important to the worldwide financial system. Farming generates about 18% of the gross domestic product of a country and performs a significant role in the financial systems of societies like the Indian subcontinent, that employ a high number of producers. the maintenance of an average 53%percentage of workers. The three years prior to 2015 have seen the nation's economic system has experienced a rise in the farming industry's gross value addition rising steadily, from 17.6% to 20.2%. The precise diagnosis of diseased plants is crucial and of extreme significance. Greater accuracy in managing farming operations can result from detection earlier. On their branches, berries, leaves, or blossoms, infections develop distinctive marks or pigmentation, every one having an individual design that aids in the identification of anomalies. Nevertheless, spotting illnesses in plants demands skill and time consuming work. Manually assessment is personal, labor intensive, and occasionally can yield false conclusions from growers or specialists.

Regarding successful detection and categorization of plant sickness, scientists have suggested a number of different techniques. These methods comprise mechanical extraction of characteristics and categorization, which are standard computational imaging methods. A stochastic artificial neural network was employed to gather environmental and analytical characteristics. Regarding successfully recognizing and categorization of plant sickness, scientists have suggested a number of different techniques. These methods comprise mechanical feature acquisition and categorization, which standard computational imaging methods. A stochastic artificial neural network was employed to gather environmental and analytical characteristics. Identification of diseases of plants has risen significantly since the development of computerised training and neural network approaches, revolutionising this area of study.

The excellent recognising and categorising capabilities of deep convolutional neural networks, particularly in the removal of minimal complicated information in pictures, have drawn a lot of interest. In a consequence, CNNs have supplanted more established techniques for automatically identifying plant diseases, producing better results. Previous investigation has shown that CNN-based forecasting algorithms are useful for classifying information and analysing images in a variety of vegetation, particularly rice plants [2]. Additionally, excellent outcomes have been achieved obtained using CNNs for disease identification in rice paddies [3]. For the categorization of various plant genera, 4 to six-layer CNN structures are frequently employed, performance techniques based on transfer learning are being utilised to enhance disease categorization performance identification [4]. There exists a restriction regarding the range of information employed, notwithstanding the advancements obtained through the CNNs as well as the claimed favourable findings [5. A dataset on plant diseases called the Plant Village information set was made public by the University of Pennsylvania [6]. This collection includes 54,305 Colour pictures from 14 distinct species that represent 38 various plant diseases classifications. Pictures of normal leaflets and damaged departs every with 256 256 pixels in size, are included in each botanical class. Examples of the dataset's photos are shown in Fig.1. Several investigations on the detection of illnesses in plants have been carried out since its publication [7,8].

CNN neural networks are increasingly common in based on pictures study because of their effectiveness in extracting low level, intricate characteristics in pictures. Deep neural network layers learning can be extremely costly, which is a hurdle for scientists. Several academics have suggested transferable learning-based approaches to overcome this problem [9]. These algorithms, including VGG-16, ResNet, DenseNet, and Inception, have been pre-trained using the ImageNet information set , containing a variety of classes. The method of transfer learning has the benefit which the characteristics whereby these algorithms acquire knowledge, including borders and boundaries, are shared throughout several dataset.

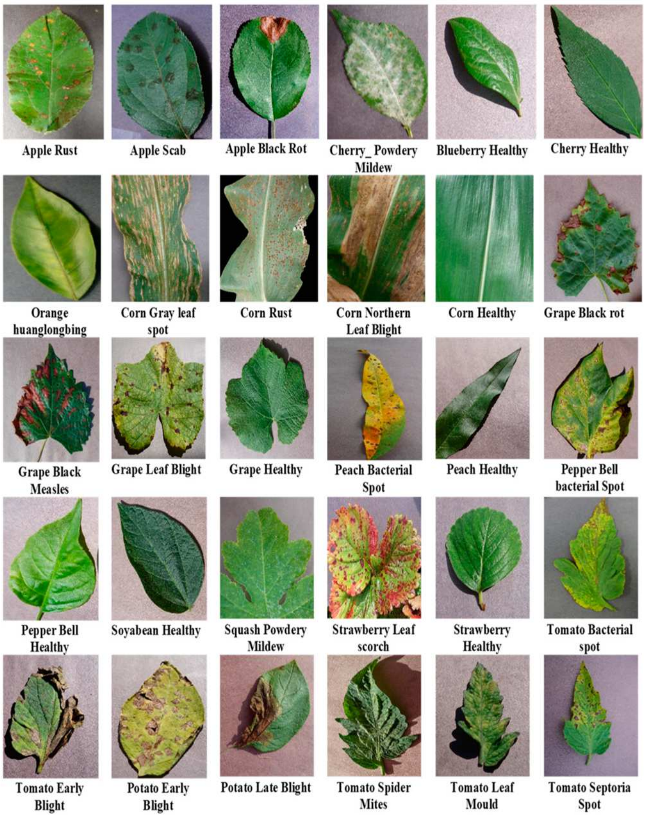

Fig.1: The information set displaying some sample of different diseases.

The method of transfer learning has the benefit which the characteristics whereby these algorithms acquire knowledge, including borders and boundaries, are shared throughout several dataset. The exchange learning method is therefore appropriate and reliable for recognising pictures problems [11-14]. Despite utilising smaller amounts of data, transferable learning has been demonstrated to be advantageous. The underlying idea underlying transferable learning is depicted in the fig.2. By employing suspended layering during simulation training, transferred learning increases task performance [15]. To increase detection rate and decrease delays, this study contrasts approaches using transfer learning using sophisticated CNNs. Employing trained CNN algorithms such VGG-16, DenseNet121, ResNet-50, and Inception V4, trials use the Plantation Villages datasets.

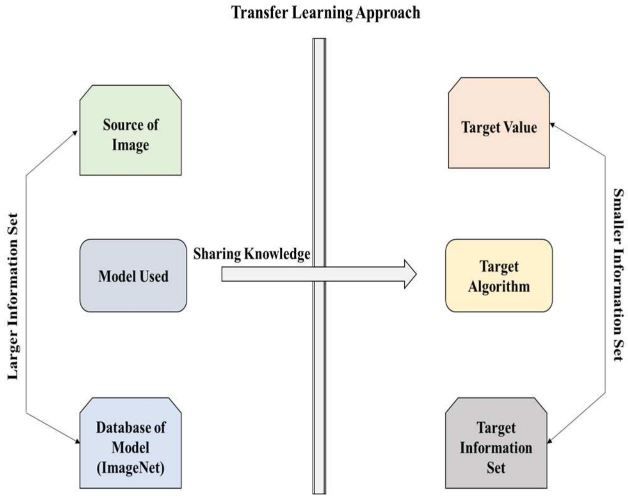

Fig. 2: Knowledge transfer for efficiency

II. RELATED WORK

Skipping the earliest indications of illnesses in plants may outcome in major declines of crop agricultural produce, which could have a negative impact on the world's economic performance [16]. A thorough overview of the most recent studies on identifying leaf diseases is provided in the following paragraphs. A CNN-based neural network system was put forth by a single investigation [17] for the reliable identification of plant diseases. 87,000 RGB photos from a publicly accessible data set were used to train the algorithm. Despite having an identification rate of 93.5%, the algorithm had trouble determining certain groups, which caused uncertainty in later phases because there was a lack of knowledge. Narayanan et al. [18] developed an amalgamated convolutional neural network to categories bananas plant illnesses in order to increase recognition speed. A 99% classification precision was achieved using the combination of SVM and CNN. CNN outperformed standard procedures in terms of quality, but its strategy missed novelty. A separate investigation by Jadhav et al. [19] suggested utilizing models with prior training like AlexNet and GoogleNet to train a CNN for identifying diseases of plants. Although it produced more favourable outcomes, the algorithm had trouble grouping various plant groups. sicknesses, primarily because there aren't plenty of records to build models based on deep learning on different plant species.

In order to tackle the problem of inadequate information, Jadhav et al. [20] developed an innovative graphic modification method. They improved recognition precision by creating artificial photographs utilising the poor-quality sample photos. In order to get around information shortages issues during the model's initial development stages and deliver better results, artificial visuals were created through updated colour intensity distributed. The generation of artificial photographs of tomatoes foliage using generative adversarial networks with conditions was investigated in later studies [21]. Additionally presented [22], benchmark-based multi-leaf classifiers with already trained Mobile Network CNN algorithms had a 96.58% accuracy rate. In order to more effectively identify diseases of plants, EfficientNet—a convolutional neural network designed for multi-label as well as multi-class classification—was developed. With the Plant

Village the information set, an efficient, loss-fused, robust CNN algorithm has been established with an estimated categorization accuracy of 98.93%.

While used on actual time photos in a variety of natural settings, the human subject ran into difficulties. The last thing to do was to suggest a network powered by CNN and transfer learning capabilities for three plant illnesses [23], with Mobile Net producing extremely accurate forecasts. With the help of leaf rot databases and cassava 2019, excessive fitting in deep learning algorithms was reduced, increasing the test's reliability to 84.51%.

TABLE 1: Showing the existing work done by the Researchers

Reference	Crop Focus	Disease Addressed	Dataset	Classes	Model	Model Performance
[24]	Several	Citrus canker, black mould, bacterial blight, etc.	Plant disease symptoms database	12 56 diseases under 12 classes	CNN GoogleNet with tenfold cross-validation	Accuracy: 84%
[25]	Several	Black rot, late blight, early blight	Self-collected database	527 species of diseases under 5 classes	CNN	Accuracy: 96.5%
[26]	Tomato plant	Various diseases and pests in tomato plant	Self-generated database	9	Faster Region- based CNN with SSD 1 and Region-based Fully Convolutional Network	Precision: 85.98%
[27]	Several	Powdery mildew, early and late blights, cucumber mosaic, downy mildew, etc.	Open dataset	58	CNN with pre- trained VGG network	Accuracy: 99.53%
[28]	Several	Black rot, late blight, early blight	Plant Village	38	VGG-16, Inception V4, ResNet with 50, 101, and 152 layers, and DenseNet with 121 layers	Accuracy: 99.75%
[29]	Several	Pepper bell bacterial spot, tomato early and late blight	Plant Village	38	Pre-trained with ImageNet, GoogleNet, and VGG-16 models	Accuracy: 99.09%
[30]	Apple	Apple scab, apple grey spot, general and serious cedar apple rust, serious apple scab	Al-Challenger plant disease recognition	6	DenseNet-121	Accuracy: 93.71%
[31]	Tomato	ToMV, leaf mould fungus, powdery mildew, blight	Al-Challenger plant disease recognition	4	Faster regional CNN	Accuracy: 98.54%
[32]	Several	Rice leaf smut, maize common rust, maize eyespot, rice bacterial leaf streak	Public database	7	Pre-trained models	Accuracy: 92%
[33]	Rice plant	Sheath blight, rice blast, bacterial blight	Self-generated database	4	Pre-trained CNN with SVM classifier	Accuracy: 91.37%

III. METHODOLOGY

Despite its suitability need photo detection and categorization applications, CNN algorithms have drawbacks such lengthy hours of training and the requirement for massive databases. Deeper neural nets are required for extracting low-level and complicated characteristics from photographs, which increases the difficulty of learning. Techniques for transferringknowledge provide answers to these problems. The learnt model settings form a single set of data can be extended to different issues by using pre-trained systems. This section examines the techniques that were used in this research.

Multinomial categorization: Photographs of sick and normal specimens of plants are categorized in databases for plant diseases. For instance, the class of plants that produce bananas has four separate illness types: bunchy top virus is apparent fusarium caused wilt, Xanthomonas wilting and black sigatoka. In a multiclass system, the characteristics that were determined by the starting point picture are used to categories the target picture according to its particular category. In other words, the testing stage's output is going to determine the precise labelling of the illness among each of the four groups mapping within that category whenever an instance of an illness is provided after learning with each of the condition groups underneath the fruit category. The distinction between all the categories inside an organization and its own group of categories is made in a system of multiple labels.

Transfer Learning: On less powerful GPU processors, retraining modern algorithms from beginning may require weeks or even days to complete. The Transfer Understanding Technique is a helpful method to circumvent this problem. On an openly available plant illness dataset, a CNN classifier educated form beginning attained 25% accuracy after 200 iterations. Nevertheless, a surprising 63% performance was achieved in approximately a hundred epochs by employing a pre-trained CNN model and performing transfers. The previously trained network algorithm that is chosen as well as the particulars of the information will determine which transfer learning techniques are used. This method increases efficiency in categorising while also considerably accelerating modelling training.

ResNet-50: ResNet-50 is an a large convolutional neural network of fifty neurons divided into five phases and identification and convolution structures in each step. These neural networks act as an underpinning framework for visual analysis applications. ResNet pioneered the technique of layering convolutions on preceding one another, along with bypass connections that let the initial input influence the system's final outcome. By inserting the skip link before the function that triggers, this layout also helps to address the disappearing gradients issue. Skip interconnections were added to leftover neural systems to deal with the issue of higher models producing additional mistakes. These associations are shortened depending on identify mappings. Considering the original imagery as "x," the relationship between each of the regressive layering as "F(x)," with the remaining projection as "H(x)." With 3 convolutional layers along with more about twentythree million variables to train, ResNet-50, which uses inversion as its distinctive building component. Following combination and batching normalisation, the shortcut connections has to have the identical outputs dimensions as "x" in order to be incorporated to the mixture layers. After getting added to the computer output, "x" goes through an intermediate layer of convolution and batch normalisation to determine the measurement if the dimensions are different.

VGG-16: The Visual Geometry Group, a research team at Oxford University created the VGG16, which stands for, sometimes shortened to as the Extremely Shallow Convolutional Network for Large-Scale Images Identification. With 16 to 19 weighted levels and over 139 million parameter sets that can be trained, it is a neural network that is deep. The system makes use of smaller 3 3 convolution adjustments to boost its thoroughness. Nevertheless, because of the design's deeper dimensions, learning takes greater time and additional memory is needed.

DenseNet-121: A deep convolutional neural network, also known as called DenseNet-121 [35] uses numerous layers having close relationships among them to classify images. Every single layer in the aforementioned structure takes more data form the layers that are above it and transmits the characteristic mappings it produced to the layer above it. Every layer uses combining them, enabling the following layer to access the pooled information of all prior layers. By transferring the characteristics of earlier layers to later ones, a network is kept thin and tight. As a result, a dense region has fewer pathways, and the expansion rate for those conduits is indicated with the letter "k." Fig.3 illustrates the operation of a block of information about algorithm used .

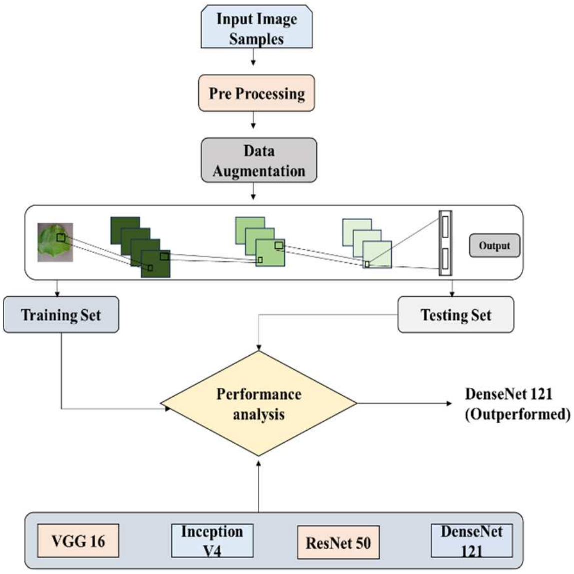

Fig.3 : Illustrates the operation of a block of information in DenseNet.

IV. EXPERIMENTS

The investigations were conducted using a Microsoft Windows 10 machine as the starting point platform an Intel Core i5 9th iteration processor speed, an AMD GeForce GTX the graphics card, 8 GB of storage, and GDDR5 graphics memory. The application's architecture made use of Anaconda3, Keras, these include OpenCV as a NumPy, Theano both of them, NVIDIA's technologies, which have been utilised for memory-efficient and quick deep-learning algorithms. Backbone versions of Theano. Different platforms have been assisted by OpenCV, and Ubuntu, Mac OS, Windows, iOS, Java, Python, and Android are just a few examples of interfaces. Therefore, it's adaptable for both professional and collegiate applications. We assessed the development and validation performance for every experiment and calculated the amount of error for every prototype in every stage. To speed up Neural Network training utilizing transferable theories, retraining was conducted using the information from Plant Village. ResNet-50, Inception V4, VGG-16, and DenseNet121 are the models with prior training that were chosen. These algorithms were then tested on the ImageNet the information set, which consists of a total of 1.2 million photos and 1000 characteristics.

Description of Data :

The free-to-use the Plant Village Data collection includes many kinds of diseased plants. It has 54,305 photos spread out over 38 categories. We separated the information by the three categories of sessions for the purpose of the study. 80% of the data set gathered from Plant Village was utilised for training the existing models, as well as the other twenty percent was used for verification and evaluation. A total of 54,305 specimens were collected for the facility's courses, of which 43,955 were utilised for training, 4902 for validation, and 5488 for testing.

Data Argumentation:

There were 38 classes in the information gathered, comprising 26 illness classifications and 14 varieties of crops. Researchers utilised colour photos using the Plant Village dataset to conform to the transferring models of learning. Since differing previously trained networking architectures required varying entry dimensions, these photos were scaled to a common length of 256*256 pixels. The data shape (height, width, as well as channels width) for VGG16, DenseNet-121, and ResNet-50 is 224 *224* 3, whereas the input structure for Inception V4 is 299*299*3. When there were over 54,000 photographs of various crop illnesses throughout the collection, the pictures were genuine and were obtained by farms using a variety of image collecting methods, including the Kinect indicators, high quality imaging devices, and cell phones.

Hyperparameters in Pre-Trained Models:

Preliminary a hyperparameter adjustment was done to standardise the variables for several pre- trained architecture. Table 2 lists the specific a hyper parameter information.

TABLE 2: Specific hyper parameters used in information

Hyperparameters	Epochs
Dropout	0.5
Epochs	30
Activation	Relu
Regularization	Batch normalization
Optimizer	Stochastic gradient descent (SGD)
Learning rate	0.001
Output classes	38

DenseNet-121, ResNet-50, VGG-16, and Inception V4 networks were optimised using probabilistic gradient descent methodology using a start learning rate of 0.001. A dropout rate percentage of 0.5 was used, and all models was trained for thirty iterations. The visualisation generated throughout the course of the study showed agreement after just a few repetitions, or roughly 30 epochs. This result demonstrated that the overfitting and degrading problems was effectively handled by the method, which increased its efficiency.

Network Architecture Model:

Pre-trained neural networks had been selected on how well they performed in classifying plant diseases. Table 3 lists the specifics for every algorithm's structure. Various dimensions of filters are used by the aforementioned networks, which is essential for retrieving specific characteristics form the attribute mappings. In the characteristic extracting manipulate, filtering are essential.

Hyperparameters optimization:

The gradient disappearance problem is solved by DenseNet-121 by deepening the neural network using convolution. It consists of four dense blocks, every of which has a unique convolution sequence. The filter thicknesses used for the second thick blocks are 1 1 and 3 3, respectively were replicated six certain points. The subsequent thick blocks uses 12 times each of the 3 3 and 1 1 filter settings. The identical size of filter is used for convolution processes twenty-four times in the third dense block and sixteen times in the final thick block. Those dense blocks are separated by transitional chunks made up of convergence and pooling layers. DenseNet-121 is able to efficiently transmit gradients therefore facilitate successful learning of features in deep neural networks thanks to those architectural choices

TABLE 3: Specific Network model structure

Network Model	VGG-16	Inception V4	ResNet-50	DenseNet-121
Total layers	16	22	50	121
Max pool layers	5	5	1	4
Dense layers	3	-	3	4
Drop-out layers	2	-	2	-
Flatten layers	1	-	1	-
Filter size	3 x 3	1 x 1,3 x 3,5 x 5	3 x 3	3 x 3, 1 x 1
Stride	2 x 2	2 x 2	2 x 2	2 x 2
Trainable parameters	41.2 M	119.6 M	23.6 M	7.05 M

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V. Results and Conclusion

Modern deep learning algorithms using the transfer learning method were used in this study's section to identify diseases in plants. The already trained deep CNN systems, that had been developed on the ImageNet information set, were modified using our openly available Plant Village information. Each of the models in the study had 38 output classifications that represented many different diseases groups, with an average learning rate of 0.01 as well as an abandonment rate of 0.5 percent. Materials for verification, testing, and training were taken from the collection of data. These developed Brainstorm V4, VGG-16, ResNet, and DenseNet- networks underwent training using Plant Village materials.

Each trainee completed 30 training phases, and the results was discovered how the simulations were starting accurately convergence within only 10 periods. The identical information set was used in the subsequent study for assessing the VGG-16 algorithm. 80% of the dataset was used for conditioning the mathematical equation, all while 10% was saved for examination. 10 percent of the remaining image samples were used for validation. The ResNet-50 model was used in the third experiment, which followed a similar procedure of standardisation and training of the dataset's hyperparameters. The final play around, meanwhile, made use of the DenseNet121 approach, which has 121 stages comprised of four compact chunks and transitional levels in among. The DenseNet model's finest precision is 99.81% during the evaluation stage that followed instruction, while the greatest validation loss that could be reported was 0.0154%. In order to guarantee outstanding profits in the farming sector, early harvest disease detection is essential. Utilising the most recent advances for early identification of plant diseases is of the utmost importance for maintaining an efficient agricultural

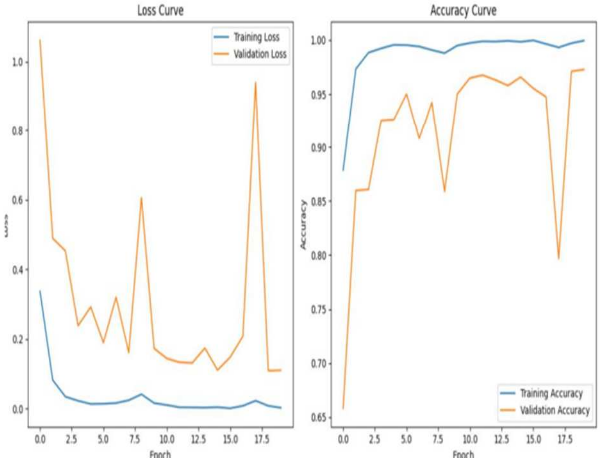

Fig. 4: Showing Loss Curve and Accuracy cure

production. A comprehensive examination of the research revealed that transferable training-based methods have been especially good in decreasing the level of detail of initialization and the amount of information needed for recognising objects involving images, as well as deep neural networks are extremely successful in these kinds of assignments.

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