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LEAF DISEASE DETECTION IN BANANA PLANTS FOR PRECISION AGRICULTURE

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Abstract

Our lives are greatly impacted by the agricultural sector. The most signiftcant area of our economy is agriculture. Profttable agricultural goods are the outcome of effective supervision. Due to their ignorance about leaves illnesses, landowners harvest little. Since productivity determines proftt & loss, detecting plant leaf diseases is crucial. One of the main components of Indian agriculture is the production of bananas. At the same time, a prevalent issue in farming is that many diseases have affected the crop. Early disease detection is critical to crop management and banana output. Banana diseases cause losses that have a direct effect on the world's fruit production and management system, which costs the nation money. To address these problems and help farmers avoid the disease in the ftrst place, a region-based separation using a suitable threshold approach and an adapted convolutional neural network are combined in the proposed method to enable banana disease detection and classiftcation. Recently, a CNN-free model on behalf of plant infection cataloguing has been used for computer vision tasks because it uses less resources during the train- ing phase and produces results that are identical to those of state-of-the-art CNN models. This hybrid model is established on a Transfer Learning-based prototypical monitored by a vision transformer (TLMViT). This study aims to present some deep learning approaches, such as support vector machines & con- volutional neural networks. Researchers may be inspired by this study to use the material to gain a deeper comprehension of associated disease prediction procedures.

Keywords: convolutional neural networks, disease detection, bananas, and leaf flaws, deep learning;

1. Introduction

The main source of fruit for beings, agriculture shows a crucial role in determining the state of our nation's budget. The main source of income for each growing nation is agricul- ture. With 29,124000 tons produced annually, India is the nation that produces the most

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bananas. India leads the world in banana output. Maharashtra produces the most, with 3924.1K tons. Tamil Nadu, at 3543.8k tons, came next. Assam, Gujarat, Andhra Pradesh, and Karnataka are the other top banana-producing states. Numerous nutrients, including vitamin B6, fiber, potassium, magnesium, & vitamin C, can be found in bananas. Around the world, banana plant leaves are impacted by numerous pests and diseases. Initial illness For crop management and banana production, diagnosis is crucial. Diseases affecting ba- nanas cause losses that have a direct effect on the world's fruit production and management system, costing the nation money. The leaves of bananas are huge, measuring between 30 and 50 centimeters. The enormous, flexible, and waterproof leaves of banana plants are referred to as banana leaves. They are employed for a variety of uses in many cultures worldwide. Numerous illnesses can harm banana plants, and occasionally the symptoms can be seen in the leaves, stem, flowers, fruit, roots, & suckers. The leaf is frequently affected by the primary illnesses.

For animals, who depend on plants for food, oxygen, & other needs, as well as for people, plants are essential. Significant steps are being taken by the government and specialists to improve food production, and they are effective in the real sphere. Every existing thing in the environment is obstructed in some method once a pathogen strikes a plant. This illness can disturb any part of the vegetal, plus the leaf, stem and branch. Even the diseases that affect plants, including fungal and bacterial infections, can vary. Climate is one of the elements that will decide the disease that affects the crops. A significant portion of the population is food insecure. This happens as a result of inadequate production of food crops. Plant development will be impacted by even major climate changes. Natural disasters of this kind are inevitable. Large-scale agricultural losses can be avoided with the help of early plant disease diagnosis. The right insecticides must be used on crops by farmers. Farmland and crops are harmed by excessive pesticide use. You can prevent the misuse of chemicals on plants by seeking professional assistance. Many researchers have focused on plants to help farmers and other agricultural professionals. It is easy to identify an illness when it is apparent to the unaided eye. If the farmer has sufficient information & regularly checks the yields, the infection may be identified and treated early. This stage, however, only occurs when crop productivity is poor or the disease is severe. After that, there are various advancements. The adoption of computerized infection recognition systems will be beneficial to farmers. The results of this method are appropriate for both small-scale and large-scale agricultural production. Crucially, the aberrations are identified swiftly, and the outcomes are precise. Deep learning and neural networks are necessary for these advancements to function. In order to identify sickness in afflicted plants and differentiate from good ones and diseased leaves, the researchers used a Deep Convolutional Neural Network. Both leaves with no illness or disease can be used with the CNN typical; the outcome of the typical is resolute by the given input leaf, which is trained using images.

Vision Transformer is one of these methods; it splits the image into many patches and uses a transformer encoder to extract the features from each patch. It could take a lot longer to extract characteristics from the entire image and remove extraneous elements, such the leaf's backdrop. Most importantly, this work offers a new method for labelling plant infec- tions applying a deep learning model that has already been trained and ViT. By removing

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the dimensionality of the image and extracting the preliminary traits since the initial con- volutional networks that have previously been refined, the pre-trained typical simplifies the subsequent step. The most important characteristics (deep features) are then extracted by passing the initialized features as input to ViT. These deep features are categorized into classes using a basic MLP.

The following highlights this paper's primary contributions:

1) Reducing the image's dimensionality using a pre-trained model to simplify the follow- ing step.

2) To increase the classifier's accuracy, extract the leaf's deep feature by combining the pre-trained model with ViT.

3) Try five distinct combinations of models based on transfer learning (e.g., ResNet50, Inception V3, AlexNet, VGG19, & VGG16) using ViT.

4) Five more transfer learning-based copies are compared to the TLMViT.

Basics of banana leaf disease types

Panama wilt: Fusarium wilt of banana is another name for Panama wilt disease. The banana plant is afflicted by this kind of fungal disease. The presence of panama wilt disease may cause banana plants to produce less fruit and jeopardize the quality of that fruit. Crop rotation is one suitable method that can be spent to stop the spread of panama fade infection. Furthermore, the use of fungicides can greatly reduce the disease's spread. The poorer leaves of the banana herb first seem grey, but with time, the yellow coloring moves near the centre of the leaf, ultimately turning the broad leaf yellow.

Yellow sigatoka: This leaf spot is another name for this species. Banana plants are affected by this noteworthy disease. The fungus Mycosphaerella musicola, formerly known as Mycosphaerella Fijiensis, is the cause of this illness. Small yellow acnes on banana plant leaves are the first sign of yellow sigatoka disease. As the condition worsens, the spots get bigger & might ultimately combine to form a grander lesion. Banana plants must be spaced appropriately to allow for adequate air circulation, which can successfully reduce humidity & prevent the development of disease.

Black sigatoka: The fungal disease identified as black sigatoka, or black leaf streak disease, mostly disturbs banana plants, principally the cavendish type, it is among the most extensively cultivated types of bananas worldwide. Black sigatoka is characterized by small, dark blemishes on the bottom leaves of banana plants at first. As the illness worsens, these spots grow into irregularly shaped, shadowy brown to black lesions. The effects of black leaf maculation on banana output are twofold. Firstly, it reduces the area of the leaves and hinders their ability to photosynthesize, which significantly affects the mass of clusters. Second, it shortened the green lifespan duration.

Bunchy top virus: The bunchy highest virus, commonly known as the Banana Bunchy Top Virus (BBTV), has a unfavorable outcome on the growth and outward appearance of banana trees. Should an infected tree bear fruit, the bunch will be small and asymmetrical. Banana aphids spread the virus from one plant to another by consuming sick trees and subsequently spreading it to healthy ones. Unfortunately, there isn't a cure for BBTV at the moment, therefore all afflicted trees

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must be removed.

Cucumber mosaic virus: The output of bananas is significantly impacted by a numberof viral infections. One of the most economically damaging diseases that causes economic losses for banana growers is the cucumber mosaic virus. (Figure 1).

Figure 1:

Figure 2:

A B

Figure 3:

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C D

Figure 1. Banana leaf diseases.

Figure 4:

2. Yellow Sigatoka; B Panama wilt; C Cucumber mosaic virus; D Black sigatoka

3. Literature Survey

Because bananas are vulnerable to a number of diseases and result in large losses for agronomists, disease documentation in the field has demonstrated more challenging. Con- sequently, this study offers better image processing techniques for early banana leaf disease recognition. The pictures are segmented consuming a region-based edge normalization after being pre-processed using a histogram pixel localization technique with a average filter. Here, a convolution repeated neural net & Gabor-based binary models are combined to create a novel cohesive arrangement for feature mining. Lastly, to progress the accuracy of disease diagnosis, a region-based convolution neural network is utilized to determine the infection area by removing & labelling material. When tested on a dataset containing composite image educations, the suggested Convolutional Recurrent Neural Network–Region-Based Convolutional Neural Network (CRNN–RCNN) classifier yields a precision score of 97.7%, a recall score of 97.7%, & a compassion score of 98.69%. The precision of the suggested CRNN–RCNN model for the banana dataset is 98%, developed than that of CNN (87.6%), DCNN (88.9%), KNN (79.56%), & SVM (92.63%) [1]. Numerous diseases have been doc- umented to afflict banana production, causing significant losses for impoverished farmers. Modern image processing and soft computing techniques can be used to identify problems early on and take the necessary safeguards to prevent further harm and improve the number of healthy productions. In this study, banana illnesses were detected at an earlier stage. A soft coring filter is applied to remove noise after the image is supplied to force standard- ization using the pre-processing technique. Following the completion of the color, shape, & texture features for feature extraction, arrangement methods are applied. Two algorithms are employed in these categorization techniques: case-based reasoning and the Neuro-Fuzzy Adaptive Inference System. Confused reasoning is then used to make the choice. The sug- gested technique was examined using the Receiver Operating Characteristics (ROC) curve. A reasoning based on cases system is outperformed by an adaptive neuro-fuzzy interpreta- tion technology, according to the investigation [2]. An inventive practice that helps raise the amount and quality of the nation's cultivated output, including tomatoes, is the smart farm-ng system

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that makes use of the required infrastructure. Infections cannot be disallowed since love apple plant cultivation takes into interpretation a number of factors, including the environment, soil, and sunshine levels. Deep learning has coarse the route for camera- captured tomato leaf disease in the current state of advanced computer system innovation. This investigate shaped a novel method for effectively detecting tomato plant diseases. To recognize & establish leaf diseases, a motor exact image apprehending box was designed to take images of individually tomato plant from four dissimilar positions. Diamante Max, a particular tomato breed, served as the test subject. Leaf Miner, Phroma Rot, & Target Spot are the ailments that the technique was created to detect. Both healthy and sick plant leaves are included in the dataset. Next, identify three illnesses by training a deep convolution neu- ral network. To determine which tomato disease was existing on the tomato plants beneath thought, the system hired a convolution neural network. While the Transfer Learning illness appreciation model obtains an accuracy of 95.75%, the F-RCNN trained glitch exposure prototypical generated a assurance score of 80%. After the computerised picture apprehen- sion classification was put into practice, it recognized tomato plant leaf infections with an exactness of 91.67% [3]. Our lives are greatly impacted by the agricultural sector. The most significant area of our economy is farming. Agronomists harvest less because it is tough to identify leaf disease. Conversely, videos and pictures of leaves give agricultural scientists a greater perspective and can help them come up with a recovering clarification. In direction to statement the concern of crop syndrome. It must be noted that a crop has a greater risk of delivering adequate nourishment if its output is affected by illness. because technology has advanced to the point where gadgets can now identify and detect plant ailments. Re- duce the adverse properties on harvest by recognizing infections early and handling them. This explore concentrations on the use of picture processing performances to identify plant infections. In mandate to recognise the infection of four classes, this study charity semi- supervised approaches for crop kinds and accessed an available dataset of 5000 photos of both healthy & contaminated plant leaves [4]. Plant diseases partake a detrimental effect on the agriculture sector, resulting in crop and financial loss. Since traditional approaches can be expensive and time-consuming, exact & rapid verdict is essential for supervision & controlling plant diseases. Depending on how well the convolutional-free ViT prototypical uses the self-consideration apparatus to translate an image into a series of reinforcements for dispensation by a typical moderniser encode, deep learning-based tools can distinguish shrub illnesses. Notwithstanding the tiny size of the dataset, they achieved a great performance. They argued that a small number of classes, transfer learning, and data augmentation were the reasons for this [5]. This study examines 5 apple leaf diseases: rust, mosaic, aria leaf spot, brown spot, & grey spot. That has an effect on Apple. This study castoff deep learn- ing methods to progress convolution neural networks (CNNs) for the identification of apple leaf decay. This broadside uses the Apple Leaf Disease dataset (ALDD), which comprises of complicated & workshop photos, to create a new deep-CNN-based apple leaf infection detection model. Data augmentation & picture explanation skills are used to create the re- maining images. Google Net Ception pattern and rainbow conjunction are employed. Five common apple leaf illnesses are identified by the proposed INAR-model after it has been trained using 26,377 pictures of apple leaf maladies from the trial data set. The experimentaldata shows that the INAR-SSD algorithm delivers 78.80% recognition efficiency with a high identification rate of 23.13

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frames per second. The results show that the novel INAR-SSD model provides an outstanding durability method for rapid identification of apple leaves dis- eases, identifying them in real time more quickly and accurately than previous methods [5]. Convolution neural networks (CNNs) with deep learning procedures are used to recognize plant leaf viruses. A 39-class open dataset of plant leaf diseases and background photos are used to train the convolutional neural network model. Rotation, noise injecting, gamma correcting picture flipping, prime constituent analysis (PCA), color augmenting, & scaling are the six categories of data augmentation techniques that are used. The usage of data augmentation is known to all. That could enhance the device's functionality. The system was trained consuming a array of periods, batch sizes, and dropouts. Then, in contrast to transfer learning methods, the proposed approach performs better than CNN. while utilizing the validation data. The proposed model has a 96.46% classification precision in spite of modeling. The accuracy of CNN is higher than that other transfer learning methods [6]. Harvest infections have suggestively increased in current years outstanding to unadorned en- vironment variation and a lack of crop immunity. Large-scale crop destruction results from this, which also reduces cultivation and ultimately costs farmers money. Disease diagnosis and treatment have become extremely difficult due to the variety of diseases' rapid increase and farmers' lack of expertise. Similarities in texture and appearance among the leaves help identify the type of illness. Consequently, the explanation to this problem lies in the com- bination of deep learning and computer vision. This study suggests a deep learning-based model that is trained on a publicly available dataset that includes pictures of both healthy and sick crop leaves. The model accomplishes its goal by categorizing photos of leaves into unhealthy groups according to the defect pattern [7]. Added than just a resource of nursing the world's expanding populace, agriculture has evolved into much more. It's significant in any Asian nation where more than 70% of the people is employed in agriculture. This indi- cates that it feeds a wide variety of people. First and foremost, fewer crops of higher quality must be considered due to disease. Farming expenditures may be avoided by identifying leaf diseases. The unbiassed is to develop a software program that can recognize & classify illnesses instantly. These procedures—image capture, segmentation, pre-processing, extrac- tion, & classification—include the identification of illnesses. Plant diseases are detected by taking pictures of the leaves. Therefore, identifying and classifying farming illnesses em- ploying the image processing method [8]. Productivity gains in agriculture boost the Indian economy. With this goal in mind, this article subsidizes to the documentation of diseased leaves using image dispensation performances in order to create an effective & intellectual farming system. Ladies finger plant leaves are selected and analyzed for this purpose in order to detect early stages of a number of illnesses, including leaf spot, powdery mildew, and yellow mosaic vein. To regulate if a leaf is strong or contaminated, it is photographed, analyzed, segmented, characteristics extracted, and then classed. Because of real-world lim- itations in terms of climate & supplementary terrain locations, noisy image data sets are also generated and taken into account. the application of K- is used for segmentation, and SVM and ANN are used for prediction. In this work, PCA is utilized to diminish the feature set. The findings show that a median detection success rates of SVM and ANN is eighty-fivepercent and 97 percent, respectively. In the absence of noise, they are 92% and 98%, respec- tively. This endeavor will eventually lead to the wide-ranging automation of the agriculture sector [9]. Plant diseases play a significant role in agricultural

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output, which impacts food security and lowers farmer profits. The secret to preventing losses is identifying plant ill- nesses so that appropriate feeding practices can treat them early and prevent productivity declines. The authors of this study classified and identified healthy and sick tomato leaves using two different techniques. The k-nearest neighbour method is used in the first strategy to classify the tomato leaf as moreover vigorous or morbid. Later, in the second method, they use a probabilistic neural network and the k-nearest neighbor strategy to categorize the diseased tomato leaf. Gabor, Color, and GLCM are examples of structures that are utilized for classification. The dramatists' own dataset is used for experimentation. That includes 600 leaves, both healthy and sick. The results of the experiment show that the combination slant with PNN classified works better than alternative techniques [10].

Existing system: The present method of identifying and detecting diseases in banana plants depends on experts making visual observations; this strategy necessitates a big squad of authorities & ongoing nursing, especially in India. Agronomists lack the finances and expertise to consult experts, who could charge exorbitant rates and take up valuable time. The suggested method, which uses visual clues from banana plant leaves to automatically diagnose diseases, provides a more effective and economical way to monitor huge crop fields.

Classiftcation techniques

Methods for classification are a collection of methods used in machine knowledge & deep learning to group images into distinct lessons, such as healthy and diseased leaves, according to their attributes. These are a few typical methods of classification.

Convolutional Neural Network (CNN): CNNs are specialized machine learning algorithms that are mostly used for task recognition of objects, which includes classification of images, being detected, & segment. The capacity of CNNs to operate autonomously collect components on a broad scale sets them apart from other machine learning techniques. This capability boosts efficiency and removes the need for manual components engineering. The fundamental machineries of a convolutional neural network are the reconditioned direct unit of service, merging section, fully associated section, & convolutional unit.

By using convolutional, pooling, and fully connected layers, a CNN's structure works with data that is arranged in matrices (images). A collection of specially designed filters (kernels) for edge and texture detection—two essential components of visual interpretation—are used to train the convolutional layers. In order to add non-linearity to the classical & make it easier to learn intricate shapes in data representations, the repaired direct unit (ReLU) beginning meaning is integrated into the secreted layers. In order to reduce dimensionality while maintaining the most crucial information from the identified features, the pooling method is necessary. The inference process is finally completed by the fully connected layers, which carry out the prediction step using the feature representations that were retrieved in the earlier layers.

As CNNs have evolved, a number of topologies have been developed to enhance their ac- curacy, efficiency, and depth of operation. Three models—VGG, ResNet, and AlexNet—have been taken into consideration for this study because of their extensive application in picturearrangement tasks and their

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capacity to extract pertinent features for crop disease analysis. These models were selected because of their capacity to identify intricate visual patterns, their versatility in handling various image situations, and their ability to strike a compromise between computing efficiency and accuracy.

Support Vector Machine (SVM): The Support Vector Machine (SVM), a reliable automated learning model for cataloging & worsening applications, is based on the theories of statistical learning, convex optimizing, while structural threat elimination. In order to efficiently separate classes while increasing proximity to the nearby examples, SVM looks for the ideal border in the features space that enhances the allowance among various classes. Because of its versatility, SVMs can be everyday to a wide series of domains, such as cate- gorization of content, object identification, computer vision, and classification of photos.

Artiftcial Neural Network (ANN): The custom of artificial neural networks, espe- cially CNNs, is very beneficial for the diagnosis of banana plant leaf ailment. The primary detection of viruses similar sigatoka, which frequently afflict banana plants, is greatly aided by these cutting-edge technology. CNNs, such as the BananaSqueezeNet model, provide outstanding precision, recall, and specificity in the recognition of a variation of banana leaf diseases, in contrast to labor-intensive & time-consuming outmoded procedures that call for knowledge and human work. Banana output eventually improved significantly as a result. In addition, the amalgamation of image processing with machine learning & deep learning practices enables initial illness diagnosis, reducing crop victims & enabling farmers to take preventative action.

AlexNet: A convolutional neural network called AlexNet has been used to identify dis- eases, especially in banana plants. AlexNet, which is well-known for its ability to detect objects in pictures, has been modified to detect diseases in banana plants. This is a difficult work because there are many dissimilar types of leaf illnesses. An advanced plant disease detection system was created by training the modified AlexNet on a dataset that was col- lected through human annotations. The system's ability to detect plant illnesses has shown remarkable promise. This method makes it calmer to identify infections early, empowering farmers to take preemptive procedures and lessen crop harm.

(Residual Network) ResNet-50: A deep learning model called ResNet-50 has been used in a variety of fields, such as product recommendation systems. It is a well recog- nized architecture that is well-known for its efficacy in tasks including picture classification and feature extraction, as well as plant disease classification and emotional reconstruction. Even when working with visually comparable elements, ResNet-50 is ideally suited for tasks requiring high precision and recall because of its remarkable capacity to extract intricate patterns and characteristics from images. By addressing problems like threatened hill & allowing training on larger networks for improved accuracy, ResNet-50's skip connections help to reuse learned features. Because of its effectiveness in using computational resources, the architecture may be implemented on a variety of devices, including embedded systems and smartphones, construction it a flexible choice for a range of submissions.

(Visual Geometry Group) VGG-16: Using image analysis, the deep learning model VGG-16 is used to identify plant illnesses. It belongs to a group of models used in this field, such as VGG-19

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and ResNet-50. Studies have shown that VGG-16 and VGG-19 work

well together to detect plant diseases, with an exactness level of about 86% & a high F-1 score. The model automatically detects and classifies plant disease from leaf pictures using a convolutional neural network & the Rectified Linear Unit (ReLU) instigation meaning. This helps with early and accurate disease diagnosis to increase agricultural productivity and lower pesticide use (Table 1).

Segmentation techniques

Techniques for segmenting a dataset into discrete parts according to specific attributes are referred to as segmentation procedures. In order to detect leaf illnesses in banana plants, segmentation techniques are crucial. Several studies have looked into using state-of-the-art technologies to identify diseases accurately and quickly.

Adaptive fusion of K-means resign growing: K-Means Resign Adaptive Fusion Plant leaf defects are segmented using growing. This technique yields accurate segmenta- tion results by combining region growth with the K-Means Algorithm. AFKMRG is used to improve classification models and the features extraction process. The segmentation, cat- aloguing, & feature extraction processes are improved by the incorporation of AFKMRG, which results in high and accurate rates of multi-disease organization of plant trees.

Region-based convolutional neural network: The application of region-based non- volution neural networks has shown great potential in the detection of plant diseases. Inno- vative methods to increase feature extraction and model performance have been proposed in a number of research. One noteworthy instance is the combination of position consideration block through transfer learning, which has shown enhanced feature extraction capabilities and a high accuracy rate in wheat disease diagnosis. Furthermore, the merging of local and global features has been made possible by the inclusion of multi-scale mechanisms in hybrid models such as MSCVT, leading to improved crop disease recognition ability. This devel- opment emphasizes how crucial region-based CNN architecture is to plant disease detection systems' precision and effectiveness.

K-means clustering: A traditional technique for dividing an picture into a predeter- mined number of collections according to presentation metrics is the K-Means clustering system. By grouping patterns into clusters where the patterns inside the clusters are more similar to one another (maximum intra-cluster similarity) than to patterns in other clusters (least inter-cluster similarity), this approach addresses the clustering problem. In order to minimalize the squared Euclidian detachment among the cluster center & the patterns, the clusters are created using the K Means methods (Table 2).

4. Proposed System

Disease identification, feature extraction, picture segmentation, image pre-processing, and image acquisition. We visited fields and gathered pictures of banana plant leaves from a village dataset. Pre-processing is done to lessen noise because of differences in size, shape, & noise gratified. In order to identify the areas of interest within the input image, the pre- processed pictures are further segmented consuming region-based segmentation with ideal beginning approach. The segmented areas of the duplicate are used to extract features, which are then used to classify diseases.

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Table 1: Classification techniques.

Sl. No.	Classification techniques	Advantage	Disadvantage
1	CNNs	CNNs have a high accurateness rate, can handle high-dimensional data, and facilitate information transmission across layers, which improves data processing efficiency.	Due to the limited processing capacity and low power consumption requirements in edge applications, CNN implementation can be difficult.
2	SVM	SVM's 99.6% accuracy rate in detection is one of its primary advantages.	Recognizing that SVM training on huge datasets may necessitate significant computer resources is crucial.
3	ANN	In large-scale data processing, artificial neural networks perform very well because they provide optimal prediction at reduced computational costs.	The way ANNs work lacks transparency because the solutions they generate don't provide any information about the processes or justifications for their conclusions.
4	Alex Net	When it comes to plant disease detection, AlexNet outperforms VGG-16 and Lenet-5 in relations of accuracy. It identifies a wide range of agricultural diseases with an impressive 96.76% accuracy rate .	AlexNets' limited scalability in plant disease diagnosis stems from its focus on a specific dataset, in contrast to the more versatile VGG and ResNet Models that are widely used in the industry.
5	ResNet-50	Because to ResNet-50's feature reuse, ability to reduce the waning gradients problem, & provision for training on profounder networks, it greatly improves the accuracy of plant disease classification, beating shallower models.	One popular and effective model is ResNet-50. Its capacity to efficiently extract intricate information from images may be constrained by its comparatively low parameter count. This may therefore have an impact on how well it performs overall while performing tasks requiring complex data extraction and processing.
6	VGG-16	When it comes to plant disease identification, VGG-16 outperforms CNNs and MobileNet, with accuracy rates of 89%, 95%, & 92% for tomato, potato, and apple illness, individually.	In order to progress the VGG-16 model's presentation, the issue of class imbalance must be resolved by making sure that images are distributed fairly among all classes.

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Table 2: Segmentation technique.

Sl. No.	Segmentation techniques	Advantage	Disadvantage
1	Adaptive Fusion of K-Means Region Increasing	With rates as high as 98.35% and 98.40%, the incorporation of the K-Means Region significantly improves the segmentation of abnormalities in plant leaves, resulting in a notable improvement in accuracy and exactness for multi-disease classification.	
2	Region Growing Fast Peak Detection (RGFPD)	The RGFPD algorithms have proven to be more effective than traditional methods like CNN segmentation and fuzzy C-means. They have a number of benefits, such as lower calculation costs, quicker segmentation without the need for initial condition pre-setting, and shorter algorithm execution times.	
3	Region-based Convolutional Neural Network	Region-based convolutional neural networks, or R-CNNs, offer many advantages for the documentation of plant diseases. They were used to create lightweight models, which makes them extremely effective for use in real-time applications.	

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The pre-configuration of beginning conditions is required by K-Means Region Growing, which leads to local optimization and a lack of self-adaptive subdivision.

When compared to specialized deep learning algorithms or

hyper-spectral imaging techniques, RGFPD may not provide the level of accuracy and specificity required for accurate plant disease identification.

R-CNNs can necessitate a lot of time and computational cost to process a full leaf image,

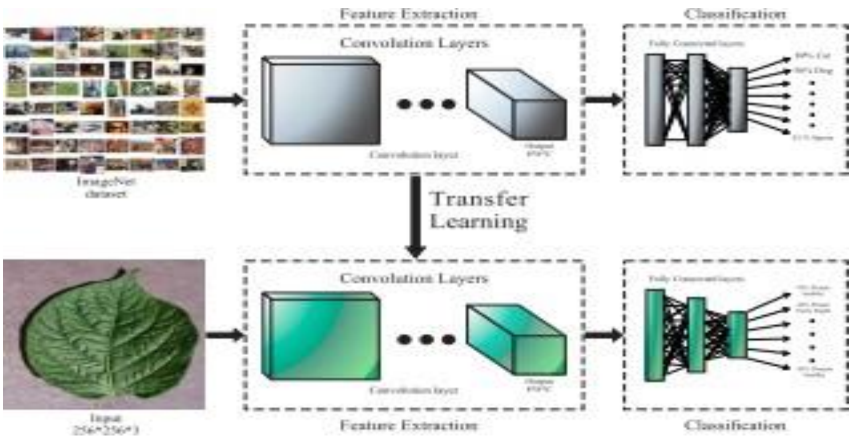
which can affect performance because the training data is of poor quality.

4.1. rning

In order to speechless the failings of deep learning, transfer learning representations or pre-trained representations like ResNet50, AlexNet, Inception V3, VGG16, & VGG19 are highly effective. In order to build a deep learning model with masses of limitations, a large number of occasionally appropriate training samples must be gathered, as well as an excessive amount of training time. A pre-trained model's knowledge is transferred to another model, which is then trained for an arrangement job, using the transfer learning technique. Because the model is not trained from scratch, the training period is shortened. Additionally, it is used to get around the overfitting problem and train the deep learning

model on a tiny dataset. The most widely used architecture in transfer learning is called fine-tuning, in which the model is pre-trained on a sizable dataset before its parameters are frozen and moved to the target prototypical to be fine-tuned with its dense sheets. Lastly, the dataset related to the intended classification task should be used to train the dense layers with appropriate parameters. The procedure for exercise a new model to organize a fresh dataset using the transfer learning model is portrayed in Figure 2.

Figure 5: 2. An photograph of using a Pre-Trained based prototypical to organize a new dataset.



4.2. VISION TRANSFORMER (ViT

In the beginning, the converter was utilized to display mainstay nets using SASA and the local relational network (LR-Net). By limiting self-attention addition to a local slid- ing window, both models increased accurateness over ResNet though using the identical hypothetical computational resource. Although LR-Net is significantly slower in practice, it shares the same theoretical & computational complication as ResNet. Previously used exclusively in natural language processing

applications, the ViT model is an effective im- age classifier and the first modernizer construction in computer vision applications. When trained on vast amounts of picture data, ViT outperforms conventional CNN architectures in image classification. To create a vector representation of each patch, the input image is split up into patches, which are then flattened & combined over the image's channels. The vectors are linearly projected using a dense layer to determine the patch embeddings. By generating positional embeddings, the ViT model is able to fully examine the input image and analyze the patches in an ordered manner. The input of the transformer's encoder is then obtained by appending each patch to the matching positional embedding. The encoder is completed up of a only block that is run multiple times, with a thick layer after a multi- head self-attention in the block's design. Lastly, MLP uses the transformer's encoder output to classify the input image.

A model based on Transfer Learning & a vision transformer (TLMViT) is suggested. There are four stages in TLMViT: 1) Data gathering, in which the suggested model is trained and assessed using the PlantVillage and wheat datasets. 2) Image augmentation to get over the overfitting problem and expand the number of training examples.3) Leaf feature extraction is done in two stages: first, using a pre-trained model, and then, using the ViT model, for deep features.

4) The MLP classifier is used for classification. Five models that have already been trained are used to test TLMViT, and ViT is then tested separately.

With validation accuracy of 98.81% & 99.86% for VGG19 and the ViT model on Plant Village and banana leaf datasets, individually, TLMViT performs well in the categorization of plant diseases. Additionally, pre-trained-based architecture and TLMViT are contrasted. According to the comparison result, TLMViT outperformed the transfer learning-based pro- totypical for the PlantVillage & wheat datasets by 1.11% and 1.099% in terms of endorse- ment accuracy, 2.576% and 2.92% in terms of validation forfeiture, respectively. Thus, the suggested prototypical demonstrates how well ViT can be used to extract deep information from the leaf.

The suggested work's methodology is depicted in Figure 3.

Figure 6: Flow chart for the identification of banana leaf diseases.

Information gathering: Approximately 1000 photos of mutually healthy & contaminated banana plant

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leaves are included in the data set for the planned study. These images were captured from several locations in the Madhya Pradesh and Maharashtra districts of central India. The photos were gathered in different resolutions and were taken using a mobile device's VGA and digital cameras.

Image pre-processing: This technique is used to increase the quality of the obtained images for the following stages. This procedure does not change the image's default data. In order to locate disease information on the banana leaf, it resizes photos and applies certain useful effects. Because the resolutions of the imags that were shot and saved as

a data collection varied, resizing the images is necessary. The normal fixed resolution size (M*N) must be used. By using image filtering techniques like the median filter, additional noise in the photos is removed. Segmenting an image entails separating the area of interest from the other areas of the picture. To differentiate between the diseased and healthy parts of the leaf, region-based image separation is used.

Feature extraction: Feature extraction is the development of routinely locating & ex- tracting relevant features from raw input data. Instead of manually designing features, which can be time-consuming and domain-specific, feature withdrawal is predicated on the notion that we can let the neural network to learn the most pertinent characteristics straight from the data during training. This improves our performance on difficult tasks like speech or image recognition and does away with the requirement for manual feature engineering or in-depth subject expertise.

Image classification: A crucial problem in deep learning and computer vision is image classification, which entails training a computer system to routinely identify and categorize visual pictures into pre-established classes or labels. Because of their ability to directly ex- tract intricate patterns & characteristics from the raw image data, deep learning algorithms such as Modified Convolutional Neural Networks (CNNs) are frequently utilized for this type of assignment.

Dataset Collection

By taking the mean, an average pooling layer averages the input data. The banana leaf dataset is the sample. Figure 4 shows that 900 photos of banana leaves were gathered and categorized into three groups: Three hundred pictures of Black Sigatoka-affected leaves, three hundred pictures of Cordana-affected leaves, and three hundred pictures of healthy leaves.

We went to a number of banana fields to get pictures. We were able to recognize and categorize the aforementioned illnesses with the help of an agronomic, guaranteeing that the pictures gathered were representative and pertinent to the research.

The next step was data preparation, which included data cleaning to eliminate pictures with noise or in which the leaf was obscured by blur or low quality. Furthermore, the photos were divided into three groups: Cordana-affected, Black Sigatoka-affected, and healthy.

To guarantee uniformity in the model's input, the photos were scaled to 224 22∗ pixels after classification. In terms of data augmentation, it was determined to use the TensorFlow Keras Image Data Generator class to expand the amount of photos, even if at first 900 images (300 per class) were employed. Rotations up to 45 degrees, shifts up to 20% horizontally and vertically, cropping

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changes with a series of 0.2, random zoom up to 20%, horizontal flipping with a 50% likelihood, & illumination modifications between 50% and 150% were among the transformations. By increasing the picture variability, these methods produced a larger dataset of 9000 photos, which enhanced the representativeness of the model.

The dataset was split interested in two sections: the drill set, which comprised 80% of the photos, and the validation set, which had the outstanding 20%, in order to guarantee that the archetypal could oversimplify well and prevent underfitting. By keeping a distinct dataset to assess the model's performance on photos not seen during training, this separation enabled the model to train on a broad range of samples. By avoiding over fitting the preparation

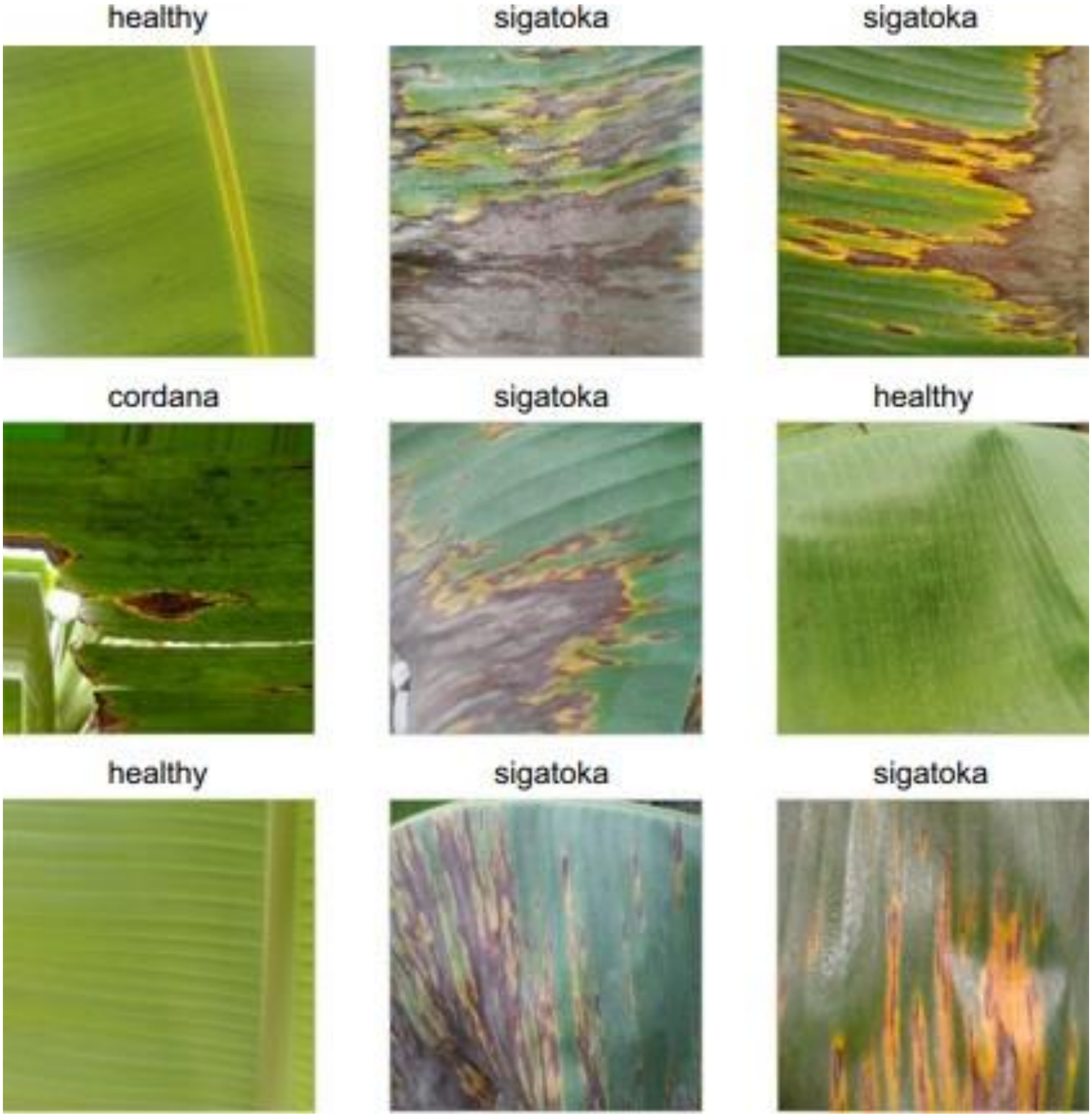

Figure 7: ample leaves for the banana leaf dataset

data and encouraging a more impartial evaluation of the model's performance, this tactic assisted in obtaining a more accurate degree of the model's capacity for oversimplification.

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Model

Convolutional neural networks (CNNs) used for leaf disease cataloguing were the subject of a deep learning analysis. Because of these designs' shown resilience in managing massive data sets, we are able to create systems that are applicable to a wide range ofsituations.

Three primary models were assessed, although other designs, including NasNetLarge, Inception ResNetV2, AlexNet, and MobileNet, were also put to the test. However, these latter models had to be eliminated because of overfitting problems, which resulted in an

accuracy of about 33% with no increase. Consequently, three models that showed superior presentation & generalization skills were chosen.

A detailed description of the deep learning prototypical architectures employed in this study is provided. From the input layers to the output layers, their structural elements are examined, highlighting the unique setups of each model and the adjustments made to best classify banana leaf illnesses.

The architecture starts with 224 224 pi×el pictures as input and moves through a number of convolutional layers, emphasizing the usage of MBConv mobile layers, as seen in Figure 5. These layers make it easier to identify patterns in the leaves by gradually decreasing the spatial resolution and deepening the retrieved features.

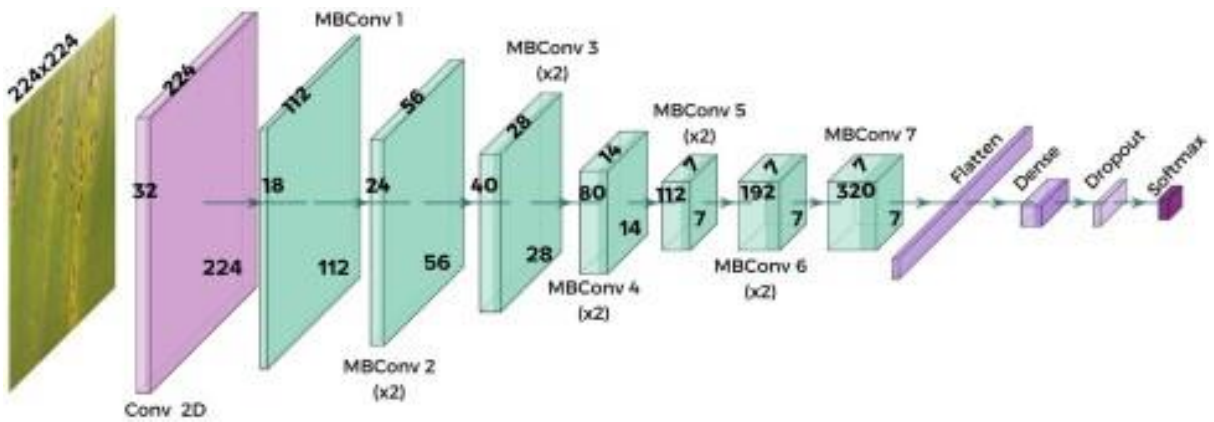

Figure 8: Custom extension layers integrated with the AlexNet architecture.

In order to improve the recognition of visually comparable features, the network is made up of seven MBConv blocks that are applied repeatedly. A dense layer with 32 neurons is then in charge of classification after a flattening layer converts the landscapes into a one- dimensional vector. The building ends with a softmax layer that divides the ideas into three groups and incorporates a dropout layer to lower the chance of overfitting.

As illustrated in Figure 5, which details the architecture's development and data input, the model depicted in Figure 6 preserves the previously mentioned overall structure.

This version, however, has five convolutional blocks, in contrast to its predecessor. Start- ing with the 64-filter conv1 layer, the model moves on to the conv2, conv3, conv4, and conv5 layers, snowballing

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the quantity of filters to 128, 256, & 512, individually, as the spatial steadfastness steadily drops.

As seen in Figures 5 and 6, the prototypical in Figure 7 also has a similar structure, but it starts off differently by adding the conv1 layer with 64 filters.

The model advances from this layer to convolution 2, convolution 3, convolution 4, and convolution 5, progressively increasing the number of filters to 128, 256, and 512. This change makes it possible to capture more intricate details in the leaf photos, and the blocks' well-designed layout with several filters improves the model's learning ability.

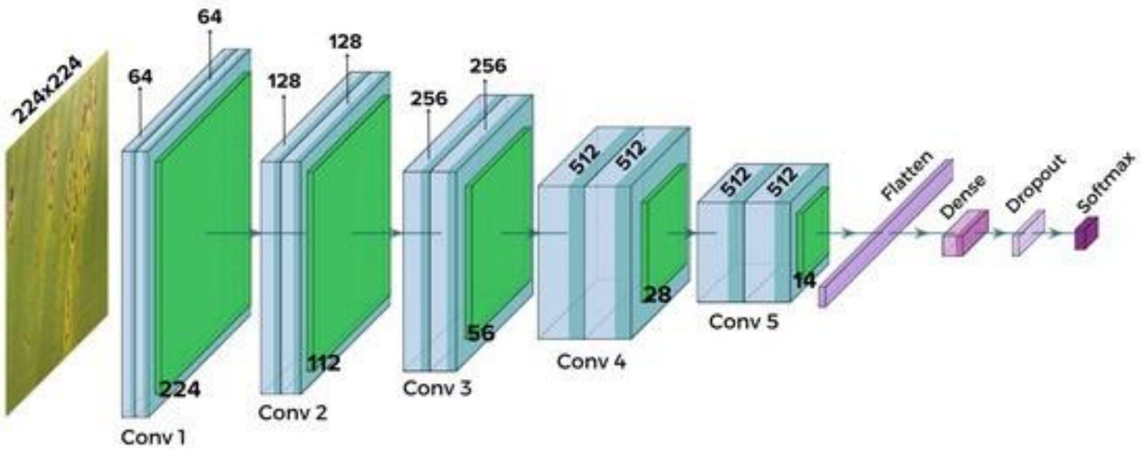

Figure 9: ResNet50's integrated architecture with unique extension levels.

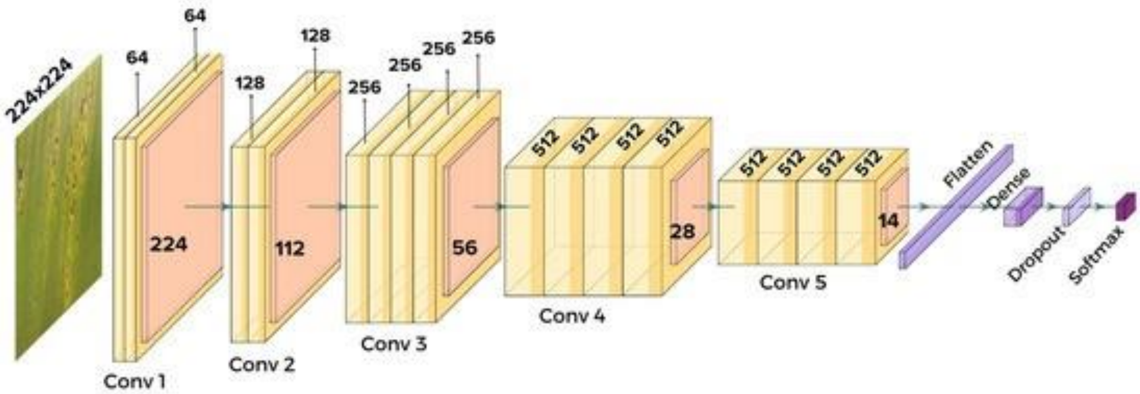

Figure 10: hows the VGG19 integrated design with unique extension stages.

Three pre-trained deep learning manners—ResNet50, AlexNet, & VGG19—all with pre- liminary weights pre-trained on ImageNet were then used for the models' training and com- parison. Only the pre-trained neural network was altered in each of the three scenarios, with the hyperparameter configuration (Table 3) remaining the same to provide a fair comparison. Except for the initial top layer, which was swapped out for task-specific layers, a hierar- chical architecture was employed. In order to preserve the knowledge already gained with the ImageNet dataset, the layers of the pre-trained network were maintained frozen, meaning that their weights were not changed throughout training. Custom layers were incorporated after the pre-trained network: an intense layer with 32 neurons and

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a function to activate ReLU, to which L2 regulation was done to avoid overfitting, and a flatten layer to flatten the data. A 50% dropout layer was then included to further lower the chance of overfitting. Lastly, the inputs were categorized into the three related groups of Cordana, Black Sigatoka,

and healthy by a dense layer with softmax initiation.

The typical, which is apposite for multi-class sorting tasks, was assembled using the Adam optimizer with a learning rate of 0.001 and the loss job (categorical_crossentropy).

Table 3: Parameterconformation.

Parameter	**Value**
Input size	224×224 Number of epochs 100
Batch size	64
Optimizer	Adam
Weights	ImageNet
Learning rate	1×10^{-3}
Include_top	False
Pooling	Flatten
Classes	3
Classifier activation	Softmax

A batch size of 64 was used for the 100 epochs of training. TensorBoard, which was used to track the training results, made it possible to visualize the accuracy and loss curves for both exercise & endorsement data, enabling a thorough evaluation of the model's perfor- mance. Additionally, in accordance with common pre-trained representations like AlexNet, ResNet50, and VGG19, an input size of 224 224 pixels was used. By using pre-trained Im- ageNet weights, this decision enhanced the representation's concert and sped up conjunction by offering superior restriction initialization.

In order to balance firmness & computational effectiveness without requiring unnecessary memory consumption, a batch size of 64 was chosen for training. To guarantee proper convergence and reduce the possibility of early overfitting, one hundred epochs were chosen.

The Adam optimizer, which is renowned for energetically modifying the learning rates of every parameter and enabling more effective convergence, was employed to optimize the training procedure. Based on empirical data demonstrating its efficacy for these models, the learning rate of 0.001 was selected to ensure a compromise between stability and fast convergence.

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To make room for a final classification layer that was specifically suited to the task, the top cover of the pre-trained prototypical was neutralized (Include_top = False). Prior to classification, dimensionality was reduced using a flatten layer, which maintained crucial spatial information without sacrificing significant features. Lastly, the cataloguing layer used a softmax initiation function, which is perfect for multi-class classification issues and allows for the effective management of numerous categories.

5. Results Evaluation

Below are the outcomes of the three convolutional neural network representations (AlexNet, ResNet50, & VGG19) that were employed in this study. Significant evaluation metrics like accuracy, recall, & the F1-score were used to evaluate each model's presentation

in organising leaf diseases in banana crops. These metrics show how well each model clas- sified the images and provide an objective foundation for comparing their disease detection capabilities, including diseases like Cordana and Black Sigatoka.

To determine which of the assessed constructions performs better in this particular task, taking into account both their accuracy & oversimplification capabilities, it is important to present these measurements.

The confusion matrix of the ResNet50 model is shown in Figure 8, demonstrating how well it performs in differentiating between banana leaves that are healthy and those that are impacted by Cordana and Black Sigatoka. 57 out of 60 leaves were properly identified by the model as Cordana, with three samples being mistakenly identified as Black Sigatoka. With 59 out of 60 accurate classifications and only one mistake pertaining to Cordana, the performance was excellent for healthy leaves. However, there was considerable misunder- standing between these two diseases, as evidenced by the lower performance in classifying leaves exaggerated by Black Sigatoka, which achieved 44 out of 60 exact estimates, while 16 leaves were mistakenly labeled as Cordana.

Broadly speaking, the confusion matrix shown in Figure 8 indicates that the majority of the model's mistakes are focused on the Black Sigatoka classification. This implies that the ResNet50 model's characteristics might not be discriminative enough to distinguish amongst Cordana & Black Sigatoka. This challenge might have to do with how difficult it is to distinguish between the lesions generated by the two diseases due to their visual similarities, particularly in their severe stages.

Using a dataset of leaf photos, Figure 9 illustrates how the accuracy per epoch of the ResNet50 model changed during training and validation. The accuracy changes over 100 epochs are depicted by the curves. The accuracy steadily rises to around 90%, but after epoch 60, it starts to decline.

From epoch 30, the accuracy stabilizes at about 90%, exhibiting more stable behavior than during training. Visually, the difference between the two curves indicates that the model does not correctly generalize, but rather memorizes the training figures.

The ResNet50 model's loss evolution across 100 epochs of training and validation is shown in

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Figure 10. Early epochs show a sharp decline in loss, suggesting that the model learns efficiently at the start of the process. The loss soothes at low levels starting in epoch 10 and stays near the validation value, indicating a model free of overfitting.

Like the training loss, the validation loss exhibits a sharp decline in the early epochs. Both curves then exhibit minor oscillations but stay near one another, demonstrating the model's steady development. Both curves settle and show low, comparable loss values around epoch 50, indicating that the model has sufficiently congregated on both the exercise & validation data.

The model accomplished good optimization in a judicious amount of time, as evidenced by the training phase, which took about one and a half hours. In conclusion, as the training & validation loss curves remained consistent throughout the procedure, the whole performance of the loss indicates that the model was well fitted. Furthermore, as the validation loss did not exhibit appreciable increases in the latter epochs, there were no indications of overfitting. Figure 11's confusion matrix shows a notable trend of mistakes in the classification of

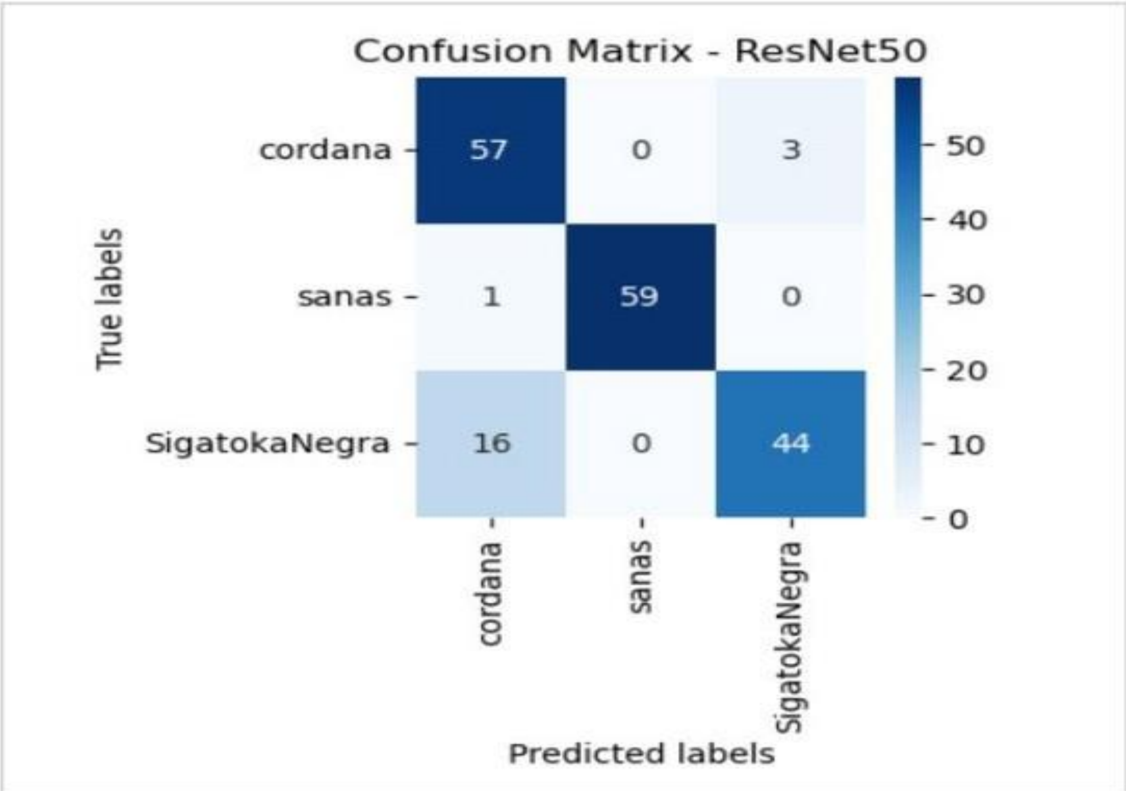

Figure 11: Confusion matrix—ResNet50.

diseased leaves, especially in the Cordana and Black Sigatoka classes. These two classes are frequently confused by the AlexNet model, which highlights the network's intrinsic inability to distinguish between the two disorders. Their symptoms, like leaf spots, are visually similar, making it difficult to distinguish between them, which is probably the cause of this mistake. However, the model successfully classifies healthy leaves, demonstrating its ability to detect the lack of symptoms.

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Figure 12 illustrates how the AlexNet model's accuracy changed over 100 epochs during training and validation. The prototypical acquires well from the training dataset, as evi- denced by the quick improvement in accurateness over the first 10 epochs, which reaches a value of 95% in the training set and alleviates with just minor variations.

The validation accuracy likewise rises quickly in the early epochs before leveling out at about 88%, demonstrating steady performance albeit marginally below that attained during training. This indicates that despite a little discrepancy between the two accuracy numbers,

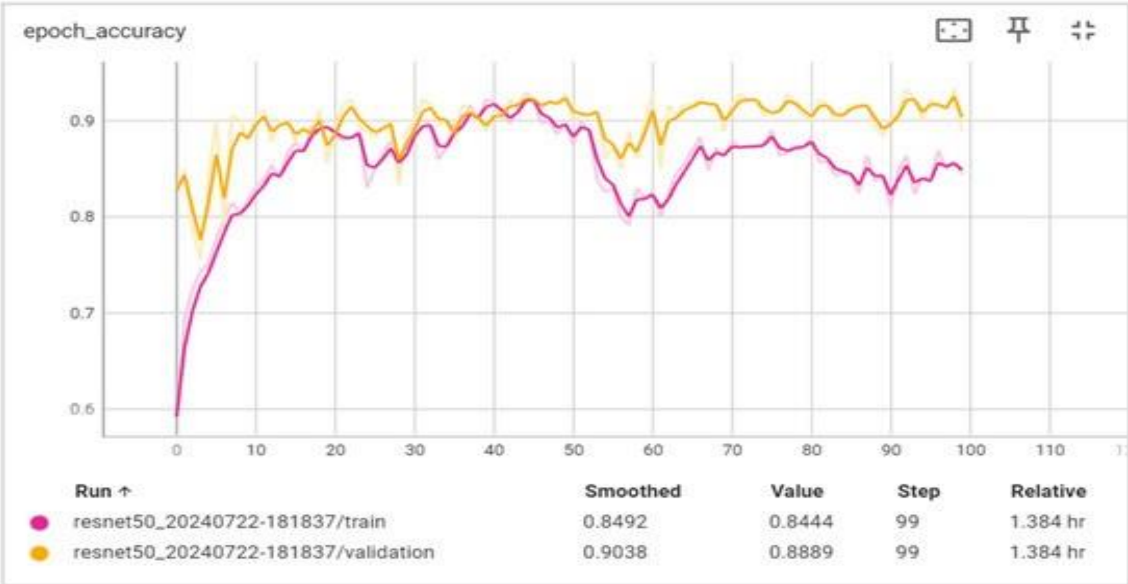

Figure 12: 9. ResNet50 model's learning evolution curve, with the training (fuchsia) and validation (yellow) lines.

the model generalizes well.

In a similar vein, Figure 13 illustrates how the AlexNet model's loss changed across 100 epochs during training and validation. In the first ten epochs, the loss rapidly decreases to low values of about 0.5, indicating that the typical learns since the preparation data effectively. The model has successfully fitted the training data when the loss stabilizes after this point, with only minor oscillations around this value. Similar to the training data, the corroboration loss likewise drops swiftly at first before stabilizing at sophisticated values, at 0.8, indicating somewhat worse routine.

The process takes roughly 30 minutes, and the AlexNet model performs well overall and fits the training data well. Similarly, we see that the accuracy & loss meanings during the 100 epochs show the positive growth of learning in Figures 9 and 10. Whereas the loss meaning rapidly declines in the primary epochs previously alleviating, signifying an operative fit to the data, the accuracy in both the training & corroboration sets converges at about 90%.

The VGG19 model's confusion matrix, displayed in Figure 14, has a pattern akin to that seen in the earlier models, with the greatest number of errors clustered in the Black Sigatoka class classification. In particular, there is a great deal of misunderstanding between Cordana and Black Sigatoka since the

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model finds it difficult to distinguish between the two groups. This might have to do with how visually similar the lesions on the leaves afflicted by the two illnesses are. It is crucial to emphasize, nonetheless, that the VGG19 model classifies healthy leaves with high accuracy because it exhibits no blunders in this group, suggesting

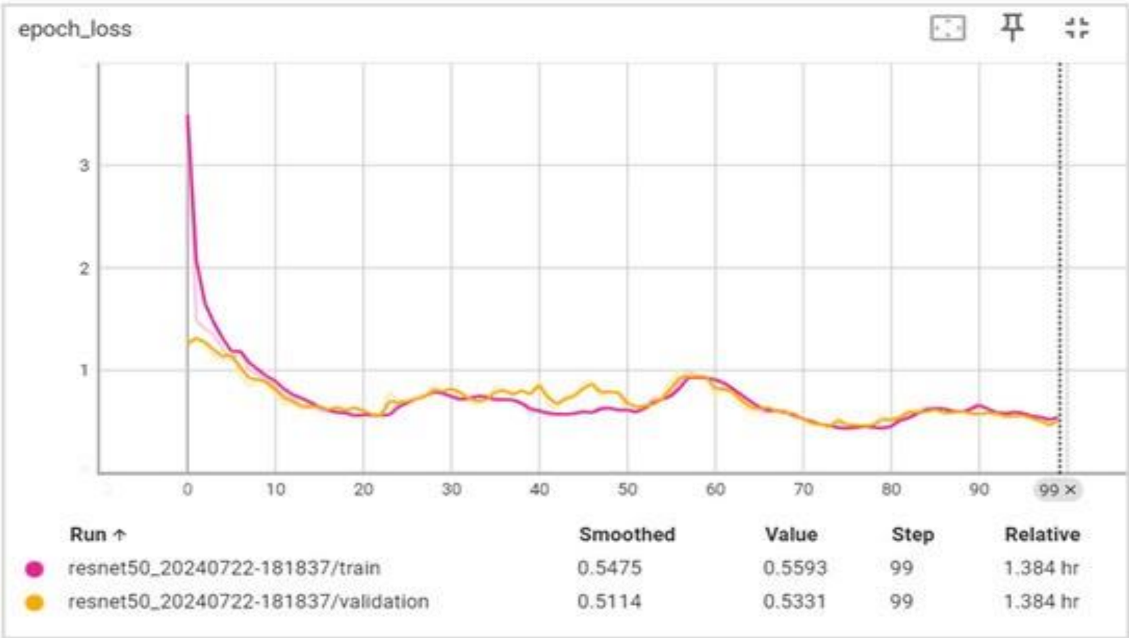

Figure 13: 10. ResNet50 model loss evolution curve: training (fuchsia line) against validation (yellow line).

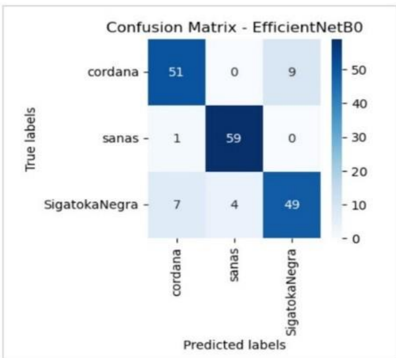

Figure 14: 11. Confusion matrix—AlexNet.

that the classical is successful in identifying the lack of indicators.

Figure 15 illustrates how the VGG19 model's accuracy changed over 100 epochs during training and validation. Over the first ten epochs, the accuracy rises quickly, approaching 88%. A successful match to the training data is indicated by the accuracy stabilizing with minor variations after this.

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The validation accuracy rapidly improves in the first 10 epochs, following a similar shape to the training accuracy. With a few slight fluctuations, it then stays steady at about 87%, indicating that the model performs well when applied to unidentified information.

Figure 15: AlexNet model's learning evolution curve, with the orange line representing validation and the green line representing training.

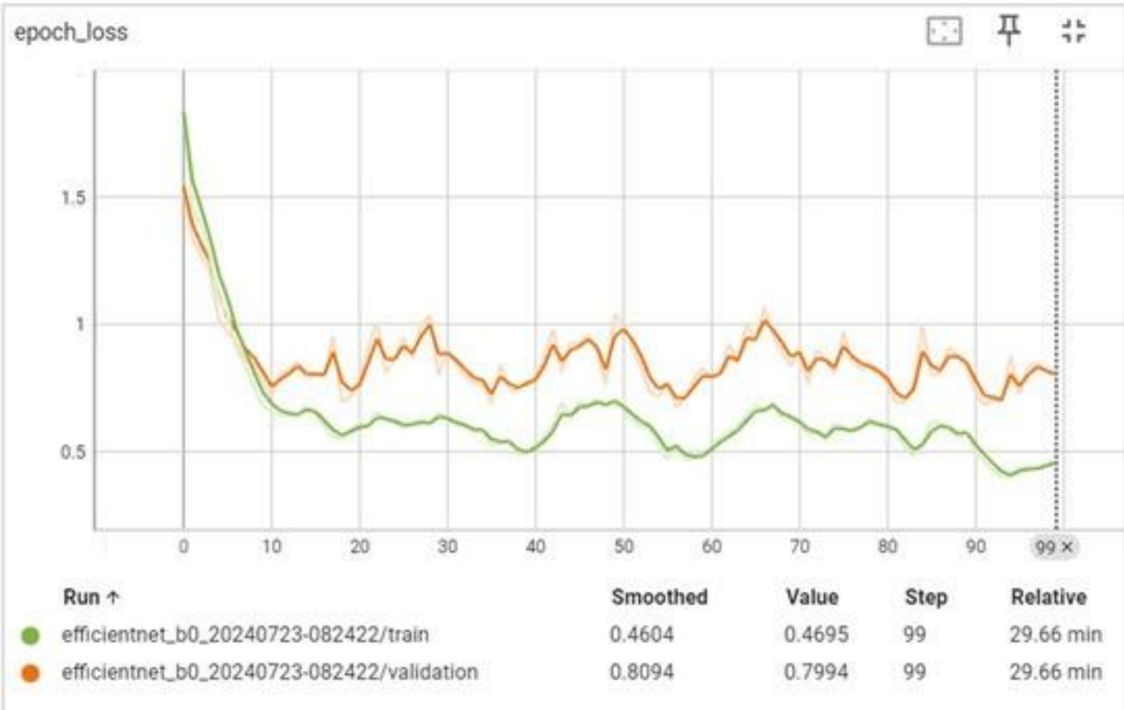

Figure 16: AlexNet model loss evolution curve: training (green line) against validation (orange line).

The VGG19 model's loss evolution across 100 epochs during training and validation is depicted in Figure 16. In the early epochs, the loss rapidly drops from over 4 to values near 0.5, indicating that the prototypical learns since the training data efficiently. The loss soothes after epoch 10 and stays at low values, demonstrating that the model fits the training data acceptably.

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With slight variations during the training period, the endorsement loss likewise drops rapidly at first before stabilizing at about 1 beginning with epoch 10. This implies that even if the model exhibits a larger loss in comparison to the training data, it oversimplifies well to the endorsement data.

The exactness & loss functions across 100 epochs reveal the positive growth of learning,

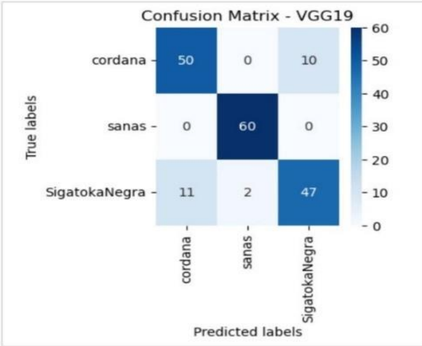

Figure 17: Confusion matrix for VGG19.

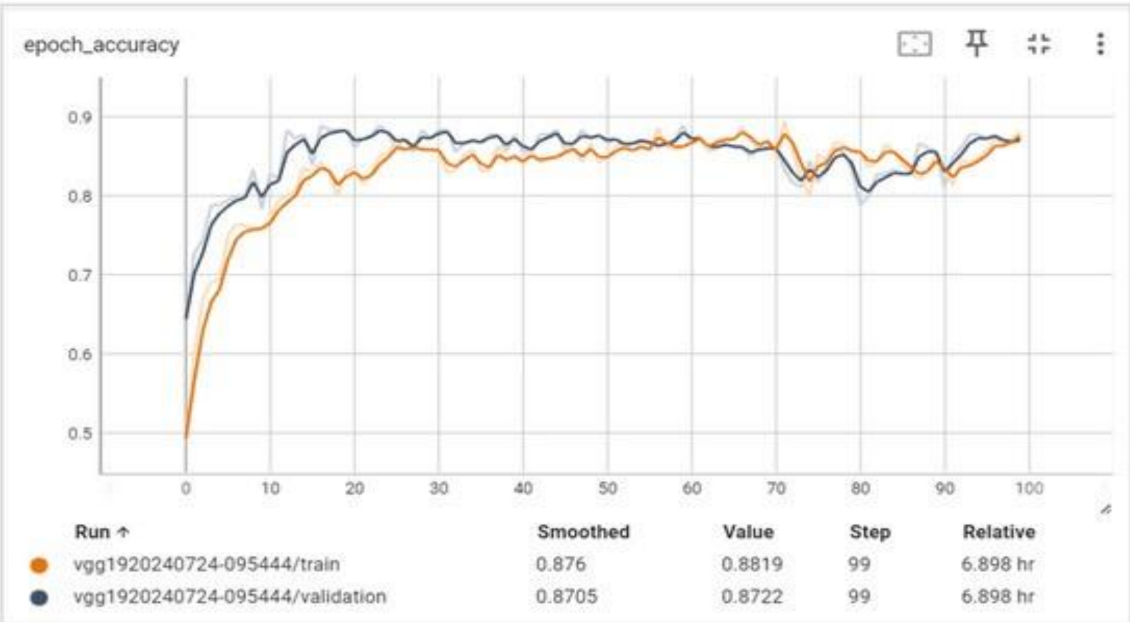

Figure 18: Learning evolution curve of the VGG19classical: orange line (training) vs. dark blue line (vali- dation).

as seen in Figures 15 and 16. It is crucial to emphasize that the training time, which was around seven hours, reflects the amount of time needed for this model because of its higher complexity and the volume of data. Although the loss product shows a good fit to information in its initial epochs, quickly decreases before calming down, its precision varies between the training & validation sets converges at about 90%.

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The accuracy, loss, generalization, and training duration of the models AlexNet, ResNet50, & VGG19 were assessed; the results were varied and could be used to

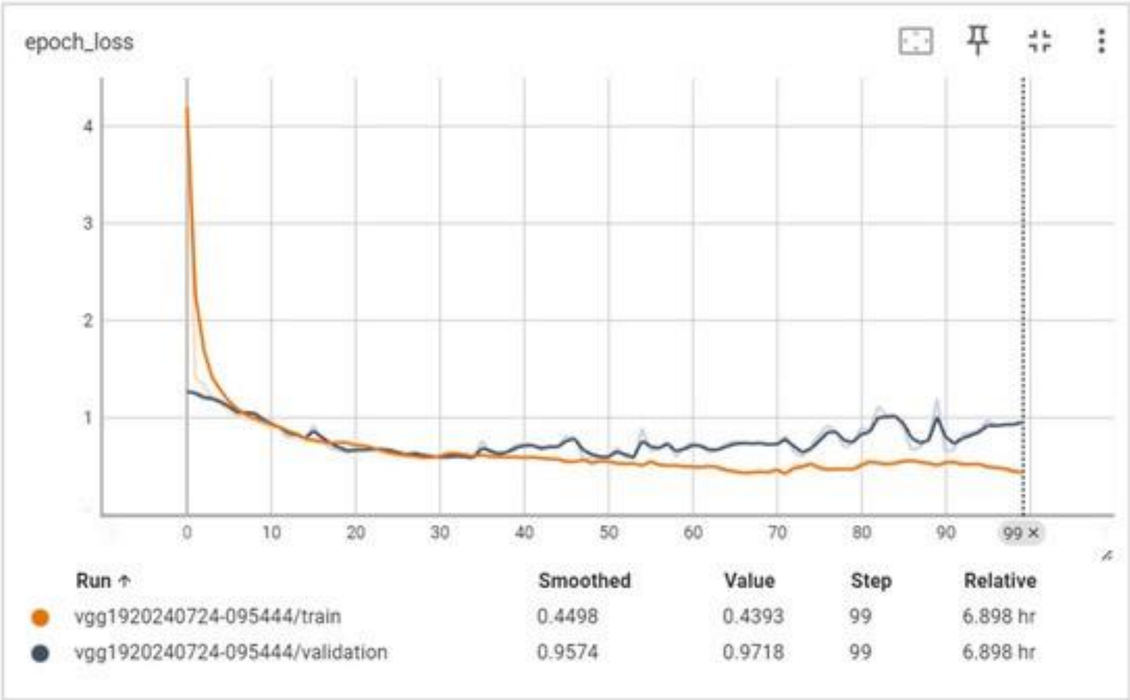

Figure 19: VGG19 model's loss evolution curve, with the training orange line and the validation dark blue line.

choose the best model for the particular needs of the leaf infection uncovering organization.

Table 4: ummarizes the outcomes for each neural network model using all of the metrics that were used during training.

Class	**Black**Metric	AccuracyRecallF1	**ResNet50**	**AlexNet**	**VGG19**
Sigatoka	score		94%73%82%	84%82%83%	82%78%80%
Cordana	AccuracyRecallF1 score		73%82%77%	82%83%86%	78%80%82%
Healthy	AccuracyRecallF1 score		100%98%99%	94%98%96%	97%100%98%
Global	Accuracy		88.90%	88.33%	87.22%

Lists the models' evaluation metrics.

Three deep learning copies (ResNet50, AlexNet, and VGG19) are compared in Table 4 for their ability to categorize three types of banana plants: Cordana, Black Sigatoka, & healthy leaves.

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Important criteria like precision, F1 score, recall, and total exactness were recycled to assess them.

ResNet50 distinguishes itself by accurately classifying the detected cases of Black Siga- toka and recognizing healthy leaves with high precision. Its weaker recall for the Black

Sigatoka class, however, suggests that it might not be able to identify every incidence of this illness that is now present. This model is the most accurate of the three since it attains the highest global accuracy overall (88.90%).

With more uniform measurements across all classes, AlexNet performs in a balanced manner. It can distinguish more examples deprived of substantially bargaining correct groupings, as evidenced by its improved balance between precision and recall, although having a little lower global accuracy than ResNet50 (88.33%). This implies that it is a flexible and trustworthy model for this kind of categorization.

In identifying healthy plants, where it attains seamless recall (1.00), VGG19 performs admirably across all criteria. It is less successful in overall categorization, though, as its global exactness is the deepest of the three replicas 87.22%.

Precision and Loss in Training and Validation

The VGG19 model had the best accuracy on the training set, approaching 88%, and a loss that dropped quickly in the first few epochs before stabilizing at about 0.44.

Conversely, AlexNet demonstrated more balanced performance, with the loss alleviating at roughly 0.80 for endorsement & 0.45 for training, and the validation accuracy conver- gent at about 88%. This conduct suggests a greater ability to generalize and a decreased propensity to overfit.

ResNet50, in contrast, showed a decent match on the preparation set but a notable differ- ence in authentication accuracy & loss, indicating difficulties with generalization, especially when it came to classifying Black Sigatoka.

Capabilities for Generalization

AlexNet was the most resilient model in terms of generalization; the training and vali- dation curves showed little variation, suggesting that both were well-balanced. The biggest disparity in the loss curves was seen in VGG19, indicating a weaker capacity for generaliza- tion. Comparing ResNet50 to the other models, it also showed a propensity for overfitting, which mostly affected the ordering of plants afflicted by Black Sigatoka.

Training Time

One important consideration in the model comparison was the training time. The most effective system was AlexNet, which took about 30 minutes to train and is therefore a good choice for systems that need to be implemented quickly without compromising accuracy. VGG19, on the other hand, required about 7 hours to train, which may not be optimal in terms of computing cost even though it achieved excellent precision. Although it took

1.5 hours to train, ResNet50 performed worse in generalization than AlexNet, marking a

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compromise in terms of time.

Disease Classiftcation Performance

In relations of disease arrangement enactment, VGG19 performed exceptionally well in distinguishing between Cordana-affected and healthy leaves. It has trouble accurately identifying leaves impacted by Black Sigatoka, though, just like ResNet50. AlexNet showed a more stable balance throughout the classes, demonstrating its ability to manage complicated datasets & reduce muddle across comparable groups, despite its propensity for errors in Black Sigatoka categorization.

Comparison with the Results of Other Studies

he scientific community is becoming more and more interested in using neural networks to identify illnesses like Cordana & Black Sigatoka in banana plantations. Nonetheless, there are still many obstacles to overcome in this field of study, which emphasizes the necessity of further honing these approaches for use in actual agricultural situations. One important factor to take into account is how similar the spots generated by the two diseases seem, which can make it more difficult to accurately differentiate them using deep learning copies. Some of the primary issues noted in the poetry are listed below:

The dearth of specialized research on neural network-based Cordana and Black Sigatoka detection;

There aren't many studies comparing how well various neural network topologies identify certain diseases;

Given how similar the foliar lesions of many diseases are, the collecting and interpretation of high-quality pictures might be challenging.

6. CONCLUSION

The banana tree's importance in Indian trade is highlighted by the fact that banana leaves are used in many tropical and subtropical countries' cuisines due to their numerous uses. Plant disease classification using a fusion prototypical (TLMViT) that combines a vision transformer with a pre-trained archetypal. Nevertheless, the frequency of banana leaf infections is a serious issue that jeopardizes the nation's economic output. Producing fruit and food for the nation and contributing to its economic growth depend heavily on agriculture, so it is critical to manage agricultural products properly and protect bananas from diseases like panama wilt, cucumber mosaic virus, and black and yellow sigatoka. By examining the banana leaf, a deep learning-based method for identifying and categorizing banana illness has been proposed in this study.

The actions listed below enable the study of different pictures from the banana plant to harvest. The suggested model detects banana leaf infections and enables immediate and suitable action to stop the disease's spread by using an improved convolutional neural network combining region-based classification with an appropriate sensitivity methodology. The study's findings demonstrate an impressive 99% accuracy rate, surpassing comparable deep learning methods. The suggested approach, which uses a CNN, yields promising results and speeds up the process of finding diseases in banana leaves. By employing cutting- edge technologies to enhance disease management and ensure consistent production, this development not only safeguards banana crops but also promotes the agricultural sector.

Deep learning methods' efficacy in identifying foliar diseases in banana crops, with a particular emphasis on Cordana and Black Sigatoka. With an accuracy of 88.33% and a training time of just 30 minutes, AlexNet was the most effective model among those exam- ined. ResNet50 and VGG19 both had somewhat greater accuracy (88.90%) but required much more training time (1.5 h), with VGG19 achieving 87.22% accuracy in 7 h. Because AlexNet can balance accuracy and processing costs, these results make it the best option for early illness diagnosis systems. The deployment of ascendable & bearable strategies for dis- ease administration in banana crops is made possible by this conclusion, which emphasizes

the significance of effective models in the agricultural environment.

Although the diseases Black Sigatoka and Cordana were the main focus of this study, its methodology can be applied to other illnesses like mosaic, moko, or Panama disease. Fur- thermore, the application of sophisticated methods, like the coarse-to-fine double limitation network for veiled object recognition, and the study of algorithms used with multispectral pictures can be taken into consideration.

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