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Identifying Disease in Crops Using Image Analysis and Convolutional Neural Networks

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Abstract: Crop diseases represent a substantial threat to agricultural productivity and food security, underscoring the importance of early detection for effective intervention. Traditional methods for disease identification predominantly rely on visual inspection, which can be labor-intensive, time-consuming, and susceptible to inaccuracies. To mitigate these challenges, automated systems utilizing image processing techniques and Convolutional Neural Networks (CNNs) have emerged as viable alternatives. This study introduces a CNN-based methodology for the precise and efficient detection of crop diseases. It encompasses preliminary image processing steps, including enhancement, segmentation, and feature extraction, aimed at improving image quality and isolating pertinent areas. The processed images are subsequently input into a CNN model that learns multi-dimensional visual features and categorizes them into distinct disease groups. The resultant model exhibits high accuracy in identifying and classifying various crop diseases, thereby providing a valuable resource for timely and effective disease management in agriculture and give a precise result.

Keywords: *Disease Detection, Convolutional Neural Network, Image-Processing.*

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I. INTRODUCTION

Crops play a vital role in sustaining life in the environment and providing nutrients to species at all levels of the food chain. They also possess medicinal properties that benefit human health. Activities like gardening and spending time in nature promote mental and physical well-being, making them essential for the planet and its inhabitants [16, 17]. However, crop diseases pose a significant threat to agricultural productivity, leading to substantial economic losses and food insecurity. According to the Food and Agriculture Organization, plant diseases account for about 20-40% of global crop losses annually [5]. Early detection and management of these diseases are crucial to minimizing their impact and ensuring sustainable agricultural practices. Traditional methods of disease detection, such as visual inspection by farmers or laboratory testing, are often time-consuming, labor-intensive, and prone to human error. Recent advancements in image processing and machine learning, particularly Convolutional Neural Networks (CNNs), have transformed the field of crop disease detection, offering automated, accurate, and scalable solutions.

The combination of image processing and deep learning methods has created new possibilities for precision agriculture. Image processing allows for the extraction of significant features from images of plants, including color, texture, and shape, which can indicate symptoms of disease. These features can be analysed using machine learning algorithms to determine the health status of crops. Among the various machine learning techniques, convolutional neural networks (CNNs) have proven to be an effective tool for detecting diseases through images because they can automatically learn layered features from raw pixel data. In contrast to traditional machine learning approaches that need manual feature extraction, CNNs are capable of directly processing images, making them particularly suitable for tasks that involve complex visual patterns.

The use of CNNs for identifying crop diseases has been extensively studied in recent research. For example,6] illustrated the potency of CNN in diagnosing diseases in and potato plants with substantial collection of plant images. Their model reached an accuracy exceeding 99%, which emphasizes the promise of deep learning in agricultural settings. In a similar vein, [7] created a CNN-based solution for spotting diseases in apple leaves, achieving notable precision and recall rates. These investigations highlight the proficiency of CNNs in managing varied datasets and their ability to generalize effectively in practical situations.

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One significant benefit of employing CNNs for identifying crop diseases is their capability to analyse high-dimensional data, multispectral or hyperspectral images, which gather information across various wavelengths. This characteristic enables the detection of minor disease symptoms that may not be apparent to the human eye. For instance, research [8] demonstrated the use of hyperspectral imaging in conjunction with CNNs to identify fungal infections in soybean plants, attaining better results than conventional approaches. The combination of sophisticated imaging techniques with deep learning models has further improved the precision and reliability of disease detection systems.

Despite encouraging outcomes, several obstacles persist in the broad implementation of CNN-based systems for detecting crop diseases. significant issue is the requirement for extensive labelled datasets to effectively deep learning models. The process of gathering and annotating these datasets can be demanding in terms of resources, especially for uncommon diseases or crops located in isolated regions. Moreover, variations in lighting, camera perspectives, and growth stages of plants can influence the efficacy of image-based models. To tackle these challenges, researchers have investigated methods such as data enhancement, transfer learning, and generative adversarial networks (GANs) to boost model performance and lessen the need for large datasets.

Another critical aspect of crop disease detection is the development of user-friendly tools that can be easily adopted by farmers and agricultural professionals. Mobile applications and cloud-based platforms have been proposed as practical solutions for deploying CNN models in the field. For example, [9] developed a mobile app that uses CNNs to diagnose diseases in cassava plants, enabling farmers to receive real-time recommendations for disease management. These tools not only make advanced technologies more accessible but also equip farmers to make well-informed choices, leading to better crop yields and minimized losses.

The capabilities of CNNs for detecting crop diseases are not limited to individual plants but extend to extensive agricultural systems. Drones fitted with high-resolution cameras and CNNs can oversee entire fields, offering early alerts of disease outbreaks and allowing for targeted interventions. Known as precision agriculture, this method utilizes data-driven insights to enhance resource efficiency and lessen environmental impact. For example, [10] showcased the effectiveness of drone-based imaging and CNNs in identifying wheat diseases, achieving high accuracy and efficiency in monitoring on a large scale.

In summary, integrating image processing and CNNs has revolutionized crop disease detection, providing a potent and scalable solution to one of agriculture's most significant challenges. By automating the detection process and offering real-time insights, these technologies have the potential to greatly improve agricultural productivity and sustainability. Nevertheless, further research is required to overcome challenges related to data availability, model robustness, and practical implementation. As deep learning and imaging technologies continue to advance, CNN-based crop disease detection systems are set to play a critical role in the future of agriculture.

Currently, automatic object localization and image classification are major research areas. Our national economy relies heavily on agricultural productivity, and any negligence in this field can have severe repercussions on crops, directly affecting our nation. Since experts and farmers are not always available to monitor crop growth, developing an automated system for real-time disease detection would be highly effective in reducing both time and costs for farmers.

Before delving into the core model development, it's important to understand the fundamental concepts of neural networks, optimization, loss functions, and model metrics discussed in this paper. Detailed explanations of these basics can be found in the sections on Artificial Neural Networks and Convolutional Neural Networks.

II. LITERATURE SURVEY

Image processing has long been utilized as a key step in crop disease detection systems. It involves extracting important features from plant images, such as color, texture, and shape, which indicate disease symptoms. Early research focused on traditional techniques like thresholding, edge detection, and morphological operations to isolate diseased areas in plant images. For instance, Al-Hiary et al. (2011) developed a system using color and texture features to detect and classify plant diseases, achieving high accuracy in identifying diseases in tomato and grape leaves, thus showing the potential of image processing for automated disease detection. However, traditional methods often depend on handcrafted features, which might not generalize well to diverse datasets or complex disease patterns. To overcome this, researchers have explored machine learning algorithms like Support Vector Machines (SVM) and Random Forests for classifying diseases based on extracted features. Mohanty et al. (2016) created a system to detect diseases in pomegranate plants using color and texture features combined with an SVM classifier. Although these methods showed promise, their performance was constrained by the quality of handcrafted features and the complexity of disease symptoms.

The emergence of deep learning, especially CNNs, has transformed crop disease detection. CNNs can automatically learn hierarchical features from raw pixel data, eliminating the need for manual feature extraction, making them highly effective for tasks involving complex visual patterns like disease detection in plant images. Mohanty et al. (2016) were among the first to show the effectiveness of CNNs in classifying diseases in tomato and potato plants. Their model, trained on a large dataset of plant images, achieved over 99% accuracy, highlighting the potential of deep learning in agriculture. Since then, many studies have explored CNNs for crop disease detection across various crops and diseases. Sladojevic et al. (2016) developed a CNN-based system for detecting diseases in apple leaves, achieving high precision

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and recall rates. Similarly, Ferentinos (2018) proposed a deep learning model to identify diseases in 58 different plant species, showing CNNs' versatility in handling diverse datasets. These studies highlight the capability of CNNs to generalize well to real-world scenarios and achieve state-of-the-art performance in disease detection tasks.

Researchers have also explored advanced techniques to further enhance CNN-based disease detection systems. Techniques like transfer learning, data augmentation, and hybrid models have been widely adopted. Transfer learning, which involves fine-tuning pre-trained CNN models on specific datasets, addresses the challenge of limited annotated data. For example, Too et al. (2019) compared the performance of several pre-trained CNN models, including VGG, ResNet, and Inception, for crop disease classification, showing that transfer learning significantly improved detection accuracy, especially for small datasets. Data augmentation, involving synthetic training data generation through transformations like rotation, scaling, and flipping, has also improved model robustness. Zhang et al. (2019) demonstrated data augmentation's effectiveness in enhancing a CNN-based system's performance for detecting wheat diseases. Additionally, hybrid models combining CNNs with other machine learning techniques like SVM or Random Forests have been proposed to leverage both approaches' strengths. For instance, Liu et al. (2020) developed a hybrid model using CNNs for feature extraction and SVM for classification, achieving superior performance compared to standalone models.

Despite significant advancements in CNN-based crop disease detection, challenges remain. A major challenge is the need for large, annotated datasets to effectively train deep learning models. Collecting and labelling such datasets can be resource-intensive, especially for rare diseases or crops grown in remote areas. To address this, researchers have explored techniques like semi-supervised learning, active learning, and generative adversarial networks (GANs) to reduce dependency on large annotated datasets. Another challenge is the variability in lighting conditions, camera angles, and plant growth stages, which can affect image-based models' performance. Future research should focus on developing robust models that can handle these variations and generalize well to real-world scenarios. Additionally, integrating advanced imaging techniques like hyperspectral and thermal imaging with deep learning models holds great promise for improving disease detection systems' accuracy and robustness.

The integration of image processing and CNN networks has transformed the scope of crop disease detection, offering a powerful and scalable solution to one of agriculture's most pressing challenges. By automating the detection process and providing real-time insights, these technologies have the potential to significantly enhance agricultural productivity and sustainability. However, further research is needed to address the challenges associated with data availability, model robustness, and practical implementation. With continued advancements in deep learning and imaging technologies, CNN-based crop disease detection systems are set to significantly influence the future of agriculture.

- *Dataset Used*

The data utilized in this paper originates from the widely-known Kaggle Plant Village. Specifically, only images of potato plants were used. For the image classification model, 2,101 training images and 311 test images were employed. To address overfitting and enhance the model's accuracy, an augmentation technique was applied.

Fig 1 Potato Plant Dataset

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III. METHODOLOGY USED

➢ *To Analyse the Dataset, Three Distinct Approaches were Undertaken:*

- Detection of plant diseases using an image classification model.
- Detection of plant diseases using real-time object detection models (YOLO, SSD, Faster R-CNN).
- Quantification of plant disease severity through the OpenCV image processing technique.

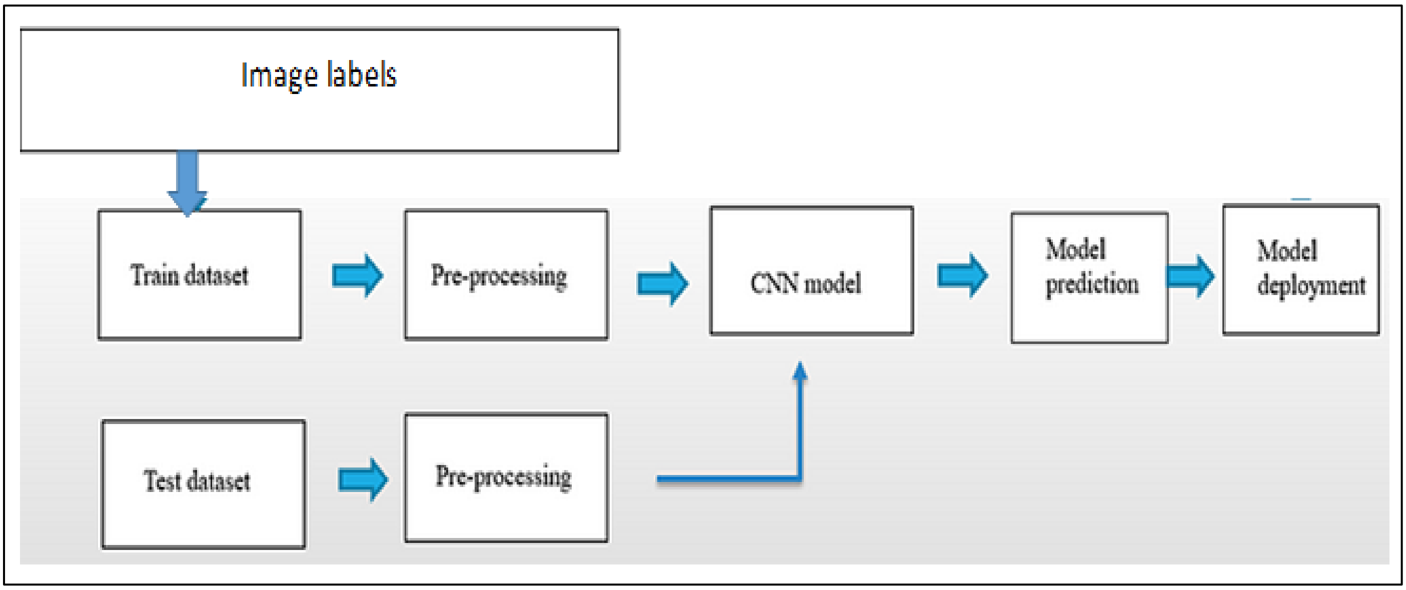

Fig 2 CNN Model Deployment

➢ *Classification and Object Detection*

Both classification and object detection utilize convolutional neural networks (CNNs) for their tasks.

- **Classification** involves categorizing images into classes without detecting specific objects. Examples include classifying digits or distinguishing between cats and dogs. Techniques used for classification include CNN models and SVM classifiers.
- **Object Detection** entails identifying the location of objects within an image and classifying those objects. The input for object detection models consists of images with annotation files (bounding box coordinates and class labels). The output is images with objects enclosed in rectangular boxes, accompanied by class labels and confidence scores. Examples of object detection tasks include plant disease detection, fruit counting, and face detection, employing models such as R-CNN, YOLO, and SSD.

➢ *Tools Used.*

- Jupyter notebook
- Keras (Python Library)
- Google colab

➢ *Image Classification using CNN*

Here, we imported all necessary python libraries which will be required in developing the project. Numpy library is imported to perform numerical operations in image. Keras library to build the model. Sklearn library is used to calculate confusion matrix and other evaluation metrics.

```
import os
import glob
import matplotlib.pyplot as plt
import keras
from keras.models import Sequential
from keras.layers import Dense,Dropout,Flatten
from keras.layers import Conv2D,MaxPooling2D,Activation,AveragePooling2D,BatchNormalization
from keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import classification_report, confusion_matrix
```

Fig 3 Image Classification

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➢ *Load Dataset*

```
there are 982 num of images of classPotato___Early_blight
there are 140 num of images of classPotato___healthy
there are 979 num of images of classPotato___Late_blight
total images 2101
there are 148 num of images of classPotato___1Early_blight
there are 133 num of images of classPotato___2Late_blight
there are 30 num of images of classPotato___3 healthy
total images 311
```

Fig 4 Load Dataset of Potato Images

➢ *Data Pre-processing*

Image pre-processing using image data generators is done and is also as important as training the model because without proper pre-processing the model may learn the input incorrectly. This can lead to improper results. Therefore, to achieve correct and accurate outcomes, pre-processing is necessary.

```
train_datagen=ImageDataGenerator(rescale=1./255,
                                 shear_range=0.2,
                                 zoom_range=0.2,
                                 horizontal_flip=True)
test_datagen=ImageDataGenerator(rescale=1./255)

img_width,img_height =256,256
input_shape=(img_width,img_height,3)
batch_size =16
train_generator =train_datagen.flow_from_directory(train_dir,target_size=(img_width,img_height), batch_size=batch_size)
valid_generator =test_datagen.flow_from_directory(valid_dir,target_size=(img_width,img_height), batch_size=batch_size)

test_generator=test_datagen.flow_from_directory(test_dir,shuffle=True,target_size=(img_width,img_height),batch_size=batch_si
```

Fig 5 Image Data Pre- processing

➢ *Model Building*

In this phase, the model is constructed and its layers are defined. The final model consists of a combination of convolutional, pooling, and fully connected layers. Specifically, this model includes 3 convolutional layers, 2 average pooling layers, 1 max pooling layer, 2 fully connected neural network layers, and a final output softmax layer.

```
model = Sequential()
model.add(Conv2D(32, (5, 5),input_shape=input_shape,activation='relu'))
model.add(AveragePooling2D(pool_size=(3, 3)))
model.add(Conv2D(32, (3, 3),activation='relu'))
model.add(AveragePooling2D(pool_size=(2, 2)))
model.add(Conv2D(32, (3, 3),activation='relu'))
model.add(AveragePooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(512,activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(128,activation='relu'))
model.add(Dense(num_classes,activation='softmax'))
model.summary()
```

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Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 252, 252, 32)	2432
average_pooling2d_1 (Average	(None, 84, 84, 32)	0
conv2d_2 (Conv2D)	(None, 82, 82, 32)	9248
average_pooling2d_2 (Average	(None, 41, 41, 32)	0
conv2d_3 (Conv2D)	(None, 39, 39, 32)	9248
max_pooling2d_1 (MaxPooling2	(None, 19, 19, 32)	0
flatten_1 (Flatten)	(None, 11552)	0
dense_1 (Dense)	(None, 512)	5915136
dropout_1 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 128)	65664
dense_3 (Dense)	(None, 3)	387

Total params: 6,002,115
Trainable params: 6,002,115
Non-trainable params: 0

Fig 6 Model Building

➢ *Training the Model*

The model is trained in a jupyter notebook. The model is compiled as a one using "model.fit.generator". The model starts to build after this statement which takes some time to completely train and build. The parameters used for training are learning rate=0.001, batch =16, optimizer=adam , loss= cross entropy, epochs=15

```
validation_generator = train_datagen.flow_from_directory(
                        valid_dir,
                        target_size=(img_height, img_width),
                        batch_size=batch_size)
opt=tf.keras.optimizers.Adam(lr=0.001)

model.compile(optimizer=opt,loss='categorical_crossentropy',metrics=['accuracy'])
train=model.fit_generator(train_generator,epochs=15,steps_per_epoch=train_generator.samples//batch_size,validation_data=vali

Found 311 images belonging to 3 classes.
Epoch 1/15
120/120 [==============================] - 63s 509ms/step - loss: 0.8273 - accuracy: 0.5699 - val_loss: 0.4171 - val_accuracy:
0.8522
Epoch 2/15
120/120 [==============================] - 62s 517ms/step - loss: 0.4190 - accuracy: 0.8264 - val_loss: 0.3609 - val_accuracy:
0.8713
Epoch 3/15
120/120 [==============================] - 61s 508ms/step - loss: 0.3183 - accuracy: 0.8959 - val_loss: 0.3177 - val_accuracy:
0.8748
Epoch 4/15
120/120 [==============================] - 62s 514ms/step - loss: 0.2466 - accuracy: 0.9001 - val_loss: 0.1711 - val_accuracy:
0.9357
Epoch 5/15
120/120 [==============================] - 62s 513ms/step - loss: 0.2012 - accuracy: 0.9241 - val_loss: 0.1179 - val_accuracy:
0.9670
Epoch 6/15
120/120 [==============================] - 61s 512ms/step - loss: 0.1833 - accuracy: 0.9297 - val_loss: 0.2755 - val_accuracy:
0.8957
```

Fig 7 Model Training

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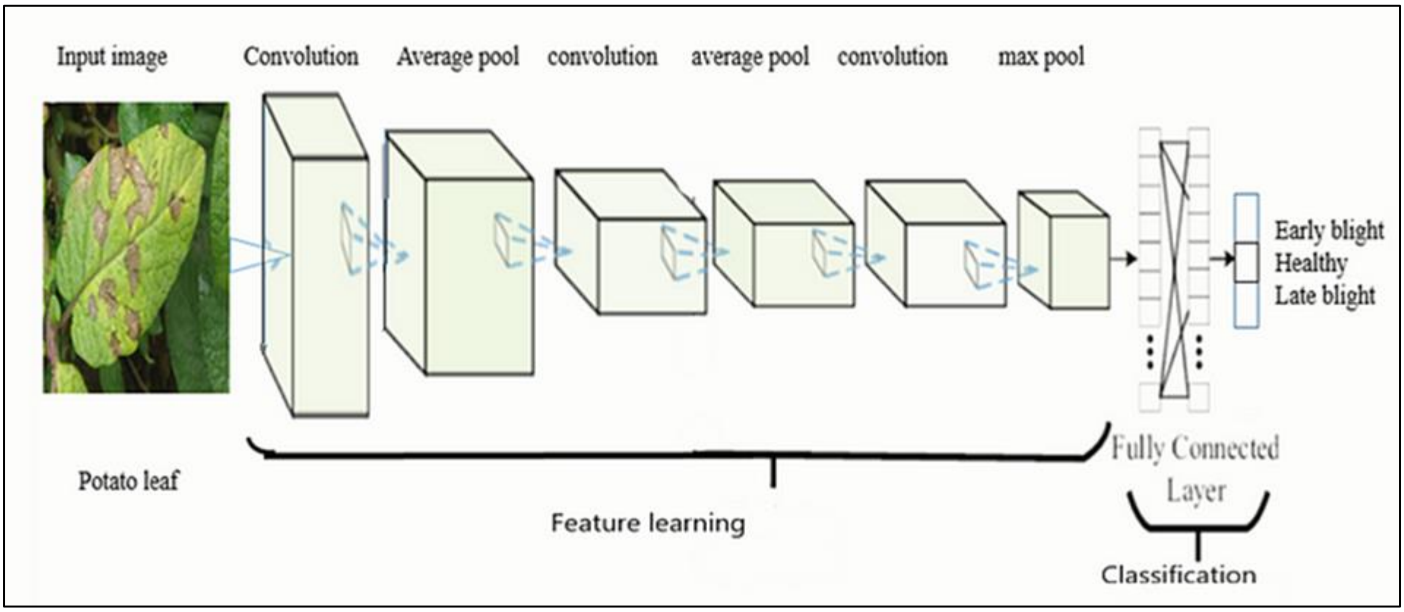

Fig 8 CNN architecture for classification model

IV. RESULTS AND DISCUSSION

The classification accuracy is determined by testing the developed CNN model with an unseen dataset. The model undergoes training for 15 epochs.

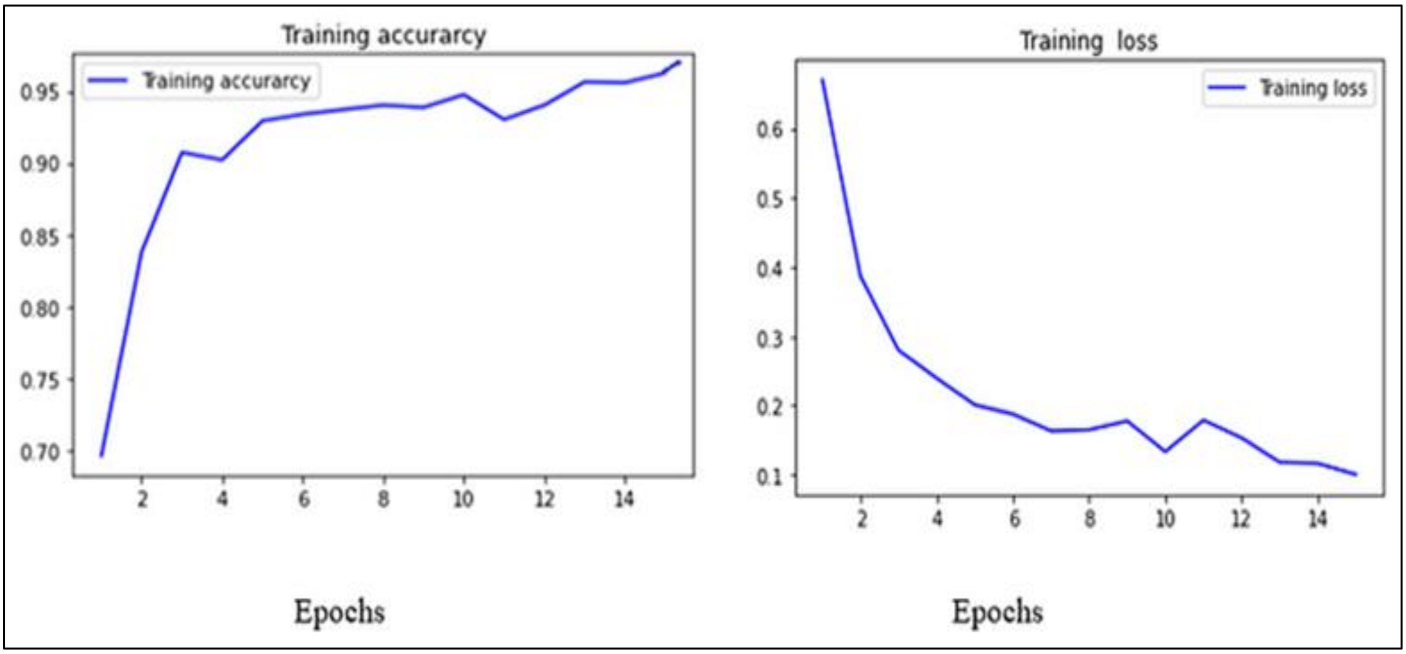

Fig 9 Training Accuracy and Training Loss

The above figure shows that training accuracy improves with more epochs. During training, it was noted that beyond 13 epochs, the model's validation accuracy stayed almost constant. Further training led to overfitting. Consequently, training was halted at 15 epochs. The model achieved training, validation, and test accuracies of 97.4%, 96.9%, and 97.1%, respectively.

Table 1 Confusion Matrix of the Model

	Potato early blight	Potato late blight	Potato healthy
Potato early blight	144	4	0
Potato late blight	0	129	4
Potato healthy	0	1	29

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Table 2 Precision, recall and F1 Score of the model for 3 Different Classes

	Precision	Recall	F1-score
Potato early blight	1.00	0.97	0.98
Potato late blight	0.96	0.97	0.96
Potato healthy	0.89	0.97	0.92

The performance of the classification model is illustrated in the table above. When tested with a dataset of 311 images, the trained model achieved 100% accuracy in predicting healthy images. However, 4 images, specifically those of late blight and early blight, were misclassified. The highest precision was observed for the early blight class.

V. CONCLUSION

So by using above method we can achieve our model for disease detection using image processing and CNN network. It shows a high level of effectiveness in plant disease classification. Its ability to accurately identify healthy images and Its high overall accuracy makes it a promising tool for automated disease detection. While minor misclassifications occurred between early and late blight, further refinement of the model, such as increasing the dataset size or employing more sophisticated feature extraction techniques, could further improve its performance.

In essence, this research has successfully developed and validated a CNN model capable of reliable plant disease classification, with potential applications in agriculture and plant health monitoring.

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