International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8096
***Article Received:** 28 June 2023 **Revised:** 24 August 2023 **Accepted:** 07 September 2023*

Efficient Disease Identification Method for Crop Leaf using Deep Learning Techniques

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Abstract— Many prime grain-producing nations have implemented steps to limit export of grains as COVID-19 has expanded over the globe; food security has sparked significant worry from a number of stakeholders. One of the most crucial concerns facing all nations is how to increase grain output. However, the diseases occur in crops remain a challenge for countless farmers, therefore it is critical to understand their severity promptly and precisely to guide the them in taking additional measures to lessen the chances of plants being affected furthermore.

This paper describes a deep learning model for the identification of crop diseases that can achieve high accuracy with low processing power. The model, called the inception v3 network, has been tested on a tomato leaf dataset and has obtained a average identification accuracy of 98.00% and further the ensemble of two inception v3 models with slight diversity achieved an accuracy of 98.11%. The results suggest that this model could be useful in improving food security by helping farmers quickly and accurately identify crop diseases and take appropriate measures to prevent further spread.

Keywords- Crop leaf disease detection, tomato leaves dataset, convolution neural network, Inception network.

I. INTRODUCTION

As nations strive to take steps during COVID epidemic, Statements were made in March 2020 from the officials of the food agriculture organization and directors of WHO and WTO to achieve food security, the nation must take action [1]. Food security has received more attention recently, and many nations and organizations are attempting to boost food production. In the view of this, numerous researches are improving our understanding of agricultural crop diseases and pests. Particularly, leaf diseases own significant impacton the crop growth and output. Effectively determining the severity of crop diseases has required a lot of research. Crop disease identification using deep learning techniques has significant background and significance in the field of agriculture and food security. Ensuring an adequate food supply for a growing global population is a major challenge. Crop diseases can have devastating effects on crop yield and quality, potentially leading to food shortages. Accurate and timely disease identification is crucial to mitigate these effects and ensure food security. Historically, crop diseases have beenidentified through visual inspection by farmers or agricultural experts. This method is labor-intensive, time-consuming, and often prone to human error. Automated disease identification using deep learning can significantly improve the efficiency and accuracy of this process. With the advent of remote sensing and drone technology, it's now possible to monitor large agricultural areas efficiently. Deep learning models can analyze satellite or drone imagery to detect crop diseases across vast expanses of farmland. Deep learning-based disease identification is a component of precision agriculture, where resources such as water, fertilizers, and pesticides are used more efficiently. By targeting specific areas affected by dis- eases, farmers can reduce input costs and minimize environ- mental impacts. Crop diseases are a global concern, affecting both developed and developing countries. Deep learning-baseddisease identification can be deployed worldwide to address this common agricultural challenge.

At the moment, there are essentially two issues that make up research on crop disease identification. One is the conventional computer vision approach, which identifies various diseases primarily by feature extraction and spectral detection. Diverse diseases produce different leaf characteristics, which resultsin a variety of leaf forms and colors when diseased and disease free crops are compared. The other issue identifies images of leaves using machine learning. In other words, sick images of the leaves

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are retrieved using ML algorithms, and the recognition is done utilizing the many characteristics of sick and disease free plants.

In this paper, the dataset is trained using inception3 model, ResNet50 model and DenseNet models respectively. The test data set is fed to each model to record the accuracy of each model and the best model for crop disease identification is proposed. The aim of this model is to improve the accuracyof identifying crop leaves and reduce the impact of disease on crops to the greatest extent possible. In order to improve test accuracy further, ensemble of two inception v3 models with slight variations trained separately and obtained the predictions. These predictions are combined and tested to record the improved accuracy.

The subsequent sections of the paper are organized in the following manner; Section 2 presents relevant prior studies. The design of disease identification model is discussed inSection 3. The results and evaluations of the experiments are provided in Section 4, while the final conclusions are outlined in Section 5.

II. RELATED WORK

The effectiveness and accuracy of crop leaf disease diagnosis have further increased with the advancement of MLalgorithms and IoT technology in agriculture [2],[3], which identifies crop diseases and pests. To identify diseases such asdifferent blights and curly leaf disease on tomato leaves, Jianget al. [4] employed deep learning technique. After constant learning through repetition, the suggested method prognosticated the classification of each disease. In this method the accuracy demonstrated in the training and test dataset grewby 0.6% and 2.3%, respectively. For the automatic recognition and classification of plant leaf diseases, Sharma et al [5] proposed an artificial intelligence-based methods for picture collection and pre-processing, picture segmentation and picture classification. This method can swiftly and efficientlyidentify crop illnesses in agriculture. Lv et al. [6] introduced leaf disease recognition technique based on the AlexNet model in which a DMS-Robust model increased the ability of featureextraction along with dilated, multiscale convolution. This network boosted the maize leaf features under environmental complexity. A GAN based leaf disease recognition model wasput forth by Liu et al. [7]. For training purpose, this model created photos of 4 non-identical leaf diseases, then combined DenseNet with instance normalization to differentiate betweenreal and false disease images and extract feature information from grape leaf scrapes. At the end, this approach enforceda deep regret gradient penalty to stabilize the training mechanism. The findings demonstrated that the GAN-based strategy for data augmentation may successfully address the over fitting issue in illness recognition and successfully increase accuracy of recognition.

Liang et al [8] introduced a technique for image recognition which is an integration of several classifiers separated into two categories: One is, after adopting a publicly available dataset of sick and disease free plant leaves, CNN is used to classify several plant illnesses, each of which was then individually assessed. Finally, the combined models were assessed for their accuracy in diagnosing plant disorders. According to experimental findings, the high accuracy close to 99.92% is attained on a split test set.

Jaisakthi et al. [9] created a grapevine spotting method bottomed on image processing techniques and machine learning algorithms. By using the grab-cut segmentation technique, mentioned system can separate grape leaves from the back-ground. By segmenting the infected region from segmented leaves, global thresholding technique and semi supervised approach were utilized. Features were then retrieved from the segmented part of the leaves and classified as late blight,healthy and rotten by various ML techniques. Notably, this technique achieved a higher SVM testing accuracy which is 93%. A continued plant disease diagnostic model set on deep neural network that can accurately detect plant varieties and illnesses was proposed by Huang et al. [10]. Plant disease classifier that rely on a two head network distinguishes the diseases using the features extracted by several pre-trained models, and the leaf segmentation section separates the leaves in the primary image from the backdrop, make up this model. According to experimental findings, this approach can identifydiseases with an accuracy of 0.8745 and 0.9807 for plants classification, respectively.

A DenseNet-based optimized corn leaf identification model with few parameters that increases work efficiency is demonstrated by Waheed et al. [11]. The outcomes of the experimentsdemonstrated the effectiveness of this strategy in identifying corn leaf disease. The study of disease identification in crop leaves is mostly focused in computer vision and machine learning, in particular the latest development of deep learning techniques used in agriculture, as can be observed from the aforementioned state-of-the-art techniques. However,approaches that may balance accuracy and efficiency are rarely used to identify agricultural leaf diseases. Identifying leaf diseases is essential for monitoring crop growth and taking prompt action. This task comprises two main approaches: detection using conventional machine learning algorithms and detection of leaf images using deep learning.

A. *TRADITIONALLY USED MACHINE LEARNING METHODS*

The following subsections illustrates the most common classical machine learning approach used in crop leaf disease identification.

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1. SUPPORT VECTOR MACHINE's: One of the most effective and powerful machine learning techniques is the SVM's [12],[13]. Given a small sample size, it can exactly strike a balance between intricacy of the model and its classification potential [14]. SVM is superior to other machine learning techniques in several ways; It can also function without any prior information and mitigate the effects of noise [15]. Modern models using SVM classifiers are widely used to identify crop diseases. A technique for diagnosing a disease in cotton leaves using image processing techniques and SVM was proposed by Bhimte and Thool [16]. For the purpose of classifying cotton leaf disease, this system first chooses appropriate picture attributes, like color and texture, then applies an SVM classifier. Results from the experiments indicate that good performance was attained. By utilizing an SVM classifier, Padol et al. [17] aimed to abet in the illness identification and classification of grape leaves. They firstidentified the damaged area to do segmentation by using KNNand later extracted features like color and texture data. By using classification techniques, they were able to identify the kind of leaf disease. This system attained good accuracy onthe test dataset which is of 88.89%.

2. K-MEANS ALGORITHM: This algorithm is one of the earliest and widely used clustering technique. K-means has received a lot of attention in the literature. It has been used ina wide range of substantive fields [20],[21],[22],[23]. Zhang et al[24] proposed combined K-means clustering and PHOG techniques with superpixel clustering to segment leaves. This technique demonstrated outstanding performance in the segmentation and identification of plant sick leaf images. A diagnosis technique for diseases in brinjal leaves using image processing facility and machine learning was proposed by Anand et al. [25]. This technique was particularly successful at identifying leaf illnesses because it applied K-means algorithm to segment disease in brinjal leaf. A leaf spot identification method using image processing was put forward by Kumari et al. [26]. Image capturing, segmentation of the image, extracting features and classification were the four stages of this procedure. The illness features were computed using K-means. The target location of a disease in cotton leavesand the accuracy of bacterial leaf spot were 90% and 80%, respectively. By extracting color, texture information and input them to a numerous class SVM classifier, Rani et al. [27] suggested leaf disease classification technique based on K-means clustering. SVM was shown to have an average classification accuracy of more than 95%.

B. DEEP LEARNING

As deep learning has advanced, a number of picture recognition models have been put out that can successfully address the issue of disease identification. The extensively utilized deep CNN models at this time are listed below.

1. ALEXNET: The creation of AlexNet was the major advancement in deep CNN's [28],[29]. As an impact, this significantly outperforms the conventional method on the umpteen of ImageNet datasets, by more than 70% to 80%.Three convergence layers, three complete connection layers, and five convolution layers make up AlexNet. These include solving the gradient dispersion problem by having ReLU activation function contrary to sigmoid or logistic function.To avoid over tuning and overlapping, dropout is utilized at the completely connected level in conjunction with local response for normalizing.

2. INCEPTION NETWORK: Layer by layer, the prior networks conduct convolutions, and the output is input tothe following layer. Inception, on the other hand, specifiesa module that performs several operations of convolution and at the last combines various convolution processes asoutput. According to exploratory findings, it performs well. The Inception network, as depicted in figure 1, differs fromthe conventional CNN in that its convolution layer has many convolution kernels of various sizes, and its output is the extentknitting of the feature map [30].

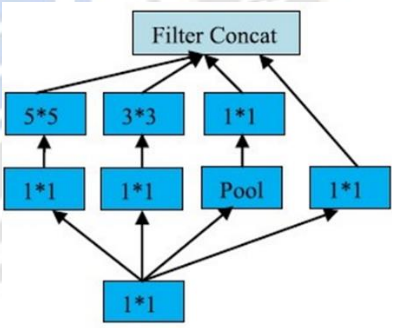

Fig. 1. Inception Network

3. RESIDUAL NETWORK: The residual network, which is shown in Figure 2, have undergone significant improvements in depth and architecture compared to its previous networks. This incorporates shortcut connections that enable the network to act as a reconstruction of itself. The identity shortcuts can be utilized directly when the input and output have the same dimensions [31]. Deep residual networks have won the ImageNet detection and localization, COCO(Common Objects in Context) detection and segmentation tasks.

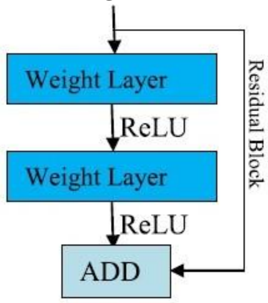

Fig. 2. Residual Network

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4. DENSE NETWORK: This architecture as depicted in figure 3 features a feed-forward connection of every layer to every another layer. It has L(L+1)/2 direct connections, unlike traditional convolutional networks with L layers that have only L connections, one between each layer and the next. Each layer takes as inputs the feature maps from all layers before it and serves as input for all layers after it. [32].

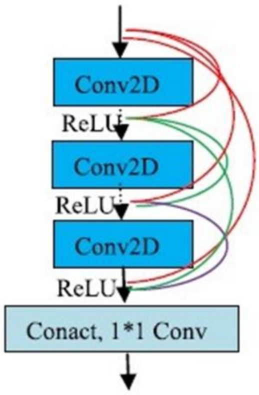

Fig. 3. Dense Network

5. RESIDUAL DENSE NETWORK (RDN): This is introduced as a solution for image super-resolution and de-noising challenges. As illustrated in Figure 4, the residual dense block (RDB) utilizes densely connected convolutional layersto extract rich local features and enables contiguous memory (CM) [33],[34] through direct links from the previous RDB state to all layers of the current RDB.

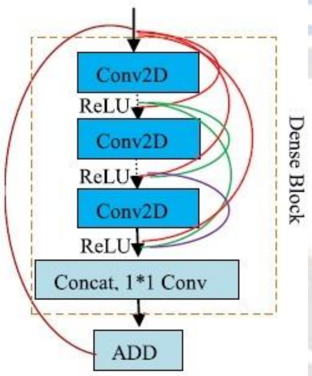

Fig. 4. Residual Dense Network

6. *RESTRUCTURED RESIDUAL DENSE NETWORK:* RRDN[35] addresses the identification of crop leaf disease. The input photos do not include any dimension reduction operations because the original model was utilized for image super-resolution, albeit this may still be possible in a single block. However, thousands of images are entered into the image classification task, which will use a lot more computational resources and be inefficient. The Res-Dense-Block(RDB) starts with convolving the input image, followed by batch normalization of the tensor, as shown in Figure 5.

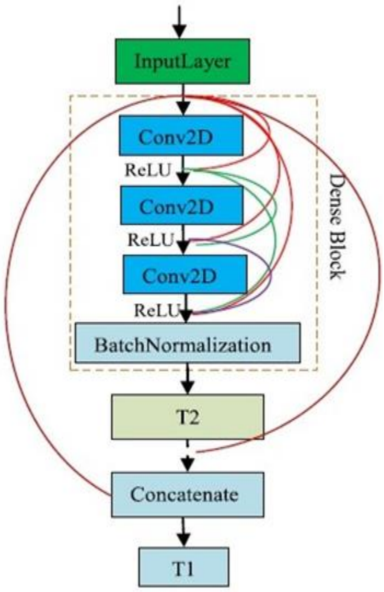

Fig. 5. Restructured Residual Dense Network

III. DISEASE IDENTIFICATION MODEL BUILDING

In this article, we concatenated Inception-v3 with a DCGAN model to train and classify the tomato leaves and compare the accuracy with pre-trained ResNet50, DenseNet121 models. For this first we trained the DCGAN model on the dataset and then used trained generator of the DCGAN to generate new images. After that, we use the Inception-v3 model to classify the generated images.

A. DCGAN NETWORK: The DCGAN method combines CNN and GAN for supervised and unsupervised learning respectively, and can be considered as an extension of GAN to the field of CNN. The advantage of GAN is that it can learn appropriate feature representation and doesn't need a specific cost function, but training GAN is quite unstable and frequently results in generators producing nonsense output.To increase the caliber of samples and the rate of convergence, DCGAN made certain adjustments to the convolutionalneural network's structure in comparison to GAN. In this system, pooling layers are replaced with strided convolutions and fractional-strided convolutions to bring improvements. The networks for the generator and discriminator were batch normalized. The DCGAN's architecture has discriminator andgenerator as shown in figure 6. A CNN without link layeris used as a discriminator network. The generator network employs the ReLU activation function in its other layers, while the tanh activation function is used on its output layer. The discriminator network uses LeakyReLU activation functions for its binary problem.

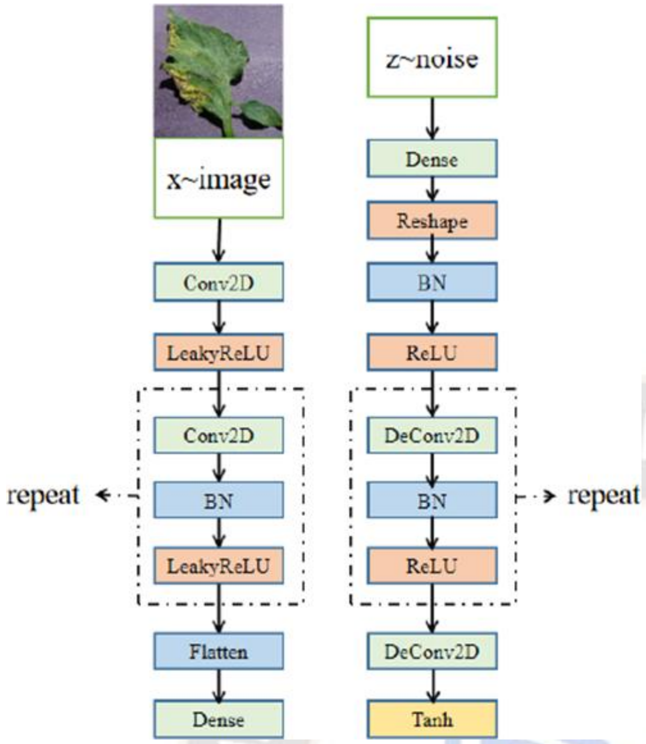

Fig. 6. Architecture of discriminator and generator in DCGAN

B. IMAGE IDENTIFICATION NETWORK MODEL BUILDING:

Following the aforementioned paradigm of DCGAN increasing training set, we apply a deep learning based framework for image recognition that has shown promising results in recent past. Traditional neural networks which exist are inaccurate, however machine learning techniques like random forests have shown that overfitting will always exist in problems involving classification or regression along with noise. We choose deep neural networks as a result. The advancement of deep learning has allowed computer vision to do well in contests for ImageNet dataset under the Large Scale Visual Recognition Challenge (ILSVRC) [18], with rate of error which is lower than that of human vision.

In the current study, conducted corresponding experiments in order to evaluate the effectiveness of models to compare the inception v3 model, ResNet50, and DenseNet121 and to determine more suitable CNN model for the classification problem. Several metrics, including accuracy, precision and recall were utilized to gauge the success of our studies. For the sake of simplicity, the accuracy metric alone is included. The rest of the measurements fall in accordance with the datasets high degree of balance, considering them redundant [19].

1. Inception V3: This model is simply the upgraded and improved version of Inception V1 model. The Inception V3 model has several optimizations to enhance its adaptability, such as auxiliary classifiers used as regularizer and a deeper network. Despite the increase in the number of layers to 42, compared to Inception V1 and V2, its computation cost remains low and its performance is exceptional. Table 1 provides an overview of the Inception V3 components.

TABLE I
COMPONENTS OF THE INCEPTION-V3 MODEL

COMPONENT TYPE	SIZE OF PATCH	SIZE OF INPUT
Convolve	3×3/2	299×299×3
Convolve	3×3/1	149×149×32
Convolve padded	3×3/1	147×147×32
Pool	3×3/2	147×147×64
Convolve	3×3/1	73×73×64
Convolve	3×3/2	71×71×80
Convolve	3×3/1	35×35×192
3 X Inception	Module 1	35×35×288
5 X Inception	Module 2	17×17×768
2 X Inception	Module 3	8×8×1280
Pool	8 × 8	8 × 8 × 2048
Linear	Logits	1 × 1 × 2048
Softmax	Classifier	1 × 1 × 1000

2.ResNet: Kaiming et al.[31] first proposed ResNet in 2015 and won first place in the ImageNet competition's classification problem by introducing a novel design with ”shortcut connections” and significant batch normalization. Shortcut, as its name suggests, means to choose shortest path. The ResNet structure that we refer to as a ”building block” is shown in figure 7.

The supposed shortcut connection is visible as ”a curved line.” The entire graph, which was created for ResNet-50/101/152, is also referred to as a ”bottleneck design.” Itis to simplify things by lowering the number of factors, to be clear at a glance. The 256-dimensional channel is initially reduced to 64 dimensions using a 1x1 convolution, and is then recovered by a 1x1 convolution. This work utilized the ResNet-50 model.

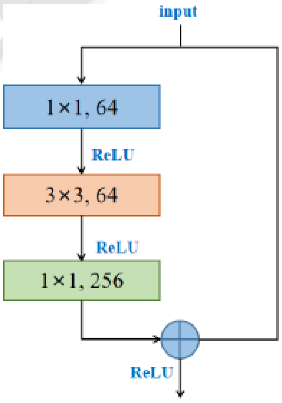

Fig. 7. ResNet's bottleneck building block

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3. DenseNet: The first layer in a traditional feed-forward convolutional neural network (CNN) is the convolutional layer that receives the input. It creates an output feature map which is passed on to the next layer. The "vanishing gradient" problem arises when the CNN has a deeper architecture and the information being passed from input to output layers becomes longer, causing information to be lost and hindering the network's ability to learn effectively.

DenseNets solve this issue by altering the typical CNN architecture and making direct connections between every layer, giving rise to the term "Densely Connected Convolutional Network." This architecture results in L(L+1)/2 direct connections between L layers.

In this study, DenseNet121 architecture is utilized consisting of 1 7x7 Convolution layer, 58 3x3 Convolution layers, 61 1x1 Convolution layer, 4 Average Pooling layers, and 1 Fully Connected layer. In total, DenseNet-121 has 4 Average Pooling and 120 Convolutional layers. The architecture enables deeper layers to leverage features extracted from earlier layers asall layers, including those within the same dense block and transition layers, share their weights across multiple inputs. The output of transition layers receives the lowest weight fromthe second and third dense blocks, as they produce redundant features.

4. Ensemble of Inception V3: This work is further extended with ensemble of Inception V3 models, which are deep convolutional neural networks (CNNs), to improve the accuracy of disease identification in tomato leaf images. This ensemble uses 2 inception v3 models in which each model have slightly different architectures (e.g., different dropout rates, different fully connected layers) to introduce diversity in the ensemble. This diversity in model architectures helps to improve the ensemble's performance.

The first Inception V3 model is loaded with pre-trained weights from the ImageNet dataset. Then applied a global average pooling 2D layer to the output of this model. Global average pooling reduces the spatial dimensions and retains important features. Subsequently a fully connected layer with 1024 neurons and a ReLU activation function is added. This layer is used for feature extraction and complexity. Dropout is a regularization technique to reduce overfitting. This model uses a dropout layer with a rate of 0.5, meaning that during training, 50% of the neurons in the previous layer are randomly dropped out. Finally output layer is added softmax activation function to produce class probabilities.

The second Inception V3 model, identical to the first one. But uses a different fully connected layer with 512 neurons and a ReLU activation function with a dropout rate of 0.3. Finally create two separate Keras models, model 1 and model 2, by specifying their inputs (the input layer of Inception V3) and outputs (the custom prediction layers). After defining these models, typically trained them separately on the training data. After training, used each individual model to make predictions on the test dataset and combine the predictions from each model to make a final prediction. Then evaluate the ensemble's performance on the test dataset.

IV. EXPERIMENTAL ANALYSIS

A. *SETTING OF THE EXPERIMENT*

The experiment environment is shown in TABLE 2.

TABLE II
EXPERIMENTAL SETTING

Component	Specification
Operating System	Windows 10
Language	Python 3.8
CPU	Intel(R) Xeon(R) E5-2620 V-4@2.10GHZGPU
Framework	Google colab
GPU	NVIDIA GeForce-G TX-TITAN Xp(12G) RAM
RAM	16GB

B. *DATASET*

This experiment uses the dataset of diseased tomato leaves, which consists of 2700 photos divided into 3 classes and all have the same resolution of 224x224 pixels. This dataset is produced in such a way that, in each class 50% of the images from publicly available dataset is mixed with 50% of the images which are captured manually in the farm field. TABLE 3 displays the details of the dataset. FIGURE 8 displays a portion of the photos of tomato leaf disease.

TABLE III
DETAILS OF THE DATASET

Class Type	Images in Number
Tomato Healthy	900
Tomato Early blight	900
Tomato Bacterial spot	900

C. *DETAILS OF THE TRAINING PROCESS*

1. PARTITIONING THE DATASET: The tomato dataset is split into three parts for the purpose of training, validation and testing the Inception v3, ResNet50, and DenseNet121models using NVIDIA GeForce GTX TITAN Xp GPU. 60% of the dataset is used for training, 20% for validation, and the remaining 20% is used for testing.

2. ACTIVATION FUNCTION: In the architecture, the activation function ReLU is used after the convolution operation and LeakyReLU is used after normalization to prevent the "dead neuron" issue.

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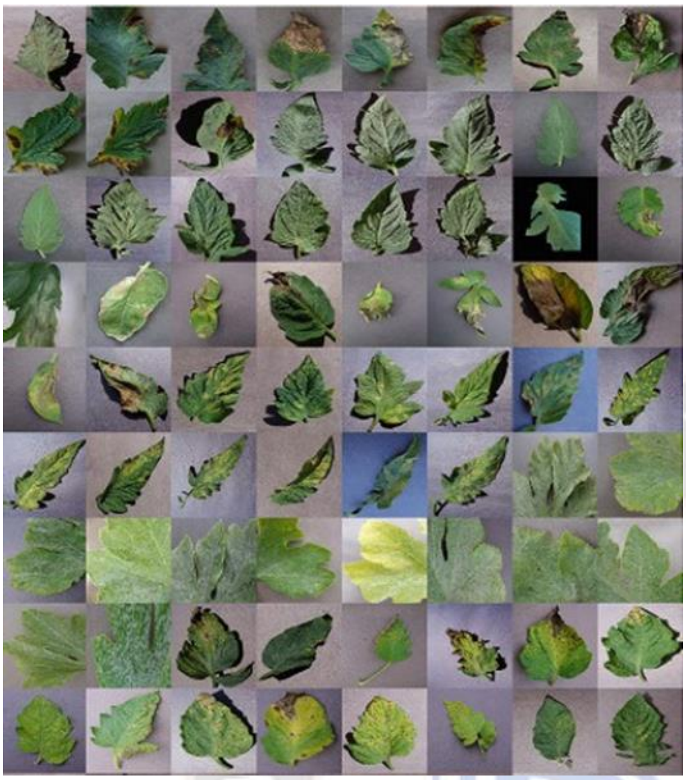

Fig. 8. Some images of the diseased tomato leaves

3. *LOSS FUNCTION:* The cross-entropy loss function and the softmax activation function are used to address the multiclassification problem in the network. The cross-entropy loss is used in the loss layer and the softmax activation function is used in the output layer to make the problem simpler.

4. *OPTIMIZER PERFORMANCE:* Loss function is minimised and the rate of learning is accommodatively adjusted in the optimization layer using the adam optimizer.

5. *SIZE OF THE BATCH AND NUMBER OF EPOCHS :* To feed into the model select between 8, 16, or 32 as the batchsize. The model set the number to 8 as the batch size because there is a gradient fluctuation phenomena when the batch size is 16 or 32. Additionally, trained this model for 70 epochs.

D. MODEL COMPARISON:

In this experiment setting, choose some established deep learning models for comparison, including Inception v3, ResNet50, and DenseNet121. The accuracy of the trained and validated dataset of the three models is shown from figure 9 to figure 11. The accuracy achieved using deep CNN, the gradient fluctuation is clear as the number of epochs rises, and the overfitting phenomena manifests itself. The highest accuracy among the models is Inception V3 with 98.00%. The Inception V3 model outperforms both ResNet50 and DenseNet121 with a higher accuracy. The results suggest that Inception V3 is a better model for the tomato dataset compared to ResNet50 and DenseNet121. The training and validation loss plots shown in figure 12-14 also suggest that Inception V3 is better at convergence compared to the other models. Furthermore the ensemble of inception v3 model achieved slightly better accuracy of 98.11% compared to inception v3 alone. The accuracy of each model is displayed in TABLE 4 to more clearly demonstrate the performance.

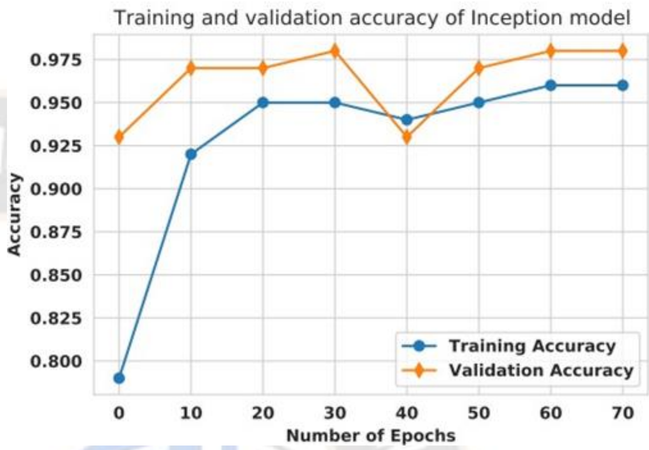

Fig. 9. Accuracy achieved in Inception model

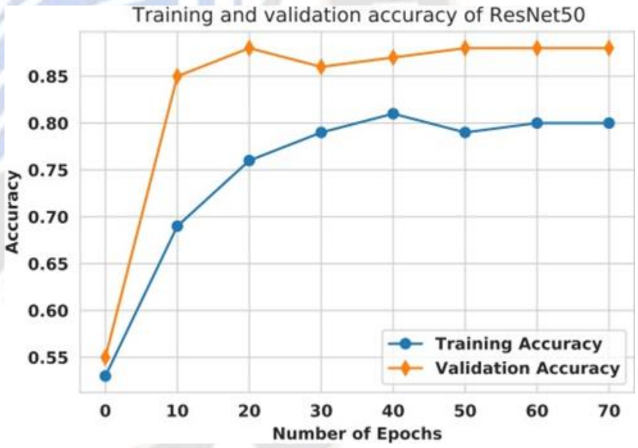

Fig. 10. Accuracy achieved in ResNet50 model

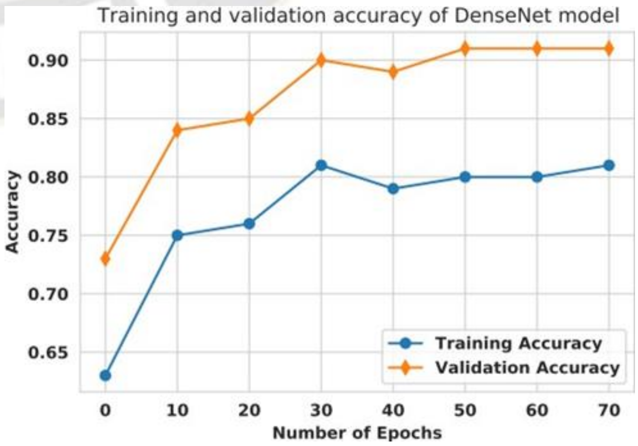

Fig. 11. Accuracy achieved in DenseNet model

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TABLE IV
Accuracy Achieved

Models trained	Accuracy
Inception-V3	98.00%
ResNet-50	80.13%
DenseNet-121	91.20%
Ensemble of Inception-V3	98.11%

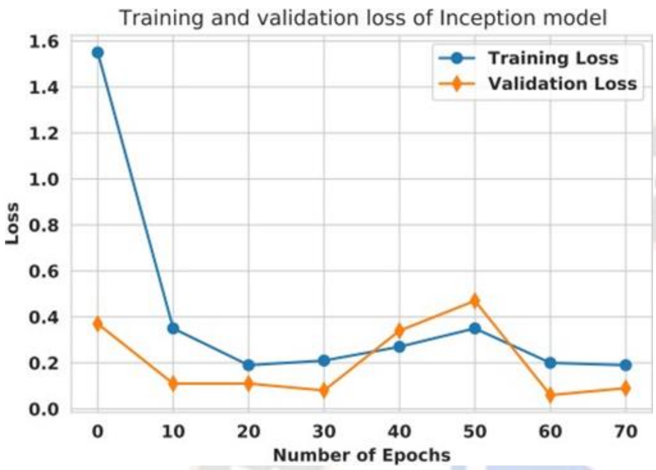

Fig. 12. Loss occurred in Inception model

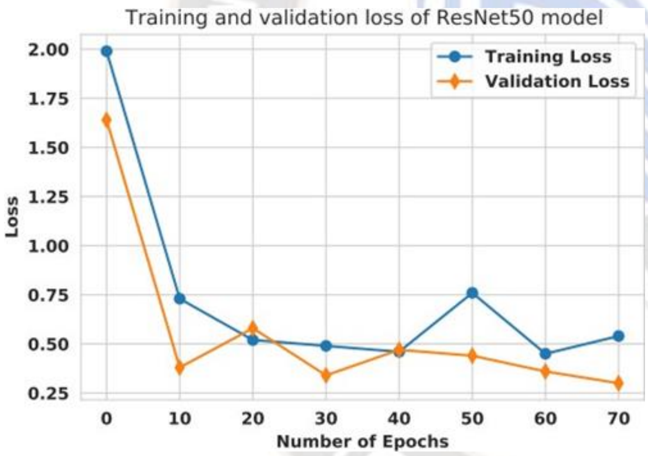

Fig. 13. Loss occurred in ResNet50 model

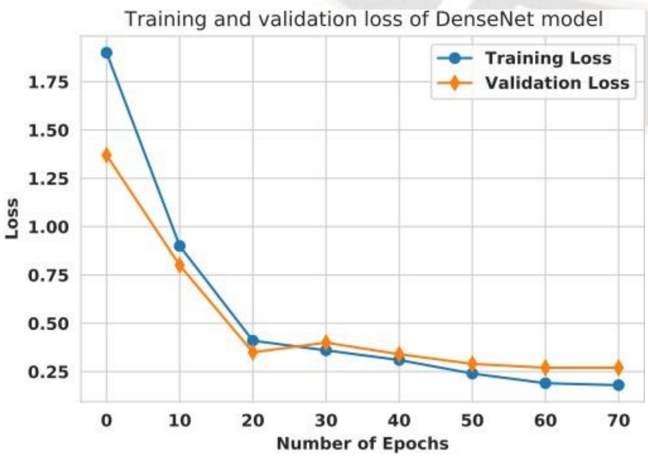

Fig. 14. Loss occurred in DenseNet model

In figure 15, a comparison of most recent researches on tomato disease identification may be seen. On 71 tomato leaf images, Raza et al [37] presented a classifier based on SVM, only managed an accuracy of 89.93%. With the use of a KNN-based model and a dataset of 14,529 photos divided into 10 groups, Prasad et al. [38] were able to attain a 93% accuracy. Luna et al[39] demonstrated automated image capture method had a 91.67% accuracy rate. Guo et al. [40] created a novel model called multiscale AlexNet, applied on 5,766 images grouped into 8 classes, obtained 92.7% accuracy. A DCGANCCNN model was proposed by Wu et al. [41] and it attained an accuracy of up to 94.33%. C. Zhou et al. [35] introduced RRDN model which produced an accuracy of 95%.

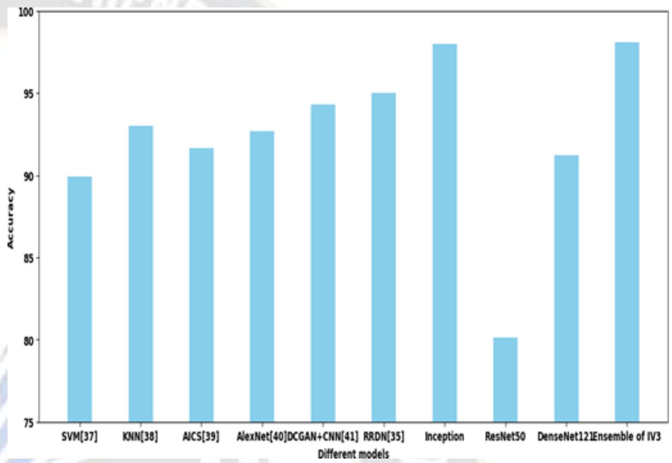

Fig. 15. Accuracy comparison with the other state-of-the-art training models

V. CONCLUSIONS

The tomato is staple food which is consumed all across the world for both food and spice. Even for amusement. The annual "Tomatina," which takes place on last Wednesday in the month of august, has its roots in Spain. Here thousands of revelers from all over the world throw tonnes of tomatoes at one another. The issue of plant infections must be solved if people are to grow tomatoes of higher quality. The diagnosis of leaf diseases is particularly crucial since plant illnesses frequently manifest on the leaves initially.

In this paper, we used DCGAN to provide data that closely resembles real images to increase the samples for training big neural networks and also to increase data diversity and ability of detection models to generalize. We obtained the best results utilized to train the CNN network that we built by merging DCGAN with inception v3 model, where augmented and actual data were blended as input of the CNN. In the interim, we also found a solution to the CNN network's difficulty in converging, which was caused by the challenging data gathering and striking similarity of characteristics.

To recognize tomato leaf disease, we intend to find a better data augmentation approach in the future. This will increase the recognition's robustness and accuracy. In practical applications, it is challenging to collect the leaves. As a result,it is vital to arrive at a solution to the few-shot learning problem (Wang et al.[36] suggested a method rely on siamese network for classification of plant leaves). Overall, we aimto continuously enhance performance by exploring innovative approaches to the identification of tomato leaf disease.

It's likely that in the future, the use of deep learning on large datasets of multiple plants and their parts will lead to advances in the field of plant analysis and classification. The increased data and computational power will enable more accurate and sophisticated models, potentially leading to new insights and applications.

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