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Crop Diseases and Pest Detection using Deep Learning and Image Processing Techniques

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Abstract: Crop pests and diseases play a significant role in yield reduction and quality. Controlling and preventing pests and crop diseases has therefore become a priority. If disease is detected at an early stage, this can increase crop production and provide benefit to farmers. Manual detection of these diseases and pests can be very tedious and time consuming for farmers, especially if they have large farms. We plan to model a crop disease and pest diagnostic system using image processing and deep learning techniques. Crop disease and pest detection can be done using deep learning and image recognition techniques on leaves and other areas of the crop.
Index Terms: Image Processing, Deep Learning

I. INTRODUCTION

The backbone of the Indian economy is agriculture[21]. It played an important role in human civilization's growth. Various Agricultural practices such as irrigation, yearly crop changes and the availability of external inputs have been established far back, but have made great strides in the past century. The production rate of crops is dependent on various parameters such as temperature, atmospheric humidity, access to water supplies, early detection of pests and crop diseases. It needs a great deal of effort, the ability to understand plant diseases, and a lot of preparation time.[1] If diseases and pests are not taken good care of, so the quality and quantity of the crop can be decreased [1]. [1] Few farmers are not well acquainted with all the diseases, do not have appropriate facilities, and are also unsure of how to approach a specialist for advice. [1] Sometimes even experienced agronomists often fail to successfully diagnose the crop. In recent years many have tried to deploy models for pest and crop disease detection using image processing and deep learning techniques. Many have used IOT devices to monitor farms and provide continuous image capturing. Crop pests are causing major damage to the world's crops, be it developing nations or developed ones. [1] According to recent studies, insect infestation and crop disease cause about half of the world's crop production to be destroyed. [1] One of the most important aspects of precision agriculture is the accurate and reliable identification of plant diseases. [1] Farmers manually inspect the field daily, weekly and monthly for manual investigation of diseases or pests. In this paper section 2 presents a brief introduction on a deep learning technique called ResNet and Image processing followed by section 3 which presents the literature work done so far. Section 4 presents the proposed methodology for this project and section 5 presents results and conclusion for this paper. [12] Since the dawn of time, humans have relied on crops for survival; our forefathers used to migrate long distances in search of food, which is nothing new considering that the first human race appeared since the advent of agriculture [12]. Crops are a necessary part of our daily lives. Humans would be unable to live in the absence of crops[12]. Agricultural yields are harmed by crop diseases. It poses a great threat when it comes to food safety[12]. Various routines may be used to identify plant pathologies. Few illnesses have no discernible symptoms or take a long time to manifest any discernible symptoms, necessitating an advanced test of these cases. However, nearly any ailment reflects itself in some way in the visible spectrum, so a visual examination by trained practitioners is essential. However, in order to detect characteristics differences exhibited by diseased crop plants and have a comprehensive report on crop disease, pathologists must have a superior observation ability set [4].

[12] It's tough because incompetent farmers and horticulturists have a harder time diagnosing it than a knowledgeable pathologist and often make incorrect diagnoses.[12] Farmers can now identify crop diseases remotely by using seed images and guidance from crop pathologists, due to developments in internet and emerging technologies. [12] Since the dawn of time, humans have relied on crops for survival; our forefathers used to migrate long distances in search of food, which is nothing new considering that the first human race appeared since the advent of agriculture. Despite the fact that the assessment in this case is error and leads to wrong judgement [12]. Furthermore, research indicates that climate changes [4] will affect the stages and rates of germ formation, as well as mutate the host, potentially leading to physiological changes [5]. The fact that infections are now more quickly spread across the planet further complicates the situation. Precise and timely identification of crop pathogens, as well as early protective steps, is the cornerstone of precision agriculture.

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II. DEEP LEARNING AND IMAGE PROCESSING

A. Deep Learning

Deep learning is a subset of machine learning that primarily focuses on ANN (artificial neural networks). A neural network is a computer model of the human brain. It addresses difficult problems while still allowing for consistency. A neural network is made up of several neurons that are connected together. The first layer is the input layer, followed by intermediate layers known as hidden layers and the output layer. Deep learning implementations in agriculture have only recently been launched, and research work is insufficient[1]. Deep learning is a form of machine learning in which the universe is learned to be represented as a nested hierarchy of concepts, with each concept described in relation to simpler concepts and more complex representations computed in terms of less abstract ones.

It achieves great strength and simplicity by learning to view the universe as a nested hierarchy of concepts, with each concept described in relation to simpler concepts and more abstract representations computed in terms of less abstract representations. Deep learning is a branch of machine learning that relies solely on artificial neural networks. Deep learning is a human brain mimic since neural networks are programmed to mimic the human brain. Deep learning does not require any direct programming. Deep learning is a not-so-new concept. It has been around for a long time. It's popular these days because it was popular in the past and and we didn't have almost as much processing power or data before. Deep learning and machine learning have emerged as computational power has grown exponentially over the last 20 years

B. Convolutional Neural Network (CNN)

A CNN, or convolutional neural network, is a deep learning neural network designed to process ordered arrays of data, such as portrayals. Lines, gradients, circles, and even eyes and faces are very well picked up by CNN in the input image. It is because of this property that convolutional neural networks are so efficient in computer vision. CNN does not require any preprocessing and can run directly on an underdone image. A feed forward neural network of up to 20 layers is known as a convolutional neural network.

A convolutional neural network's power comes from a form of layer known as the convolutional layer. CNN is made up of several convolutional layers layered on top of each other, each capable of understanding more complex patterns. A CNN, or convolutional neural network, is a deep learning neural network designed to process organised arrays of data like portrayals.CNNs are excellent at detecting design elements in input images, such as shapes, gradients, circles, and even eyes and ears.

It is because of this feature that convolutional neural networks are so effective in computer vision. CNN will run on an underdone computer. CNN does not require any pre-processing and can run directly on an underdone image. A feed forward neural network of up to 20 layers is known as a convolutional neural network. A convolutional neural network's power comes from a kind of layer known as the convolutional layer. CNN is made up of several convolutional layers stacked on top of each other, each capable of understanding more complex patterns.

CNN is made up of several convolutional layers stacked on top of each other, each capable of understanding more complex forms. Handwritten digits can be recognised with three or four convolutional layers, and individual faces can be distinguished with 25 layers. The aim of this domain is to train machines to see the world in the same way that humans do, to understand it in the same way that humans do, and to behave in the same way that humans do.

The aim of this field is to train computers to see the environment in the same way as humans do, to understand it in the same way, and to use that information for a variety of tasks such as image and video recognition, image inspection and detection, media recreation, recommendation systems, natural language processing, and so on.

A convolutional neural network is a multi-layered feed forward neural network that is built by stacking several invisible layers on top of each other in a specific order. CNN is able to learn hierarchical features because of the sequential nature. Convolutional layers are usually accompanied by grouping layers and opaque layers in CNN, and activation layers are typically followed by convolutional layers.

C. Image Processing

Digital Image Processing is a software that allows you to manipulate digital images using a computer system. It's also used to improve images and extract important data from them.It's also used in the translation of image sensor signals into digital images. In image processing, a variety of algorithms are used. Digital Image Processing offers a medium for a range of operations such as image enhancement, analogue and digital signal processing, image signals, and voice signals, among others. It offers photos in a range of formats.

D. ResNet

ResNet is a Convolutional Neural Network (CNN) architecture capable of supporting hundreds or thousands of convolutional layers. ResNet can add several layers while maintaining high performance, whereas previous architectures saw their usefulness diminish with each new layer.

The "vanishing gradient" dilemma was solved by ResNet. Back propagation is a method of training neural networks that uses gradient descent to find the best weights that minimise the loss function. When more layers are applied, the gradient becomes infinitesimally small due to constant multiplication of their derivatives, implying that adding more layers would not increase efficiency and will even degrade it. ResNet addresses this problem by using "identity shortcut connections," layers that don't do much at initial stage.

These equivalent layers are skipped during the training phase, with the activation functions from the previous layers being reused. This simplifies the network and speeds up learning by reducing it to just a few layers. When the network is retrained, the same layers extend, allowing the network to discover more of the functionality. There are two main types of blocks used in ResNet, depending mainly on whether the input and output dimensions are the same or different.

Identity Block: When the input and output activation dimensions are the same. Convolution Block: When the input and output activation dimensions are different from each other.

ResNets make it easier to train networks that are significantly deeper than before by removing the depletion problem. They also shown that ResNets are simpler to optimise and can achieve high precision at great depths. Deeper layers are unable to learn the identity function used to transport the result to the output. Instead of hoping that the layers match the desired mapping, we let them fit a residual mapping in residual networks. H(x) is the optimal mapping at first (x). However, we allowed the networks to match the residual mapping $F(x) = H(x)-x$ because the residual mapping was simpler to optimise than the original mapping. Shortcut connections, also known as skip connections, are a way of bypassing data from one layer to another.

This method helps data to flow freely between layers without impairing the deep learning model's ability to learn. The benefit of using this style of skip link is that any layer that degrades the model's output will be skipped. The skip relation is based on the idea that it is better for the network to learn to transform the value of f(x) to zero such that it acts like an identity function than it is for the network to learn to act like an identity function on its own by attempting to find the correct set of values that will give you the desired outcome. The conv block aids in the modification and reorganisation of incoming data so that the first layer's output meets the dimensions of the third layer, allowing them to be added together. These components aid deep learning models in achieving higher optimization and accuracy.

III. LITERATURE REVIEW

[1] In this paper, they have also included soil conditions, weather, rice varieties, moisture levels in soil, model training can help improve the classification. For more effective identification of diseases and pests on leaves and other parts of the crop, a deep learning method has been used. [1] In detecting crop diseases and pests, the proposed approach is effective.[1] The deep learning approaches relating to disease and pest detection have been discussed in this article, and the deep learning model is proposed for automated diagnosis of crop diseases and pests.[1] For the task of image classification, they have used CNN. [1] The solution is suggested by using CNN to overcome some of the limitations described in this paper.

[1] The proposed approach consists of the following phases: the very first step is the acquisition of images, where images will be obtained from all parts of the infected crop. The second step is the pre-processing of images, since the images may be of any size. On all the images, then augmentation is performed. [1] The dataset will eventually be ready and can be fed into the CNN model. [1] In the next step, using transfer learning, the feature extraction and classification is completed. [1] Plant disease image data was used. [1] Dataset consists of more than 50,000 pictures of healthy and unhealthy crop leaves, consisting of 38 class labels per plant based on disease types and an open-access database.[1] Initially, the leaf images of tomato crops from the Plant Village database are also used to incorporate field condition images of other parts of the crop from real fields and from the Internet to improve training model efficiency. [1] The images in the PlantVillage dataset are RGB images of random size. [1] Images downloaded from the Internet are also available in different formats that have different resolutions and output. [1] All the images collected should be preprocessed instead of using them directly to obtain more accuracy in the feature extraction of the images. [1] In the initial stage, the group of experts is expected to check the images labeled with the name of the disease that are downloaded from the Internet and taken into the fields. [1] After manual labeling and post verification, images were resized to 256×256 pixels. Many augmentations like rotation, flipping, zooming, shearing were done on the image dataset to prevent overfitting. transfer learning technique is used for the process of feature extraction and classification. [1] This paper talks about the methods used to identify plant diseases using their leaves imagery.

[21] In this paper, they have used image processing techniques like image acquisition, preprocessing, segmentation for the detecting the disease on crops better. The aim of this paper was to analyze tiny spots because they are very tiny and delicate to assess with the naked eye and can affect the fields on a large scale. [21] The suggested algorithm counts leaf pests and then estimates the sum of small spots per leaf.[21] This suggested approach has proven to be very effective in taking preventive steps in a timely manner and saves the farms from the harmful impact of the heavy use of pesticides. Technique of image segmentation for identification of plant disease.

[21] They have used the K-means clustering algorithm to distinguish foreground and background images. Features of extraction, color co-occurrence method were used. [21] End result was they uploaded several images of infected crop in jfif format, which on further preprocessing, segmentation, identifies the pests and type of pest and how much area is unaffected.[21] This paper presents the various techniques of image processing, such as feature extraction and image automatic detection. [21] The survey demonstrates the current methodologies that are successful and quick.[21] Several approaches are outlined here to obtain knowledge of various pest detection background models such as image filtering, median noise reduction filtering, image extraction and scanning detection. [21] This paper provides some promising findings in the presentation of improved techniques and [21] tools for creating fully automated pest identification including the extraction with detection. Pest groups contributes to loss rates and total losses. [21] Higher rate of crop growth in tropical and subtropical regions under high productivity conditions. [21] In such areas, however, due to the existence of favorable climatic conditions, the pest can greatly harm the crop. [21] Therefore, methods of crop protection are needed for the growth of pests. Farmers should also be conscious of such techniques. [21] Future directions of this study can be carried out to establish more sophisticated techniques for image processing.

[6] The goal of this study is to develop a banana disease and pest detection system based on AI using DCNN to help banana farmers[6]. Their dataset consists of about 18,000 field images of banana, collected by banana experts, from Bioversity International (Africa) and Tamil Nadu Agricultural University (TNAU, Southern India) [6] These farm images were captured under various environmental conditions. [6] They have utilized around [6] 12,600 images to create banana image data sets.75 images were taken as training set and 25 test set. [6] The image tagging was done using LabelImg software. They have used three different architectures, such as ResNet50, InceptionV2 and MobileNetV1. [6] For the purpose of this project they have used Faster RCNN with ResNet50 and InceptionV2 due to their accuracy. [6] object detection API was used. [6] Between 70 and 99 percent of the different models tested [6] achieved accuracy in the experimental performance.

[11] Deep convolutional neural networks have led to several breakthroughs in the field of image recognition. [11] The network depth is important, and nearly all common image classification methods use models that are extremely deep. The efficiency of the [11] Residual Network (ResNet34) for identifying and classifying plant diseases is discussed in this article. The concept of utilising Residual Networks is simple. The [11] intuition of using Residual Networks is motivated from immense success in the sphere of computer vision, for example image classification [11] and well known task of object detection [11], [11] as shown by recent studies. [11] The idea of providing alternative connections to the ordinary connections and generating residual connections is the main motivation of working with ResNet [11]. With sophisticated research, automated networks for disease detection will solve these issues. [11] Digital cameras have become a very useful technology for identifying and classifying diseases thanks to recent advancements in computer vision. Not only for nonskilled horticulturists, [11] but also for professional horticulturists, an automatic set-up designed to diagnose crop plant pathologies using crop visuals and observable symptoms will prove to be very useful. [11] As a means of clarification of disease detected and graded, not only to non-professional horticulturists but also to experienced practitioners[11]. While many [4] crop diseases, as described in the[4] introduction section, can be successfully detected and mapped using airborne or satellite imagery, the understanding of how to translate remote sensing data to realistic prescription maps is still lacking.[4] More research is required to establish operational [4] procedures for translating image classification maps to applications maps. While [4] the cotton root rot project outlined in this article should provide some guidance, each disease has its own characteristics and needs different detection and management procedures. [4] Historical imagery can be used to record the spatial and temporal continuity and dynamics of infestations that [4] recur year after year in similar areas, which would be useful prescription maps[4].

Deep learning is now commonly [13] used in our everyday lives, and the identification of crop disease severity using deep learning [13] is steadily gaining traction. The severity of [13] crop diseases is typically determined by leaf colour, form, and spot characteristics. The severity of crop diseases can be divided into several categories, according to the data given by the AI Challenge Competition[13]. Crop disease severity can be classified into a number of categories. [13] The identification accuracy rate on this data collection has not been able to reach 90SeNet + ResNet can achieve 90 percent accuracy without pre-training parameters, and 87 percent test set recognition accuracy. The SeNet + ResNet approach clearly outperforms the others.

[14]Model provides farmers with a quick and simple way to diagnose cotton diseases, as well as pesticide recommendations. It works on the basis of machine learning, which improves with each application. To maximise production, agriculture needs new concepts.[14] CottonCare (Cotton Crop Disease Detection Using Deep Learning using TensorFlow) is another step toward integrating AI into agriculture.

[15] In this article, they have introduced the fundamentals of deep learning and provided a detailed overview of recent deep learning studies in plant leaf disease identification. [15] Deep learning methods are capable of identifying plant leaf diseases with high precision if enough data is available for testing. The role of massive [15] datasets with high heterogeneity, data augmentation, transfer learning, and visualisation of CNN activation maps in enhancing classification precision, as well as the [15] importance of small sample plant leaf disease detection and hyper-spectral imaging for early plant disease detection, have all been addressed. [15] The PlantVillage dataset was used to test the success of the DL models in the majority of the studies. Despite the fact that this dataset contains a large number of photographs of various [15] plant species and their diseases, it was created in a lab. As a result, a huge [15] dataset of plant diseases in real-world conditions is predicted.

They have applied to previously unknown real-world videos, [16] most deep learning models for automated disease detection work poorly. We demonstrate in this paper that segmented and annotated [16] images can be used to train a convolutional neural network (CNN) model instead of complete images.[16] When a CNN model is trained using segmented images (SCNN) instead of Model output on [16] independent data improves from 42.3 percent to 98.6 percent as compared to testing for complete images (F-CNN).[16] In addition, a quantitative study of self-classification optimism revealed a substantial gain, with 82 percent of the survey dataset demonstrating a growth in confidence. [16] Pre-processing of images before CNN model training will become increasingly important as [16] better datasets become available in the future. When evaluated on separate evidence previously unknown by the models, the S-CNN model trained using segmented images outperforms the F-CNN model by more than double its output to 98.6 percent accuracy when compared to the F-CNN model trained using complete images. Not just that, but we demonstrate that by [16] using a tomato plant and a target spot disease type as an example, the self-classification trust for the S-CNN model improves.

[17] This research suggests a promising method for detecting disease in different leaves. A deep CNN model based on Bayesian learning is used to identify and classify leaf diseases in this study. For effective feature learning, Bayesian learning is implemented on top of the residual network because it increases pixel dependence. The plantVillage database was used in this project of 20,639 photos of 15 different classes of safe and bad tomato, squash, and pepper bell leaf images In terms of accuracy, precision, recall, and F-score, a comparison was made between the proposed DCNN and a standard classifier.

The results revealed that the suggested model is a useful method for disease identification and classification. [17]A total of 20,639 images from plantVillage were used in this study, with [17] 15 different groups of stable and contaminated leaf images of potato, tomato, and pepper bell. The implementation of a Bayesian method at the top of the [17] residual network for effective feature learning is the main goal of this study. An inquiry was carried out to compare proposed DCNNs.

We also successfully created a rice plant disease identification software for smartphones. [18] The findings showed that the smartphone-based rice plant disease detection programme worked well, detecting different [18] types of rice plant diseases based on image processing of rice plant leaves with [18] VGG16 with a train accuracy of 100

[19] Smart devices, which have recently become more widely available, [19]can be used to provide automated detection of corn diseases and avoid serious crop losses. [19] This paper proposes a real-time approach for detecting corn leaf disease based on a deep convolutional neural network. On a machine with GPU, [19] tuning the hyper-parameters and changing the pooling combinations improves deep neural network efficiency.

In addition, the number of established model's number of parameters has been reduced to [19] make it optimal for real-time inference. [19] The Intel Movidius Neural Compute Stick, which contains dedicated CNN hardware blocks, was used to deploy the [19] pre-trained deep CNN model onto the Raspberry Pi 3. The deep learning model reaches a precision of 88.46 percent when recognising corn leaf diseases, showing the method's viability. [19] The presented corn plant disease identification model is capable of running on standalone smart devices like raspberry-pi or smart-phone and drones.

IV. PROPOSED METHODOLOGY

The following stages of the proposed work are : First step is image acquisition, which involves collecting photographs of all aspects of the infected plant. The second step is image pre-processing, which includes image resizing so the files can be of any dimension. After that, all of the images are augmented by performing rotation, height and width shift, zooming, horizontal flipping. The dataset is then fed to the ResNet model.

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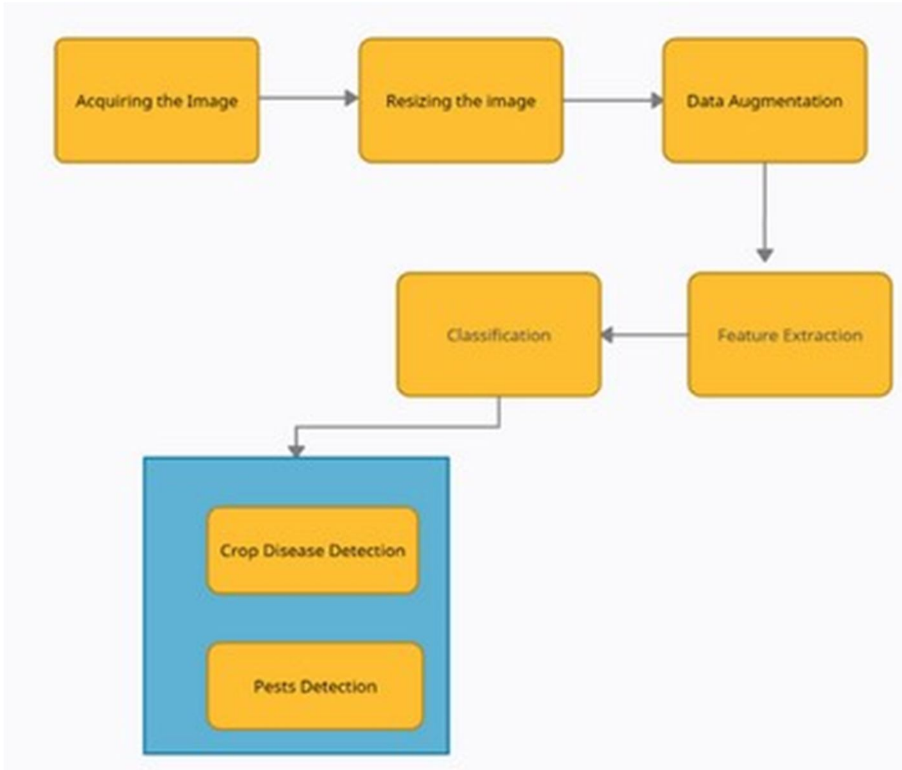

Fig. 1. Proposed Methodology

A. Image Acquisition

It is the process of acquiring images from a source. It is the first step in the proposed work because without image there is no processing. The obtained images are completely unprocessed. Data sets needed for the preparation, testing, and validation phases of the Convolutional Neural Network deep learning method are obtained. There are just a few images in the data sets of plant disease [6]. The PlantVillage dataset obtained contains over 15000 photographs of stable and diseased crop leaves, as well as 15 class marks dependent on disease forms per plant and the dataset is open-source.

B. Image Resizing

The scaling of images is referred to as image resizing. Scaling is useful in a variety of image recognition and machine learning applications. It aids in the reduction of the amount of pixels in an image, which has many benefits, for example. It will reduce the time it takes to train a neural network since the more pixels in an image there are, the more input nodes there are, which increases the complexity. It also aids in image zooming. To meet the size requirements, we often need to resize the file, either shrinking it or scaling it up.

C. Data Augmentation

The method of growing the volume and variety of data is known as data augmentation. We don't gather new data; instead, we convert existing data. Data augmentation is an important part of deep learning because it requires vast volumes of data, which can be difficult to obtain in some situations. In these cases, data augmentation comes to the rescue. It aids us in ing the dataset's scale and add variability into the dataset. some of the operations that can be done by image processing are as follows:

1) Rotation operation as the name implies, it rotates the image to specified degree. We have applied rotation of 25 degrees on the images.
2) Shearing is often used to adjust the image's orientation. we have used a shearing range of 0.2 in the project.
3) Zooming operation enables us to zoom in and zoom out on the image. We have used a zooming range of 0.2.
4) Flipping helps one to change the image's orientation. We have the choice of flipping horizontally or vertically. For data augmentation we have used Keras using function called ImageDataGenerator

D. Feature Extraction

A step in the dimensionality reduction process that separates and reduces a vast array of raw data into smaller units is feature extraction. As a result, processing will be a lot easier. The fact that these huge data sets have a vast number of variables is the most notable aspect.

A significant amount of computing power is needed to process these variables. Feature selection assists in the retrieval of the ideal feature from vast data sets by sorting and merging variables into features, thus reducing data volume. When it comes to When you have a huge data set and need to reduce the amount of resources without missing any significant or related information, the feature extraction technique comes in handy.

Feature extraction aids in the reduction of duplicate data in a data package. Finally, reducing the data allows the computer to create the model with less effort and improve the learning speed.

E. Classification and Algorithm

We used ResNet, also known as a residual neural network, for this research. ResNet is a Convolutional Neural Network (CNN) architecture with hundreds or thousands of convolutional layers. ResNet can add layers while retaining high performance, whereas previous architectures saw their utility diminish with each additional layer.

The “vanishing gradient” dilemma was solved by ResNet. Backpropagation is a method of training neural networks that uses gradient descent to find the best weights that minimise the loss function. When more layers are applied, the gradient becomes infinitesimally small due to constant multiplication of their derivatives, implying that adding more layers would not increase efficiency and will even degrade it. ResNet addresses this problem by using “identity shortcut connections,” layers that don’t do much at initial stage.

These equivalent layers are skipped during the training phase, with the activation functions from the previous layers being reused. This simplifies the network and speeds up learning by reducing it to just a few layers. When the network is retrained, the same layers extend, allowing the network to discover more of the functionality. There are two main types of blocks used in ResNet, depending mainly on whether the input and output dimensions are the same or different.

Identity Block: When the input and output activation dimensions are the same. Convolution Block: When the input and output activation dimensions are different from each other.

ResNets make it easier to train networks that are significantly deeper than before by removing the depletion problem. They also shown that ResNets are simpler to optimise and can achieve high precision at great depths. Deeper layers are unable to learn the identity function used to transport the result to the output. Instead of hoping that the layers match the desired mapping, we let them fit a residual mapping in residual networks. $H(x)$ is the optimal mapping at first (x). However, we allowed the networks to match the residual mapping $F(x) = H(x)-x$ because the residual mapping was simpler to optimise than the original mapping. Shortcut connections, also known as skip connections, are a way of bypassing data from one layer to another.

This method helps data to flow freely between layers without impairing the deep learning model’s ability to learn. The benefit of using this style of skip link is that any layer that degrades the model’s output will be skipped. The skip relation is based on the idea that it is better for the network to learn to transform the value of $f(x)$ to zero such that it acts like an identity function than it is for the network to learn to act like an identity function on its own by attempting to find the correct set of values that will give you the desired outcome. The conv block aids in the modification and reorganisation of incoming data so that the first layer’s output meets the dimensions of the third layer, allowing them to be added together. These components aid deep learning models in achieving higher optimization and accuracy.

Following the implementation of the work with one crop, the procedure can be repeated with additional crops, allowing any of the crop datasets from the PlantVillage dataset, as well as other field condition images, to be applied and evaluated on the same platform. Final result will predict the disease on the newly given image. The training size is 70 percent and testing size is 30 percent

V. RESULTS AND DISCUSSION

The model is trained over 7025 images of 3 crops pepper, potato, tomato . The model yeilds a training accuracy of 98 percent and validation accuracy of 94.1 percent for 20 epochs. We are still working on training the model further to reduce loss and misclassification of few crop diseases over other crop diseases. We have also made the confusion matrix to know how many crop diseases are classified and not classified properly. Given any new crop image, model predicts the disease of crop. We are currently working on training and improving the model for other crops.

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VI. CONCLUSION

In the agricultural domain, detecting crop disease and pests is a big problem. Since most farmers are unaware of all of the diseases and pests that harm their crops, how to identify

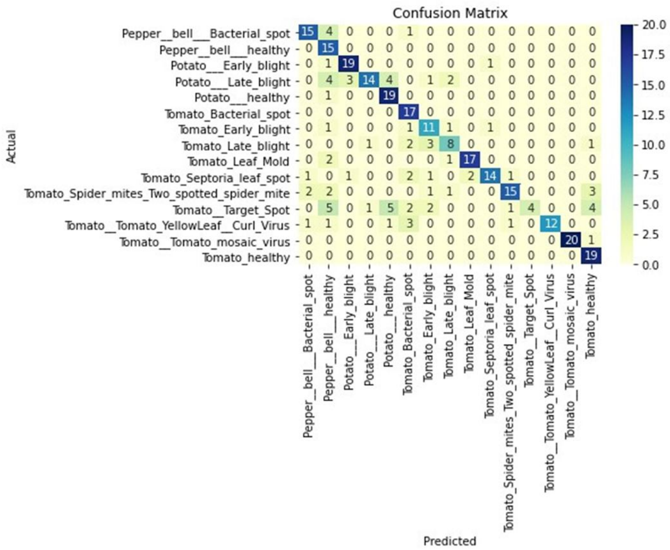

Fig. 2. Confusion Matrix for Predicted Vs Actual

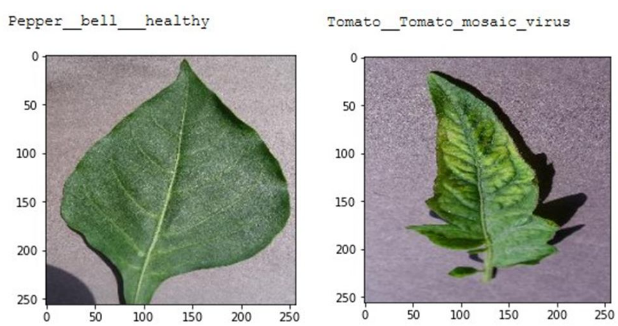

Fig. 3. The above results show the predicted diseases of tomato and pepper crops.

them, and what steps to take, automation aids them in their agricultural tasks. The aim of this research is to assist farmers in increasing agricultural production by detecting disease and pests. The approach is suggested for crop disease and pest detection using deep learning using the fine-tuning methodology for ResNet models. It analyses photos of all infected areas of the plant, including the upper and lower sides of the leaf, the stem, the root, and the fruit. This study can also be used to estimate the magnitude of a disease identified. Aim of the research reduce the crop diseases and pests that infecting the crop and increase crop production. We plan to use field images captured through camera and use the ResNet model to predict the crop diseases affecting the crop. Once the model identifies the diseases, appropriate advisory solution can be provided for that particular crop being affected.

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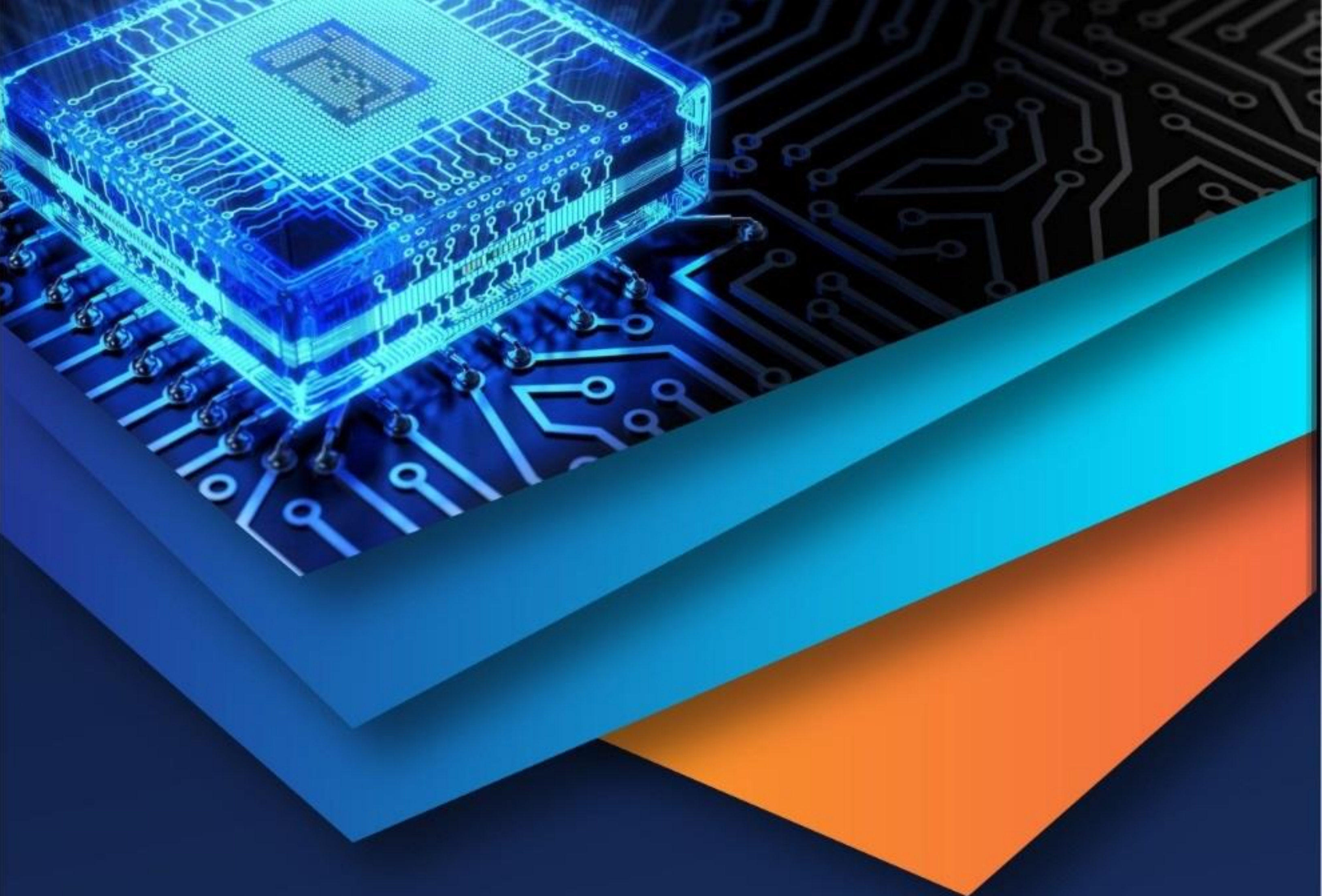

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