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Enhancing Crop Health Through Image Analysis of Leaf Diseases Prediction and Remedial Suggestion

Ravi Ray Chaudhari[1] , Dr. Sanjay Jain[2] , Dr. Shashikant Gupta[3]

[1]ITM University(Computer Science & Engineering), Gwalior(MP), India

[2]ITM University(Computer Science & Engineering), Gwalior(MP), India

[3]ITM University(Computer Science & Engineering), Gwalior(MP), India

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KEYWORDS

Deep Learning, CNN, Crop leaf disease, Smart Agriculture

ABSTRACT:

Introduction The spread of crop diseases has posed serious problems for the agricultural industry recently, as it can lead to significant yield losses and monetary difficulties for farmers. Early and accurate diagnosis is essential for the management and control of these diseases. This work introduces a deep learning method using convolutional neural networks (CNNs) for the detection and classification of various crop leaf illness. With the use of an extensive dataset that includes a range of leaf images impacted by distinct diseases, our CNN model is skilled in correctly identifying and categorizing illnesses. The suggested method offers a reliable, automated, and scalable crop disease monitoring solution, showcasing. The possibilities of deep learning methods in agricultural applications. According to experimental results, our model performs better than conventional image processing techniques, achieving high recall rates and precision for a variety of disease classes. This study highlights how incorporating artificial intelligence into agriculture can have a revolutionary effect and open the door to more intelligent and effective disease management techniques.

Future research could focus on expanding the dataset to include more crop types and rare diseases to improve model generalization. Additionally, the development of real-time, mobile-based applications that incorporate this technology could also be explored, enabling farmers to detect diseases on-site and take timely remedial suggestion to mitigate potential crop losses.

Objectives: To determine the plant disease's identify, this section of the study used cutting edge deep learning models with a transfer learning methodology. After pre-training the deep CNN networks with the ImageNet dataset, they were further trained using Plant Village, a publicly accessible dataset

Methods: CNN models perform well for object recognition and classification when used with image databases. CNNs have advantages, but they also have disadvantages, such as the requirement for large datasets and a protracted training period. The complex and low-level features in the images can only be extracted by deep CNN models, which complicates the model training process.

Results: To determine the plant disease's diagnosis, this section of the study used cutting edge deep learning models with a pretrain model. After pre-training the deep CNN networks with the ImageNet dataset, they were further trained using Plant Village, a publicly accessible dataset. Each model was set up for our experiment with 38 output classes, a 0.5 dropout rate, and a 0.01 learning rate. Three samples were extracted from the dataset: training, test, and validation. Eighty percent of the PlantVillage samples were utilized in order to train the Inception V4. The model was run for ten epochs for each crop, and it was discovered our model started to converge with high accuracy following ten epochs.

Conclusions: In this work, we were able to analyse the different crop diseases using the CNN model. The latest generation of convolutional neural networks were standardized and assessed using deep learning techniques based on F1 score, sensitivity, specificity, and classification accuracy from the Inception V4's performance analysis.

1. Introduction

An essential function of agriculture, the foundation of human civilization, is in the sustenance and economic stability of societies worldwide. Central to this agricultural productivity is the health of crop plants, which can be significantly compromised by various diseases affecting their leaves. The timely and precise identification of these illnesses is essential in mitigating losses, ensuring food security, and enhancing the efficiency of crop management practices.

Crop leaf diseases manifest through a range of symptoms such as discoloration, spots, blights, wilting, and deformities. These symptoms are often indicative of underlying issues caused by pathogens including fungi, bacteria, viruses, and pests. Traditionally, the identification and diagnosis of these diseases have relied heavily on expert knowledge and manual inspection, a process that is both laborious and prone to mistakes made by people.

Technological developments have opened the door for creative methods of illness detection in recent years. Leveraging machine learning and image processing, and artificial intelligence, modern techniques offer the potential for rapid, accurate, and automated detection of crop leaf diseases. These methods utilize various algorithms to analyze leaf images, identify patterns, and classify diseases with high precision, thus empowering farmers and agricultural professionals with actionable insights.

The integration of these advanced technologies into agricultural practices not only enhances the capability to monitor and manage crop health but also contributes to the sustainable use of resources. By detecting diseases early, farmers can adopt prompt and deliberate action, reducing the need for extensive chemical treatments and encouraging farming methods that are friendly to the environment.

This introduction highlights the crucial role that crop leaves disease detection plays in contemporary agriculture and lays the groundwork for a deeper examination of the techniques, advantages, and difficulties related to it.

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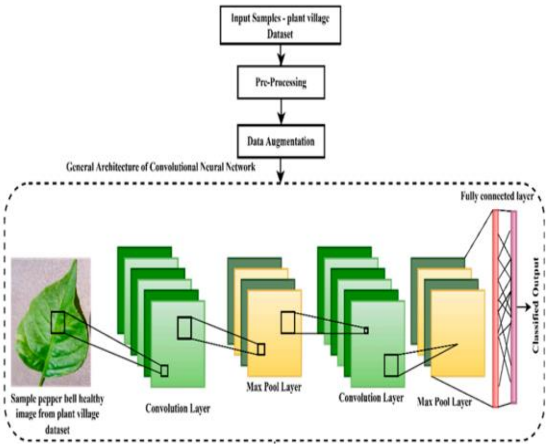

Figure1: Workflow diagram

2.Background Survey:

When it comes to agricultural output while disregarding plant disease's early warning signals could cause losses in food crops, which may ultimately collapse global economic conditions [30]. This segment provides a thorough summary of recent advancements Regarding the identification of leaf diseases:

A deep learning model based on CNN for precise plant classification was presented within [31]. The model underwent training on an 87,000 RGB image dataset that was made available to the public. First, preprocessing was done, and then division. CNN was utilized for classification. Even though the recognition accuracy was 93.5%, this model was unable to classify certain classes, which caused confusion with the classes in subsequent phases. In addition, the model's performance declined as a result of the scant data available. Nevertheless, Narayanan et al. [32] suggested in order to increase recognition accuracy classifying banana plant diseases utilizing a convolutional neural network hybrid. They applied a median filter to preserve the typical picture size while preprocessing the raw input image without modifying any of the pre-set parameters. This method combined a CNN and an SVM. In phase 1, the SVM was utilized to determine whether the banana leaves were diseased or not, a multiclass During the testing stage, SVM was utilized to determine the kind of disease or infection present in the contaminated banana leaflets. The support vector machine was fed the classified CNN output, which obtained a classification accuracy of 99%. Prior studies have shown that CNN yielded more accurate results than conventional techniques, but this strategy lacked variety.

Jadhav et al. [33] suggested using a CNN to diagnose plant diseases. This technique used previously trained CNN models to recognize soybean plant diseases. Pre-trained transfer learning methods like AlexNet and GoogleNet were used in the experiments produced better results, but the model's classification diversity was not as high. Rather than creating a model to classify different plant diseases, many of the models that are currently in use concentrate on identifying specific classes of plant diseases. This is mostly because there aren't enough databases with a wide range of various plant species for deep learning model training. It was Jadhav et al. [34] who initially present a new histogram transformation technique that produced synthetic image samples from the test set's poorer quality photos, improving the recognition accuracy of deep learning models. The objective of the goal of this project was to improve the dataset's photos of cassava leaf disease. by applying motion blurring, over-exposure, down sampling the resolution, and Gaussian blurring using a changed rendition of the neural network model MobileNetV2. To overcome the data scarcity that must be overcome during training by a data-hungry deep learning model, they produced artificial photos with altered color value distributions.

In accordance with Abbas and Olusola et al. [35] presented An adversarial network with conditional generation in their work to produce a collection of fake photos of the leaves of tomatoes. Thanks to the advancement regarding generative networks, real-time data collection and purchase that was formerly costly, time-consuming, and labor-intensive is now possible. utilizing a MobileNet CNN model that has been trained beforehand, A benchmark multi-leaf classification model based on datasets was presented by Anh et al. [36], who discovered that it performed well in classification, consistently achieving 96.58% accuracy. Furthermore, a multi-label CNN known as DenseNet, Inception, Xception, ResNet, In [20], VGG and MobileNet were proposed to classify different plant diseases using the application of transfer learning techniques. The authors claim that this is the first study to classify 28 distinct plant disease classes using a multi-label CNN. It was suggested in [37] to use the Ensemble Classifier for plant disease classification. Two datasets, Taiwan Tomato Leaves and Plant Village, were used to evaluate the best ensemble classifier.

Regarding the classification of multiple labels and classes, Pradeep et al. [21] proposed the EfficientNet model, which makes use of a neural network with convolution. The CNN's covert network had a greater influence on the identification of plant diseases. When benchmark datasets were used for validation, the model did not perform as well. An effective, resilient, Convolutional neural networks (CNNs) that are loss-fused were presented in [38] and attained a 98.93% classification accuracy using PlantVillage, a benchmark dataset that is accessible to the general public. When real-time images were used in different environmental settings, the model performed poorly even though this approach increased the classification accuracy. Afterwards, Enkvetchakul and Surinta [39] proposed a CNN network employing a transfer learning technique for two plant diseases. 2022; Agronomy 12, 2395 Out of 19 illnesses, 6. Plant diseases were classified using The pair of previously trained network models, NASMobileNet and MobileNetV2. The model based on the NASMobileNet algorithm produced the most accurate prediction results out of all of these. The data augmentation technique can be used to address overfitting in deep learning. Cut-out, rotation, zoom, shift, brightness, and mix-up were all included in the experimental setup that employed the data augmentation technique. The two types of datasets used were I Cassava 2019 and leaf disease datasets. The highest test accuracy attained after the evaluation was 84.51%.

The use of machine learning (ML) techniques in crop management is critically examined in Chaudhary R.R.[54] et al.'s article from 2024, with an emphasis on how these technologies can be used for precise and intelligent farming. The usefulness of different machine learning algorithms in optimizing agricultural practices, including crop prediction, disease detection, and yield estimation, is examined by the writers. They stress how machine learning (ML) can help make better decisions, which will increase farming's sustainability and productivity. In order to fully realize machine learning's potential in precision farming, further research and development are necessary, as the study also highlights when discussing the difficulties and potential paths for integrating ML into agriculture.

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Reference	Crop Name	Disease Name	Dataset	Classes	Model	Accuracy
[29]	Several	Citrus canker, black mould, bacterial blight, etc.	Plant disease symptoms database	56 diseases under 12 classe	CNN GoogLeNet with tenfold cross-validation	84%
[40]	Several	Black rot, late blight, early blight	Self-collected database	527 species of diseases under 5 classes	CNN	96.5%
[41]	Tomato plant	Various diseases and pests in tomato plant	Self-generated database	9	Faster Region-based CNN with SSD 1 and Region-based Fully Convolutional Network	Precision: 85.98
[42]	Several	Powdery mildew, early and late blights, cucumber mosaic, downy mildew, etc.	Open dataset	58	CNN with pre-trained VGG network	99.53%
[27]	Several	Black rot, late blight, early blight	PlantVillage	38	VGG-16, Inception V4, ResNet with 50, 101, and 152 layers, and DenseNet with 121 layers	99.75%
[43]	Several	Pepper bell bacterial spot, tomato early and late blight	PlantVillage	38	Pre-trained with ImageNet, GoogLeNet, and VGG-16 models	99.09%
[44]	Apple	Apple scab, apple grey spot, general and serious cedar apple rust, serious apple scab	AI-Challenger plant disease recognition	6	DenseNet-121	Accuracy: 93.71%
[45]	Tomato	ToMV, leaf mould fungus, powdery	AI-Challenger plant disease recognition	4	Faster regional CNN	Accuracy: 98.54

Table 1: displays the various models of convolutional neural networks that have been suggested to increase accuracy.

Data Description and Methodology

Data Description:

Plant Village is a publicly accessible dataset that contains several plant disease categories [17]. 13,969 photos in 17 classes make up this dataset. For our experimental analysis, we partitioned the dataset into samples used for testing, training, and validation. Among the Plant Village dataset, 80% was employed to instruct the pre-trained models, and the remaining 20% was used for testing and validation. Additionally, out of the 13969 samples that were available for the plant classes, 12,252 were utilized for testing (1523), validation (1368), and training. All 17 classes of various plant diseases are covered by the train, test, and validation sets. The details of the split dataset are shown in Table 2.

Plant Type	Diseases Classes	Total Samples	Training Samples	Test Samples	Validation Samples
Apple	Apple_scab	573	510	63	57
	Apple_black_rot	565	502	63	56
	Apple_cedar_apple_rust	250	222	28	25
	Apple_healthy	1497	1332	165	148
Cherry	Cherry_powdery_mildew	957	851	106	95
	Cherry_healthy	777	691	86	77
Corn	Corn_gray_leaf_spot	466	414	52	47
	Corn_common_rust	1084	964	120	108
	Corn_northern_leaf_blight	896	797	99	89
	Corn_healthy	1057	940	117	105
Grapes	Grape_black_rot	1073	955	118	107
	Grape_black_measles	1258	1119	139	125
	Grape_leaf_blight	979	871	108	97
	Grape_healthy	385	342	43	38
Potato	Potato_early_blight	1000	810	100	90
	Potato_healthy	1000	810	100	90
	Potato_late_blight	152	122	16	14

Table 2: Split Dataset

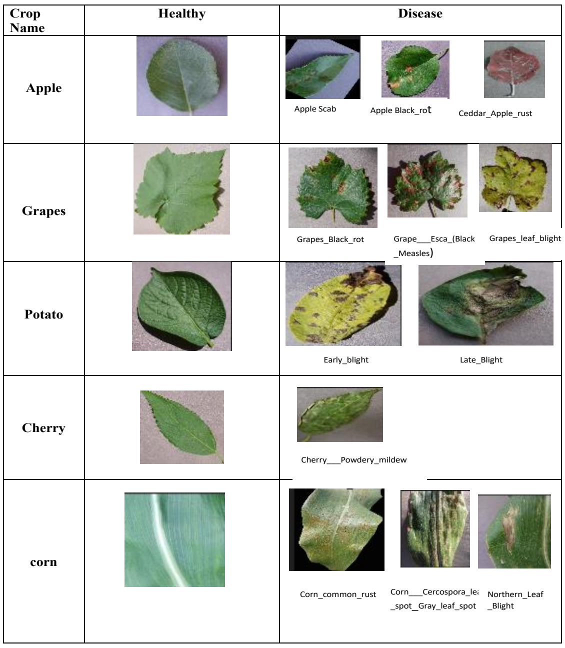

Table 3: Representation of the dataset

4.Preprocessing and Data Augmentation

There were 17 classes in the dataset, 12 diseases, and 5 crop species. We utilized the

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PlantVillage dataset's color photos for our experiment because they worked well with the deep learning models. Given that we employed a variety of pre-trained network models with varying input size requirements, the images were standardized to 256 × 256 pixels. Images in the format 299 × 299 × 3 (height, width, and channel width) are the input shape for Inception V4. Despite the size of the dataset—roughly 13,969 photos of various crop diseases—the photos are consistent with actual photos taken by farmers with various image acquisition methods, including High-definition cameras, Kinect sensors, and smartphones. Moreover, with this magnitude of a dataset overfitting is a common issue. In order to address Consequently, overfitting regularization methods were developed, for example, adding data after preprocessing. Augmentation techniques using the preprocessed images included rescaling, rotating the images clockwise and counterclockwise, flipping the images horizontally and vertically, and enlarging the zoom. Because the images were augmented during the training phase rather than duplicated, The enhanced photos were printed in hard copy form only used temporarily in the process. When real-world plant disease photos are classified using this model, the classification accuracy is higher because the The augmentation technique prevents both overfitting and model loss in addition to makes it more robust.

5.Methodology:

CNN models perform well for object recognition and classification when used with image databases. CNNs have advantages, but they also have disadvantages, such as the requirement for large datasets and a protracted training period. The complex and low-level features in the images can only be extracted by deep CNN models, which complicates the model training process.

Multi-class classification

Differential Classification datasets on plant diseases contain several pictures of both diseased and robust plant specimens, every of which corresponds to a specific class. If we think about bananas plants as a whole, for instance, Every image of a sample of plants, both healthy and sick, will be mapped to the same class. Currently The intended recipient is classified using only the characteristics that were taken out of the original picture. The four disease groups that make up the banana class, to use the banana plant as an example, are Fusarium wilt, black sigatoka, bunchy top virus, and xanthomonas wilt [32] When an input After training with all four sets of disease samples under the banana class, a sample of a specific disease is fetched.

The results of the testing phase will identify which of the four categories mapped under that specific class corresponds to the specific disease label. In multi-label classification, each category within a class is regarded as a separate class, but in multi-class classification, classes are mutually exclusive. When N classes are present, N multi-classes are referred to, when M categories are present in N classes, then each category in N classes are regarded as distinct classes.

6. Inception V4

Pictures can range in size and are packed with important details and features. It is difficult to select the ideal filter size for feature extraction because of these size variations. A larger For extracting global information, a larger the ideal kernel size is utilized, and for extracting smaller kernel size and local information.

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Convolution layer stacking may lead to issues with vanishing gradients and overfitting. In order to tackle because of this, each block in the Inception modules has a different kernel size, leading to an expansion rather than a contraction of the network model [52]. For example, after three stages of convolution, the naïve Inception module can use 3 × 3, 1 × 1, or 5 × 5 sizes for the filter.

The outcome is concatenated and sent to after max-pooling the following layer. The Inception layer's stem is used to configure a preliminary set of tasks that must be completed before the Inception module.

7. Result and Evaluation:

To determine the plant disease's diagnosis, this section of the study used cutting edge deep learning models with a transfer learning methodology. After pre-training the deep CNN networks with the ImageNet dataset, they were further trained using Plant Village, a publicly accessible dataset. Each model was set up for our experiment with 38 output classes, a 0.5 dropout rate, and a 0.01 learning rate. Three samples were extracted from the dataset: training, test, and validation. Eighty percent of the PlantVillage samples were utilized in order to train the Inception V4. The model was run for ten epochs for each crop, and it was discovered our model started to converge with high accuracy following ten epochs.

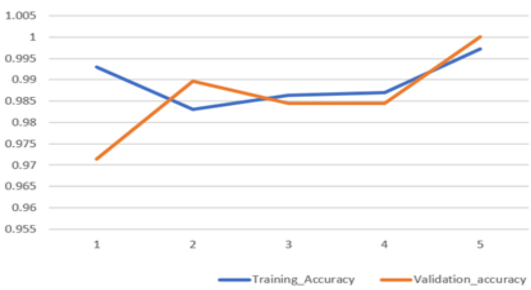

Figure 2a: Accuracy of Grape Training and Validation

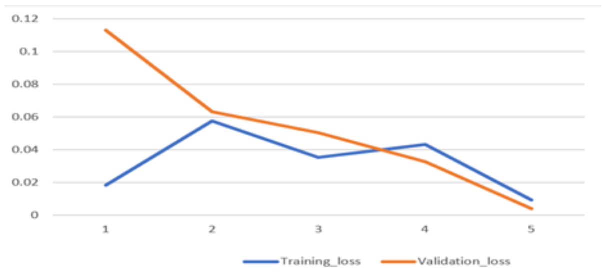

Figure 2b: loss of Grape Training and Validation

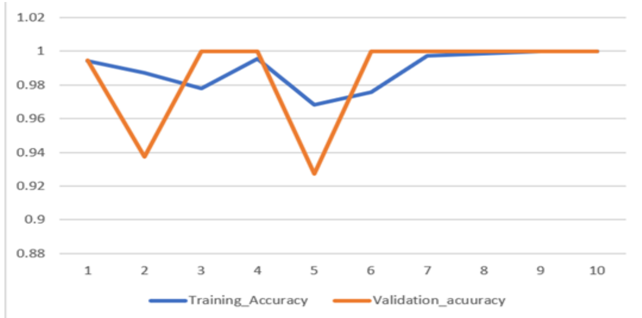

Figure 3a: Accuracy of Potato Training and Validation

Figure 3b: loss of Potato Training and Validation

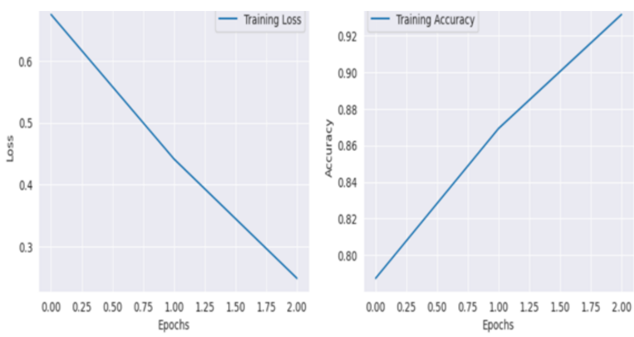

Figure 4: shows the loss and accuracy with Epocs Apple

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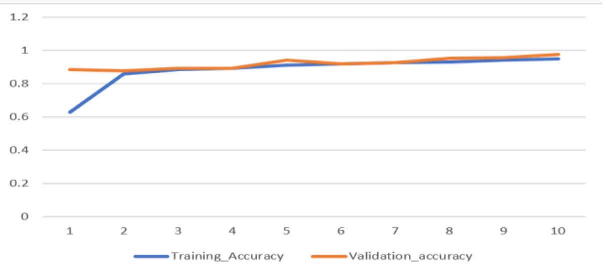


Figure 5a: Accuracy of Corn Training and Validation

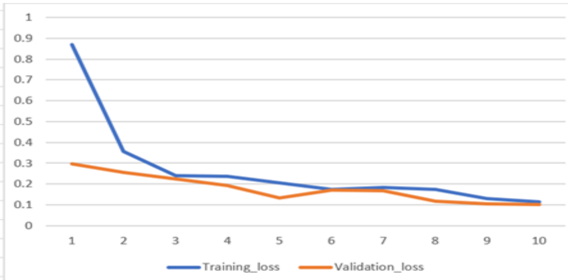


Figure 5b: loss of Corn Training and Validation

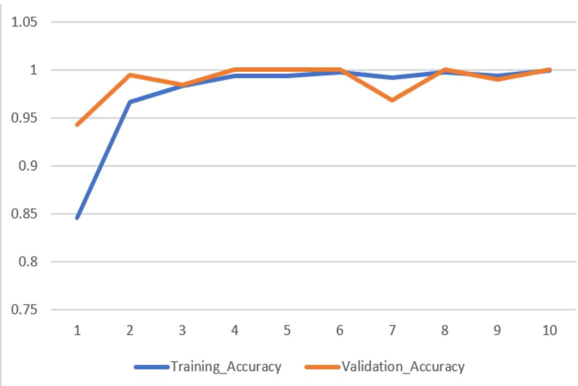


Figure 6a: Accuracy of Cherry Training and Validation

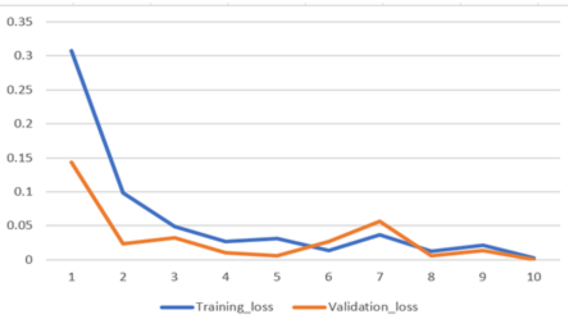


Figure 6b: loss of Cherry Training and Validation

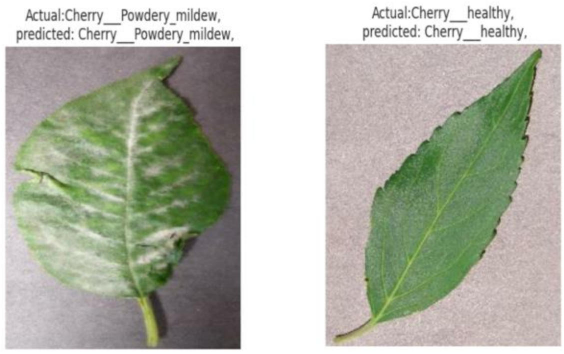
8.Testing:

In this section, we examine various crop diseases using images and test them using a Deep Learning model (CNN). Figure 7 shows the testing of various corn leaves using a CNN model to predict various diseases. Figure 7(a) shows the prediction of common rust disease, Figure 7(b) shows the prediction of a healthy image, and Figure 7(c) shows the prediction of corn Cercospora leaf spot gray.

7(a) 7(b) 7(c)

Figure 7: Corn disease Predict

Figure 8 shows the testing of various cherry leaves using a CNN model to predict various diseases. Figure 8(a) shows the prediction of cherry_Powdery_mildew disease, Figure 8(b) shows the prediction of a healthy image.



8 (a) 8(b)

Figure 8: Cherry leaves disease predict

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Figure 9 shows the testing of various Potato leaves using a CNN model to predict various diseases. Figure 9(a) shows the prediction of Potato_late_blight disease, Figure 9(b) shows the prediction of a healthy image, and Figure 9c shows the prediction of Potato_Early_blight disease.

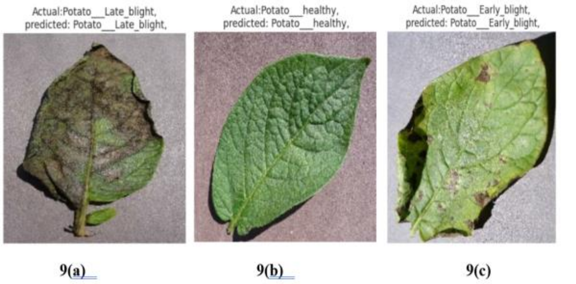

Figure 9: Potato leaves disease Predict

Figure 10 shows the testing of various Grapes leaves using a CNN model to predict various diseases. Figure 10(a) shows the prediction of Grape leaves is healthy, Figure 10(b) shows the prediction of a Grape_Leaf_blight disease, Figure 10(c) shows the prediction of Grape_Black_rot disease, and Figure 10(d) Prediction of Grape_Esca_(Black_Measles).

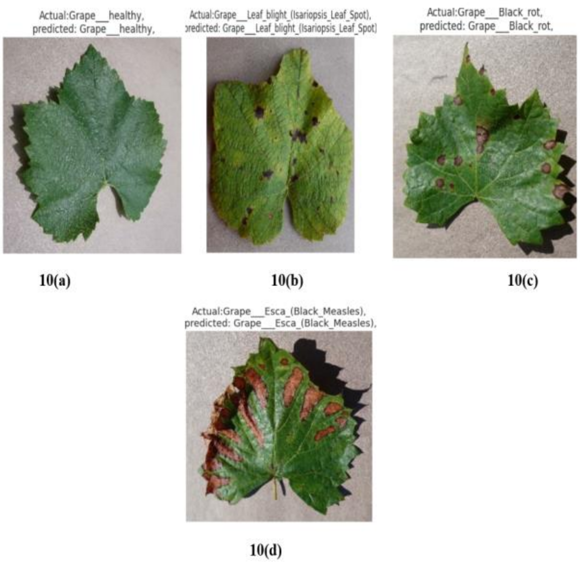

Figure 10: Grapes Leaves Disease Predict

Figure 11 shows the testing of various Apple leaves using a CNN model to predict various diseases. Such as it shows the Apple_black_rot disease.

Figure 11: Apple Leaves Disease Predict

9. Remedial Solution:

In this article mentioned remedial solution according to type of Plant Disease here showing the result of apple leaves disease predict in Figure 11 and provide the remedial solution

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Remedial Solution:  Black Rot: Apply copper-based fungicides and remove infected branches.
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Figure 12: Remedial solution for Apple Leaves Disease

10. Conclusion:

In this work, we were able to analyse the different crop diseases using the CNN model. The latest generation of convolutional neural networks were standardized and assessed using deep learning techniques based on F1 score, sensitivity, specificity, and classification accuracy from the Inception V4's performance analysis. When A novel plant illness must be added to the prototype, the CNN model is therefore more appropriate for plant disease identification because it requires less training complexity. The proposed model performed

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well, with a 99.81% classification accuracy and a 99.8% F1 score.

In the next study, We'll talk about the difficulties in real-time data gathering and create a deep learning model with multiple objects that can even recognize plant illnesses originating from several leaves as opposed to just one. We also intend to implement a mobile program using the model that was trained using this work. It will be beneficial in real time identification of leaf diseases by farmers and provide the remedial suggestion according to type of disease.

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