Identification of Anthracnose in Chillies using Deep Learning on Embedded Platforms

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***Abstract*—Chilli is among the most commonly used spices globally and is an integral part of many cuisines. Many countries like Mexico, India, China, and Korea are known for growing and consuming chillies. Amongst all, India is the largest producer of chillies worldwide. When cultivated on a large scale, these crops are highly susceptible to fungal, pests, weeds, bacterial, viral and pathogen attacks that substantially hinder production. Among these plant attacks, the most common is Chilli anthracnose, caused by the Colletotrichum fungus, which affects the leaves and the fruit of the chilli plant, causing a devastating loss to the farmers. Our paper proposes a solution based on Deep Neural Network (DNN) using transfer learning to classify disease-affected Anthracnose chillies from Healthy chillies. This study has developed a dataset by collecting the chilli samples from the University of Agricultural Sciences, Dharwad and chilli farms in Kusugal, outskirts of Hubli. The dataset consists of 4 classes with two types of chilli; red and green. Each coloured chilli has two stages; the healthy stage and the Anthracnose diseased stage. Here, different pre-trained DNN architectures and transfer learning methods are used to train the model on our dataset. Finally, the results are compared based on accuracy and model size for all architectures trained on the proposed dataset. And choose the architecture with the smallest model size and high accuracy for embedding in an edge device.**

***Index Terms*—Anthracnose, Artificial Intelligence, Machine Learning, Deep Learning, Classification, Convolutional Neural Networks(CNN) models, MobileNetV2**

I. Introduction

Indian cuisine is renowned across the globe for its tangy and spicy treat to the tongue. The flavour and aroma of any food get enhanced with the addition of spices creating a lasting taste. Among the commonly utilized spice condiments in Indian food is chilli. In addition to being an integral part of Indian cuisine, it is also one of the most economically significant crops globally. Though introduced by the Portuguese in the 17th century, India has been the major producer and exporter of crops. India alone exported around 578,800 tonnes in 2021, 8% more than the previous year. Typically, the seasons of Rabi and Kharif suit the cultivation of chillies[1]. Chilli also has various health benefits. Fresh green chilli contains more Vitamin C than that found in any other citrus fruits, while red chilli is said to have more Vitamin A content than carrots. The active component of the spice, *Capsaicin* possesses antioxidants, anti-mutagenic, anti-carcinogenic and immunosuppressive activities that can inhibit bacterial growth and platelet aggregation [24].

Lower production of chillies has spiked the prices by 80% in four months to an all-time high, and prices are most likely to stay high all year long, forcing buyers to shell out at a time of the rise in fuel and other commodity prices. Consequently, farmers worry about an output drop of around 20% [1]. Chillies are susceptible to fungal, pests, weeds, bacterial, viral and pathogen attacks on a global scale that substantially hampers chilli production.

Chilli anthracnose is one of the most devastating diseases bothering Chilli growers. The cause is *Colletotrichum* fungus. Among many different species of *Colletotrichum, Colletotrichum capsici* is a specie that spreads on chilli leaves and fruits. Initially, the symptoms of anthracnose in chillies are visible on leaves [10], typically having dark patches, sunken necrotic tissue, and concentric rings of acervuli which later form sunken lesions with dark brownish-black margins. The disease spreads quickly, resulting in a significant loss of yield [2]. Typical symptoms of Anthracnose *Colletotrichum capsici* on chilli fruit typically include dark patches, sunken necrotic tissue, and concentric rings of acervuli.

Image processing techniques are now commonly used in the agricultural industry to detect and recognize weeds, fruit-grading, identification and calculation of disease infestations

[1]Red Chilli Pepper prices surge on crop damage in top exporter India - Times of India

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of plants, and plant genomics. Deep Learning(DL) approaches are becoming increasingly prominent. DL is a machine learning approach that involves training neural networks with multiple feed-forward layers on large amounts of data [5]. There are many types of DL, commonly used are CNN. CNN has several architectures for detecting plant diseases, including MobileNet, DenseNet, ResNet, etc [12].

Simple detection and classification are possible with CNN algorithms. Through its multi-layered structure, it effectively evaluates graphical images and extracts the key features. The layers of the CNN are the input image, convolutional layer and pooling layer, fully connected layers, and output [3].

This paper proposes a solution based on Deep Learning technology using ResNet18 Architecture. We classify Anthracnose affected chillies from healthy chillies. Which have been further classified as anthracnose-affected initial and final stages based on the area of disease spread for both Red and Green chillies.

A smartphone application helps farmers easily classify the disease to reduce the growth of the disease and increase their crop productivity. With technological advancement and digitization in our nation and the world, every farmer has access to an end device, like a smartphone. Therefore we implement this model into an android application. There may be other additional applications of our project in the industrial line and production chain to classify the unhealthy chillies in a batch before the chillies are processed.

This paper is organized as follows, *Section II* explains the Literature Survey, followed by Proposed Methodology in *SectionIII*, Experiments in *SectionIV*, *Section V* shows the results, *Section VI* Summarizes the whole Paper, and the last section contains all the References.

II. Literature Survey

This section summarises the various works discussed by different researchers to implement DL models for image classification.

There are different methods used for classifying diseases in plants. Author of [20], encourages us to study and implement DL model solutions. The Author has reviewed all the works related to different methods used for plant disease detection. According to her survey, the most common Deep Learning and Machine learning techniques in plant disease detection are Random Forest Classifier, CNN, Multiple Linear Regression, and Genetic Algorithms. Her survey is inspiring and gives an in-depth idea to any researcher or student to implement DL models for plant disease identification and classification.

A Lakshmanarao et.al [11] have focused on CNN for plant disease detection and classification. They collected the PlantVillage data set from kaggle, which had 15 classes of plant leaves of 3 plants, potato, pepper and tomato. They divided the whole dataset into 3 and applied the Convnets on each of them. They achieved an accuracy of 98.3%, 98.5% and 95% for potato, pepper and tomato plant disease detection respectively.

Mishalee Lambat et.al [14] in their work have proposed a method to detect diseases in plants using InceptionV3 which was pre-trained on ImageNet dataset. The authors have used the fine tuning method for transfer learning by removing the final layers of the pre-trained model. They have used the Kaggle dataset of cotton disease which has nearly 500 images taken in laboratory condition.

Xiaolian Di et.al [4], the authors have proposed a method based on Transfer Learning on convolutional neural networks on weld flaw detection image datasets. They have illustrated the effect of Fine Tuning on the Dataset by using the frozen layer method. In an even more profound study, we gathered the information that for a small model size, the number of bits of floating-point weight should be low, which reduces the memory requirement and computational cost of using neural networks order for a small model size, as shown in *Fig 1*.

Authors of [16] have worked on a similar concept and further proposed optimization techniques on DNN architectures. Their work concludes that MobileNetV2 best suits embedded systems with the smallest model size.

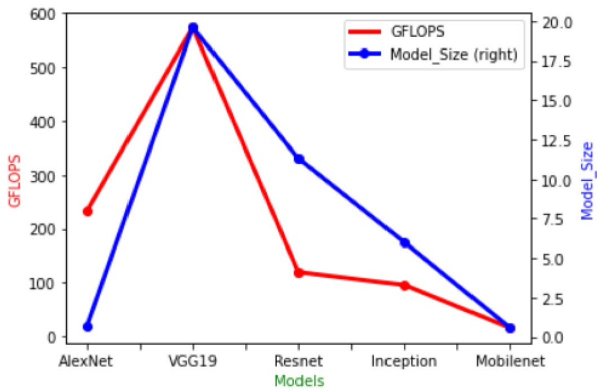

Fig. 1. GFlops Vs Model Size of Different DL Models

Rahimi Zahari et. al [26] in their work has proposed to detect diseases in the chilli plant using its leaves images based on an image processing algorithm. Two algorithms have been advanced. The first algorithm trains various Support Vector Machine(SVM) classifiers using six different SVM methods namely, Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, and Coarse Gaussian SVM. The second testing algorithm uses 8 Chilli plant images with 40 segmented results to test the trained SVM classifier. K-means clustering is used for image segmentation. Image segmentation is a technique used to partition images into multiple parts based on the characteristics of the pixels in the image. 90.9% accuracy was achieved in the classification results during training utilising quadratic and medium gaussian SVM.

A Bapat et.al [3], have proposed a plant disease recognition model using VGG-19. They have used the PlantVillage dataset released by crowdAI for training. They trained the model for 50 epochs along with early stopping and were able to achieve

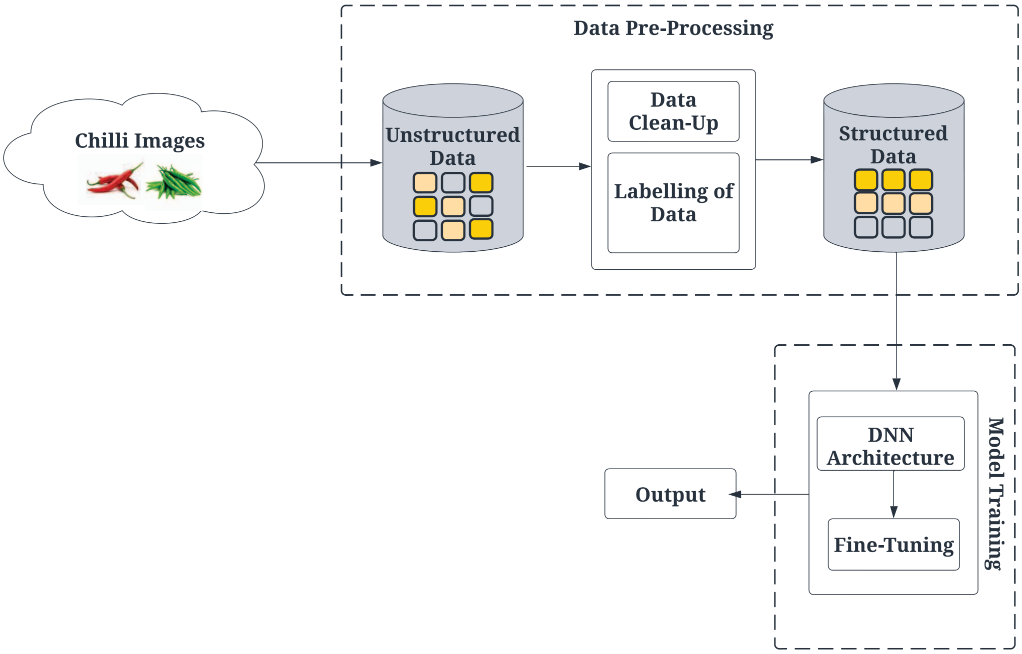

Fig. 2. Proposed Methodology

Fig. 3. Samples of Dataset (a)Healthy Green (b)Diseased Green (c)Healthy Red (d)Diseased_Red

an accuracy of 95.6%. They later converted their model to a tflite version and successfully deployed their app on an android device. Their work inspires and motivates us to develop and deploy a mobile application. Abou El-Maged et.al [5], in their work have proposed an AI model for plant diseases based on CNN. They have divided their work into 3 phases: Preprocessing, Classification and Evaluation and optimization of hyperparameters of the CNN model using the Gaussian method. They used VGG16 to train their model, which gave an accuracy of 95.87%. This result was improved to 98.67% after the Gaussian process of optimization of hyperparameters. In future, they will be using the swarm algorithm for hyperparameters optimization as a trial to enhance accuracy. Aravindan Venkataramanan et.al [25] have used a YOLOv3 object detector to extract the features of a leaf from the PlantVillage dataset. The extracted features are analyzed through a series of ResNet18 models trained using transfer learning. They have used a two-part approach where one layer helps identify the type of leaf while the following layer checks for the possibility of diseases that could occur in the plant. Through this approach, they were able to achieve an accuracy of 96%. This Literature study helped us understand how different methods work to identify plant diseases.

III. Proposed Methodology

A. Data Collection

The limited availability and lack of relevant data propelled us to collect and create our dataset, which would fulfil our requirement to implement it in the DNN architecture that classifies the Anthracnose affected chillies from healthy chillies. For the dataset, samples of chillies were collected from the University of Agricultural Sciences, Dharwad and chilli farms on the outskirts of Hubli near Kusugal. The chillies chosen were both healthy as well as disease-affected ones. With the University's help, we could get the chillies which were solely affected with Anthracnose and not be confused with other diseases. Samples of Red and Green Chilli were collected, analogous to the region. The images of the samples were taken in a controlled environment against a white background in a well-lit room. A high-resolution camera mounted on a tripod was used for equidistant pictures with an aspect ratio of 1:1. Samples of the images captured are shown in *Fig 3*.

B. Model Selection

The background study encouraged us to use MobileNetV2 as the underlying architecture with transfer learning using the dataset we collected. We briefly explain why MobileNet is preferable over other architectures. MobileNetV2 is a lightweight deep neural network architecture designed to be deployable on mobile and embedded devices efficiently. Its significant advantages lie in its design, which has efficient computation with a smaller number of parameters and computationally less expensive operations than other state-of-the-art models; it also has a small model size, reducing memory and storage requirements and making it easy to deploy on mobile and embedded devices. The architecture of MobileNetV2 makes it well-suited for transfer learning, allowing for quick fine-tuning for specific tasks with limited data.

MobileNetV2 architecture consists of two main components, inverted residuals and linear bottlenecks. The combination of 1x1 convolution layers and depthwise separable convolutions in MobileNetV2 as shown in *Fig 4*. It allows for the efficient handling of loss and the network's capacity. The use of stride 1 and stride 2 blocks within the internal components of the architecture allows for the efficient downsampling of feature maps, reducing the computation required. ReLU6 activation in the 1x1 convolution layers with linearity and the depthwise convolution with ReLU6 allows for non-linearity within the network, contributing to its ability to learn complex features.

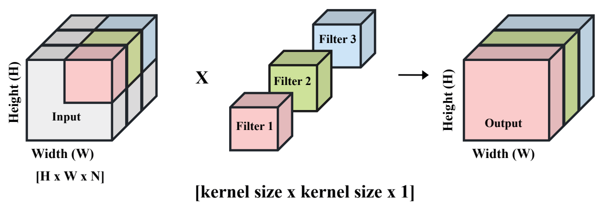

Fig. 4. Depthwise Convolution

Inverted Residuals: The use of inverted residuals in MobileNetV2 allows efficient handling of information flow within the network as shown in *Fig 6*. The combination of a 1x1 convolution to widen the network, followed by a 3x3 depthwise separable convolution to minimise the number of parameters, and then a final 1x1 convolution to match the original number of channels allows the efficient utilisation of the network's capacity. This strategy also helps preserve information from prior activations, as the start and end of the convolutional block get connected via a skip connection. Pointwise Convolution (PWC) shown in Fig *Fig 5* MobileNetV2 is also an essential aspect of the architecture, as it expands the channels after adding the input and output, contributing to the network's ability to learn complex features.

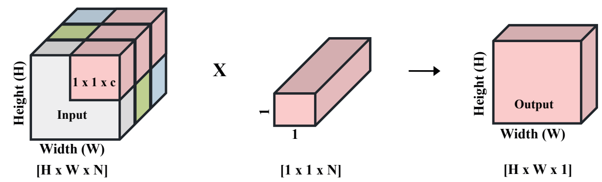

Fig. 5. Pointwise Convolution

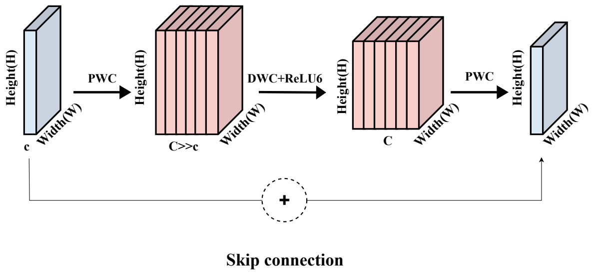

Fig. 6. Inverted residual Block

Linear Bottlenecks: Because many matrix multiplications cannot condense into a single arithmetic operation, non-linear activation functions are used in neural networks to construct Multiple-layer neural networks. Values less than zero are rejected by the ReLU activation function. Increasing the number of channels reduces the loss while expanding the network's capacity.

Transfer learning: Transfer learning is a technique in machine learning where a model trained on one task is re-purposed on a second related task as shown in *Fig 7*. The idea is to leverage the knowledge gained from the previous task to improve the model's performance on the second task. Especially useful in deep learning, where the models have many parameters, and it can be challenging to train them from scratch on a new job where the data is limited. A model pre-trained on a large dataset like ImageNet can be fine-tuned for a new task, such as object detection or image classification.

IV. EXPERIMENTS

A. Dataset Description

The images were taken for the 4 different classes (as mentioned in *SectionIII-A*): Healthy red and green chilli, Anthracnose affected red and green chilli, as shown in *Fig 8*. The images were captured in a well-lit studio-like environment with a white background. The device Samsung Galaxy S10 mounted on a tripod with a 12MP camera with optimal specifications (OIS). 300 images were captured in total. Images which were unclear or had too much noise were identified and manually deleted during pre-processing, after which 287 images remained. But the dataset size couldn't suffice our needs, so we augmented the dataset. Images were increased by rotation, inversion, and occlusion to enhance the data's features. The images were of a dimension of 3024x3024 which got resized to 224x224 for the architectures input. Out of the total images,

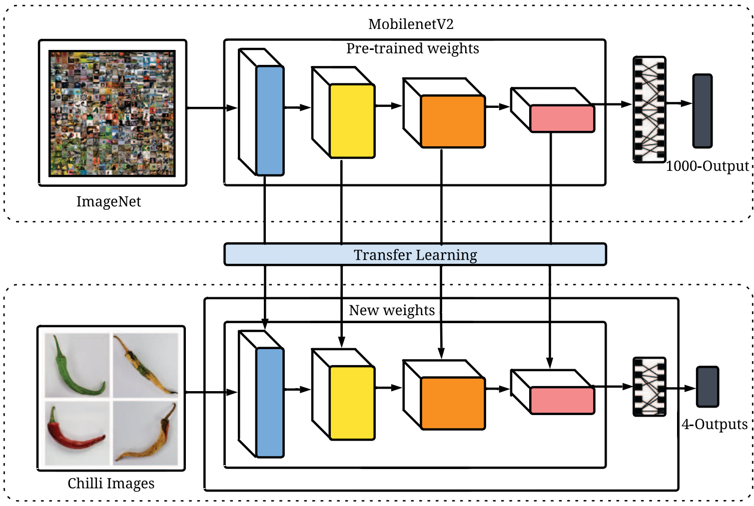

Fig. 7. Transfer Learning

80% of the images is used for training and 20% is used for testing the model. Finally, we had 1152 images in total with file size of 545MB, as described in *Table I*.

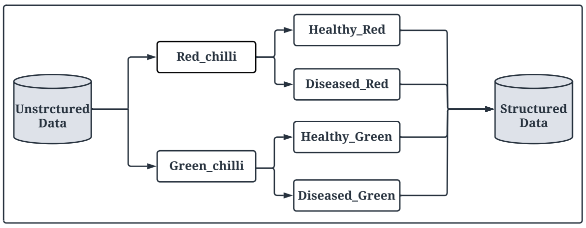

Fig. 8. Description of Dataset

TABLE I
DATA SET DESCRIPTION

Class	Training Images	Testing Images
Healthy_Green	160	40
Healthy_Red	159	40
Diseased_Green	282	71
Diseased_Red	320	80
Total	921	231

B. Implementation

We used transfer learning on the underlying MobileNetV2 architecture to classify the diseased chillies from healthy ones. Pre-trained on the ImageNet dataset, we re-trained the model using 80% of our dataset for 50 epochs with early stopping which paused at the 15th epoch. Only transfer learning wouldn't serve the purpose; hence an optimiser is needed for hyper-parameter tuning, which helps add value to the re-trained model. We used the Stochastic Gradient Descent(SGD) optimiser gave a desirable accuracy. SGD is stochastic, i.e. it picks up a random instance of training data at each step and computes the gradient, making it much faster as there are fewer data to manipulate simultaneously. It minimises the cost function by reducing the weights. The default learning rate of SGD is 0.01, which helps determine the step size at each iteration. The re-trained model gets further added with a dense, dropout, and pooling layers.

C. Embedding on Edge Device

After training, we convert the model to a TensorFlow Lite(tflite) model. Tflite is a collection of tools that allows developers to implement their models on mobile, embedded, and edge devices, which enables on-device machine learning. With the help of the tflite model, we developed an android application using the android studio editor. An application puts our model into practical use, which helps the farmers.

The application is user-friendly and easy to navigate for the farmer's use. *Fig 9* shows the application interface that classifies the chillies into different categories.

V. RESULTS

This paper proposes a solution based on the MobileNetV2 architecture to classify Anthracnose-infected chillies from healthy chillies. On re-training the model with our dataset using transfer learning, we achieved a training accuracy of 98.6% and a testing accuracy of 96.94%. *Fig10* and *Fig11* depict The Trained Loss Vs Epochs and Accuracy Vs Epochs, respectively. From *Fig10*, we can infer that the training loss is gradually decreasing, and the variance between the validation loss and training loss is minimal before early stopping, which implies that there is not much overfitting or underfitting. *Fig11* shows the increase in accuracy with every epoch and is constant at 98% from the

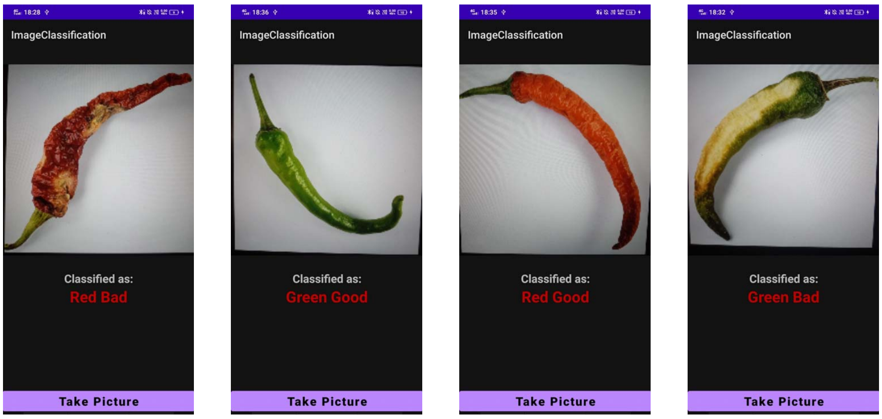

Fig. 9. Interface of Application

11th epoch while training and stopping at 98.6% with early stopping. By Comparing our developed model with other state-of-the-art architectures, we could conclude that MobilNetV2 gave the Best Results. *Table II* shows the result comparison of different models.

TABLE II
TRAINED MODELS WITH THEIR ACCURACIES AND SIZE

CNN model	Accuracy(%)	Size of the Model(MB)
VGG16	93.2	148
ResNet50	95.4	98
ResNet18	97.3	45
MobileNetV2	96.94	15

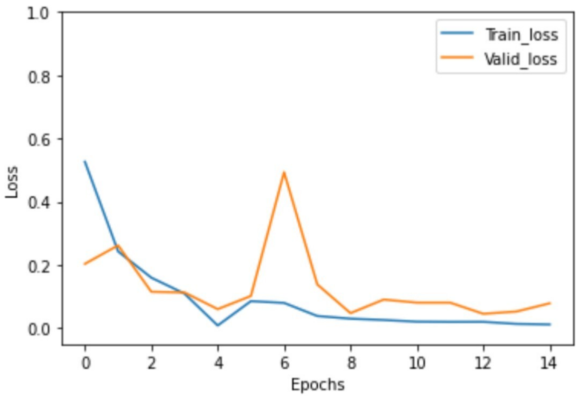

Fig. 10. Loss Vs Epochs for MobileNetV2

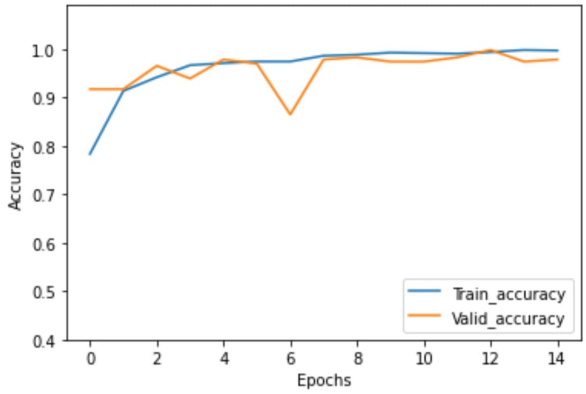

Fig. 11. Accuracy Vs Epochs for MobileNetV2

VI. CONCLUSION AND FUTURE SCOPE

India, the largest producer of chillies, is severely affected annually by various pests and pathogens that attack the crops in the field. As a result, farmers are affected severely. To overcome this problem, we propose a solution using MobileNetV2 Architecture to classify Anthracnose-infected chillies from the batch of healthy chillies to curb the spread of the disease further when it is in the early onset. Our approach proved nearly effective, with reasonable accuracy and a working mobile phone application. Intending to assist farmers nationally and globally, we were satisfied that we set on the right approach, which can be further enhanced and optimised.

In the future, we can add samples of more varieties of chillies for different colours and breeds. We can also identify the area of spread of disease in the fruits and plants, which can help us understand if the condition is curable.

VII. ACKNOWLEDGEMENT

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