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PLANT DISEASE DIAGNOSIS AND SOLUTION SYSTEM BASED ON NEURAL NETWORKS

N. V. Megha Chandra Reddy
Research Scholar,
Department of Electronics and Communication Engineering, School of Engineering, CHRIST University,
Bangalore, Karnataka, India
nandyala.veera@btech.christuniversity.in

K. Ashish Reddy
Research Scholar,
Department of Electronics and Communication Engineering, School of Engineering, CHRIST University,
Bangalore, Karnataka, India
kancham.ashish@btech.christuniversity.in

Sushanth. G
Assistant Professor,
Department of Electronics and Communication Engineering, School of Engineering, CHRIST University,
Bangalore, Karnataka, India
sushanth.g@christuniversity.in

Sujatha. S
Assistant Professor,
Department of Electronics and Communication Engineering, School of Engineering, CHRIST University,
Bangalore, Karnataka, India
sujatha.s@christuniversity.in

Abstract

Plant diseases are one of the major factors affecting crop yield. Early identification of these diseases can improve productivity and save money and time for the farmer. This paper presents a novel technique to diagnose plant diseases using a mobile application. A Convolutional Neural Network (CNN) model was built and trained using MobileNetV2 architecture with the help of image processing techniques and transfer learning. A dataset comprising 87,000 images that contain 38 classes of diseases belonging to 14 different crops was used to train the model. The model achieved an accuracy of 98.69% and a loss of 0.5373. A mobile application was built in Android Studio with the help of a trained model. The mobile application built works without a need for a remote server. The application can identify the disease, gives information regarding the identified disease and also suggests necessary remedies to tackle the disease.

***Keywords*: Convolutional Neural Network (CNN); Image Processing; MobileNet.**

1. The Main Text

India is the world's largest and one of the oldest agriculture-dependent countries. More than half of the Indian population is involved in agriculture directly and indirectly. Though with such a large workforce, agriculture is contributing only 18 % of the total Gross Domestic Product (GDP) [1]. The total factor productivity growth of India is below 2% per annum which is far lower than many other developing countries [2]. With the agricultural land shrinking exponentially, it's high time India employed productivity-improving strategies. One of the major hindrances of productivity is pest attacks. As high as 15.7 % of losses of yield is due to plant diseases in India [3]. Thus, disease identification and monitoring are crucial to increase the yield of the crop.

Disease Identification and monitoring is an arduous task and if the cultivation is done in large areas, it becomes highly impossible to control the damage and prone to errors. Importantly, many farmers don't know the different kinds of diseases affecting the plants and what remedies to be employed. To counter this, many technologies have emerged to help the farmers in monitoring the field. Geographic Information Systems (GIS) were one of the most used technologies in monitoring the field. With the help of GIS, farmers can assess crop conditions and they also have data regarding the fertility levels of the soil [4]. Unmanned Aerial Vehicles (UAV) are the most talked-about technology for crop monitoring in the past decade. Using several high-tech types of equipment like near-infrared cameras, thermal sensors and other sensors [5]. The data obtained from UAVs is reliable and gives a detailed analysis of the crop obtained from different sensors. To achieve high precision results, Satellite Imaging is used. This technology can be employed to study vast areas of cultivation with the help of high-resolution images obtained from satellites [6]. Apart from GIS, UAVs and Satellite Imaging many other technologies are being employed to assist the farmers like the Internet of Things (IoT), merging datasets, farming software with the help of neural networks.

Though all these technologies have been producing great results, their usage in farmlands is very limited especially in countries like India, where most of the farmers have no idea of how to use and study these technologies. UAVs and Satellite Imaging is very expensive which can not be afforded by Indian farmers. Also, many of these technologies need an active network connection to the database which is not feasible in remote areas. So many of these technologies are only suitable for research work but not in practical scenarios.
To assist the farmers, in specific poor and middle-class Indian farmers, this paper suggests a mobile application that does crop diagnosis. In these modern times, almost everyone in India has a smartphone. Thus, this is the best optimal way to reach maximum users. The farmer need not know about the architecture employed in the application or the process of how it works. With zero extra knowledge required, farmers can easily use this application and can get instant results about the disease affected and the remedies that need to employed to counter the disease. There is no financial problem too as this application is free to use and also no issue with the network as this application even works offline. This mobile application is the best way of assisting farmers in crop monitoring and diagnosis.

The mobile application was built in two stages. Firstly, a Convolutional Neural Network (CNN) based model was built with the help of image processing techniques and transfer learning. Lastly, the built model was made into an application with the help of Android Studio. The built mobile application can identify 38 different classes of diseases in 14 different crops.

The remainder of this paper is organized as follows: Literature Survey is carried out in Section 2. Section 3 describes the methodology used in building the model and mobile application. The experimental setup is discussed in Section 4 and it is followed by the results in Section 5. Finally, this paper is concluded in Section 6.

2. Literature Survey

Mobile applications are being widely used by millions of people around the world. Masi *et al.* [7] presented a detailed framework for technology decision making for the development of mobile applications. They discussed technologies employed, programming languages used, platforms available, platform-specific software development kits and drivers involved. They even presented various problems faced and solutions to counter them.

From entertainment, health, business, productivity and everything else are achieved and improved with the help of mobile applications. Oinas-Kukkonen and Kurkela [8] discussed extensively developing a successful mobile application. The authors talked about different scenarios, applications and key design principles in developing an application for mobile devices. Islam and Mazumder [9] presented different areas of applications of mobile applications. The authors even discussed the effect of mobile applications on society and also talked about the limitations of mobile applications. Sunitha and Elina [10] discussed the impact of mobile applications in the education sector. The authors presented different kinds of apps used in education and subject-specific mobile applications and their advantages. Ventola [11] presented about mobile devices and apps used in the field of healthcare. The author mentioned different types of applications, their need at the point of care and how health care professionals use them. Choe *et al.* [12] discussed a real-time mobile application that can identify and classify different parrot species using CNN. The authors discussed the implementation of the mobile application, how the CNN model was built, feature extraction techniques employed and presented different experimental results.

Mobile applications are also being extensively used in the field of agriculture. Dehnen-Schmutz *et al.* [13] explored the farmer's usage of mobile phone technology in agriculture. The authors presented many surprising results that say a high percentage of farmers nearly 84% used mobile applications for farm management and many other farmers used it for real-time monitoring, data collection and experimental work. Johannes *et al.* [14] presented a novel image processing method for disease identification with the help of hot-spot detection and statistical inference methods using mobile devices. Toseef and Khan [15] developed a mobile application using a fuzzy inference system for crop diagnosis and it achieved an accuracy of 99 %.

Though different algorithms are used to build the model, CNNs are considered the best and accurate method of creating a model. Jiang *et al.* [16] demonstrated a real-time detection of leaf diseases in apples. The authors developed a model called INAR–SSD using a deep learning approach. The model achieved performed with a 78.8

% mAP on the dataset used with a great speed of detection. Elhassouny and Smarandache [17] proposed a smart mobile application using CNN to recognize diseases in tomato leaves. The authors used a 7176 imaged dataset and built an application that can detect ten different types of diseases affecting tomato leaves. Esgario *et al.* [18] presented an application that identifies pests and diseases using deep learning in coffee leaves. The authors discussed how the android application can detect and classify diseases caused by biotic agents in coffee leaves with an accuracy of 97 %. Petrellis [19] presented a mobile application that runs without a server and can diagnose citrus diseases. The application achieved an accuracy of more than 90% in detecting citrus diseases. Rishiikeshwer *et al.* [20] built an application that can detect diseases in plants with an accuracy of 98% using CNN and image augmentation. The authors built a web application that requires a server to work.

Though many researchers presented a mobile application that can identify diseases, there are no papers that discuss a mobile application that can work without a remote server and can identifying diseases in 14 different crops with high accuracy. The main objective of this paper is to build a CNN model and a mobile application using the built CNN model.

3. Methodology

The proposed system is depicted in Fig. 1. The system can be broadly divided into two stages.

1. Creating a Model
2. Deploying the model

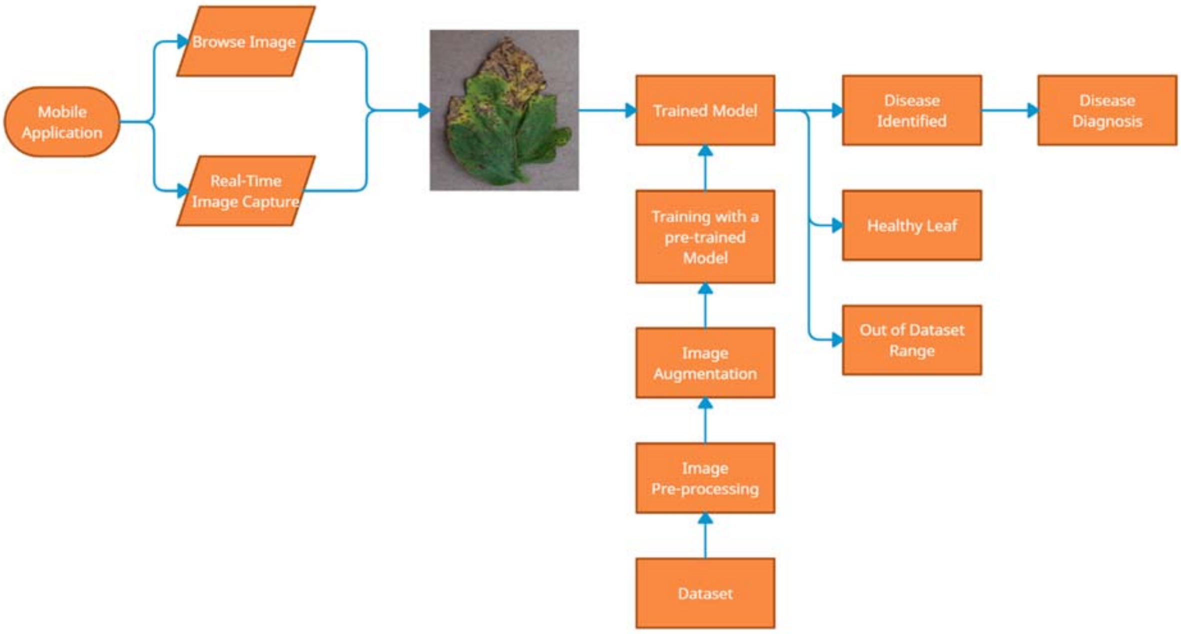


Fig. 1. Flowchart of the proposed system

3.1. *Creating a Model*

3.1.1. Dataset

The dataset used to train the model was espoused from an open-source platform [21]. It has a collection of 87000 leaf images from 14 different crops in jpeg format. Detailed information of the dataset is shown in Table 1. The dataset is partitioned into test, train and validation sets. The test set was created by picking out 20 to 30 images per disease in each crop and these selected images were removed from the main dataset. The remaining 85,851 dataset images were partitioned into train and validation sets in the ratio of 80:20 respectively.

3.1.2. Image Processing

Image pre-processing and image augmentation were the techniques utilized in training the model. As the dataset has minimal noise, no noise removal techniques were used. There was no change in the image format too as the model is trained using default jpeg images. Only image resizing is done as the default image size is 224 x 224 pixels for the model to be trained.

Table 1. Dataset

S. No	Crop Name	Disease Name	Number of images in the Train set	Number of images in the Validation set
1	Apple	Scab	2016	504
2		Black Rot	1987	497
3		Cedar Rust	1760	440
4		Healthy	2008	502
5	Blueberry	Healthy	1816	454
6	Cherry	Powdery Mildew	1683	421
7		Healthy	1826	456
8	Corn	Cercospora Leaf Spot	1642	410
9		Common Rust	1907	477
10		Northern Leaf Blight	1908	477
11		Healthy	1859	465
12	Grape	Black Rot	1888	472
13		Esca (Black Measles)	1920	480
14		Leaf Blight	1722	430
15		Healthy	1692	423
16	Orange	Citrus Greening	2010	503
17	Peach	Bacterial Spot	1838	459
18		Healthy	1728	432
19	Pepper	Bacterial Spot	1913	478
20		Healthy	1988	497
21	Potato	Early Blight	1939	485
22		Late Blight	1939	485
23		Healthy	1824	456
24	Raspberry	Healthy	1781	445
25	Soybean	Healthy	2022	505
26	Squash	Powdery Mildew	1736	434
27	Strawberry	Leaf Scorch	1774	444
28		Healthy	1824	456
29	Tomato	Bacterial Spot	1702	425
30		Early Blight	1920	480
31		Late Blight	1851	463
32		Leaf Mold	1882	470
33		Septoria Leaf Spot	1745	436
34		Two-spotted Spider Mite	1741	435
35		Target Spot	1827	457
36		Yellow Leaf Curl Virus	1961	490
37		Mosaic Virus	1790	448
38		Healthy	1926	481
Total	14	38	68279	17572

For the model to be performed well, a large size of data is needed while training the model. But in practical scenarios, satisfying such heavy data size requirements is not feasible. In such scenarios, data augmentation is done on the dataset to increase data size. In this model, image augmentation techniques like rescaling, 0.2 sheer and zoom ranging, horizontal flipping were done.

3.1.3. Training

To save time and to improve model performance with fewer data, pre-trained models were used with the help of transfer learning [22]. There are many pre-trained models available on the internet like Inception, ResNet, VGG and many others. As this paper main objective is to create a mobile application, MobileNetV2 [23] was used as the pre-trained model. The top and bottom layers of the MobieNetV2 were removed. The architecture employed to train the model using MobileNetV2 is shown in Fig. 2.

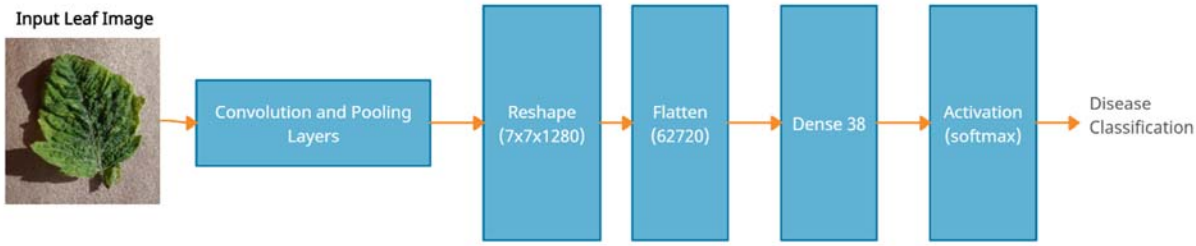


Fig. 2. The architecture of the MobileNetV2 model

3.1.4. Optimizer

Optimization is adjusting a mathematical expression. Optimizers are the methods that tune the model to reduce the losses. Adam [24] was the optimizer user in training this model. It works based on the formula shown in Eq. (1).

$$J_{min} = p - \eta \frac{M_p}{\sqrt{V_p} + \mathcal{E}}. \tag{1}$$

where p is a parameter, η is the initial learning rate, Ɛ is a very small constant (to avoid divide by 0). M_p and V_p are derived from Eq. (2) and Eq. (3) respectively.

$$M_p = \frac{m_p}{1 - \beta_1} \tag{2}$$

$$V_p = \frac{v_p}{1 - \beta_2} \tag{3}$$

where m_p and v_p are the mean and variance of the gradient respectively and β_1, β_2 are the bias correction constants.

3.2. *Deploying the Model*

The process of deploying a model as a mobile application is shown in Fig. 3.

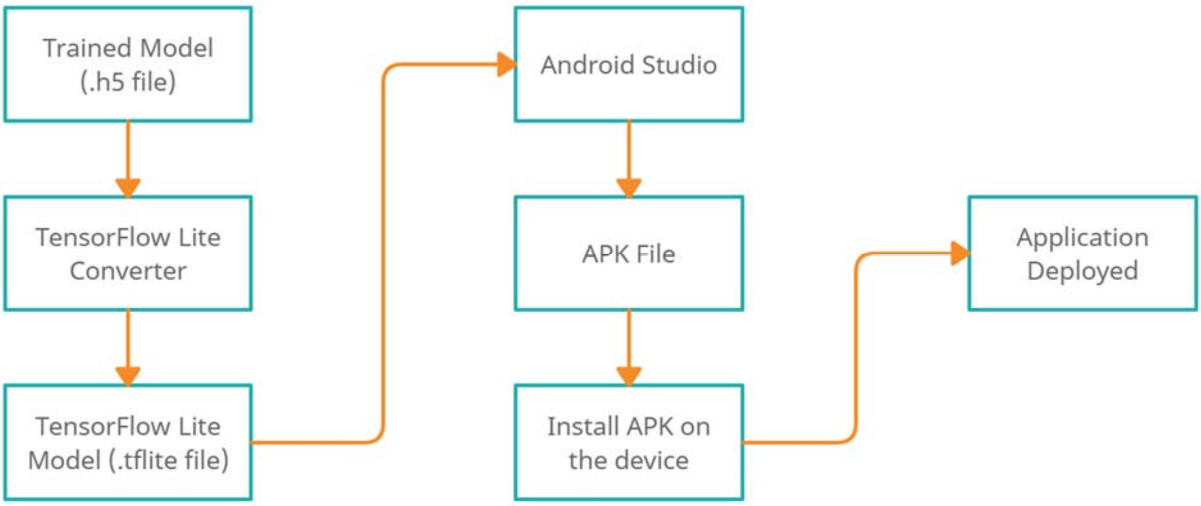


Fig. 3. Flowchart of deploying the model

The trained model directly can't be used in mobile devices due to its large size, high power consumption and incorrect formatting. Thus, the model needs to be lightweight and should have optimal power consumption. To achieve this the trained model was converted into a TensorFlow Lite file using a converter. The obtained tflite file is the speed and storage optimized version of the trained model.

The TensorFlow Lite Model was then passed on to Android Studio, an Integrated Development Environment (IDE) used for Android application development. In the Android Studio, the interface of the application was built using an interpreter and an Android Package File (APK) was created. This APK file can be shared through all Android devices. When this APK file is installed, the application is deployed on the device.

4. Experimental Setup

CNN model was built using Google Colaboratory with a Tesla T4 GPU. Libraries like Keras, Pandas, NumPy, sklearn and PyTorch were utilized to train the model. Softmax is the activation function used. Adam and categorical cross-entropy were the optimizer and loss function used respectively. Hyperparameters for adam optimizer were set to default, $\eta = 0.01$, β_1 and β_2 were set to 0.9 and 0.999 respectively. The model was trained for 50 epochs with a batch size of 32. The mobile application was built on Android Studio version 4.1.

5. Results

5.1. *CNN Model*

Results of the trained model can be seen in Fig. 4 and Fig. 5. The MobileNetV2 achieved a training accuracy of 98.69 % and a training loss of 0.5373.

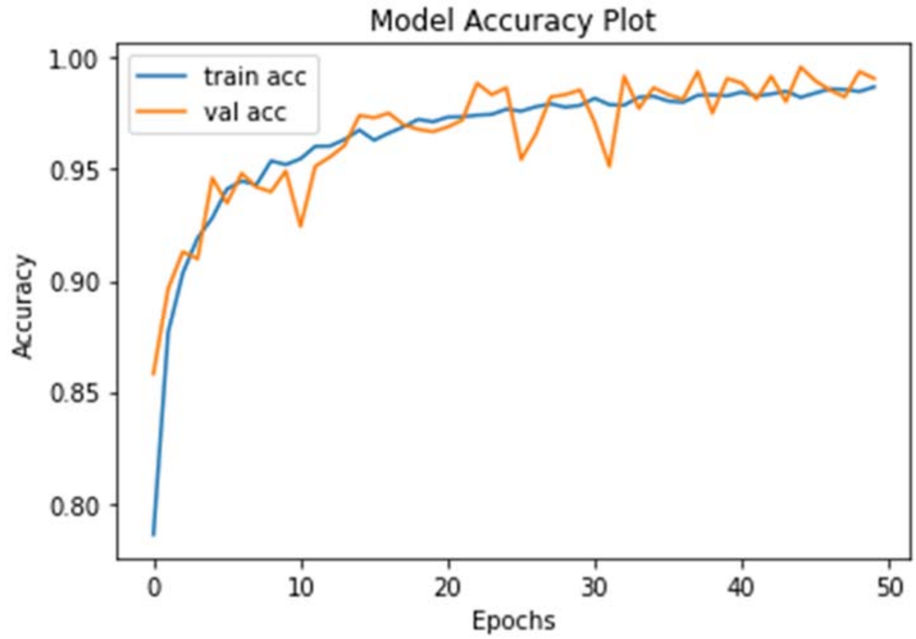


Fig. 4. Accuracy of the trained model

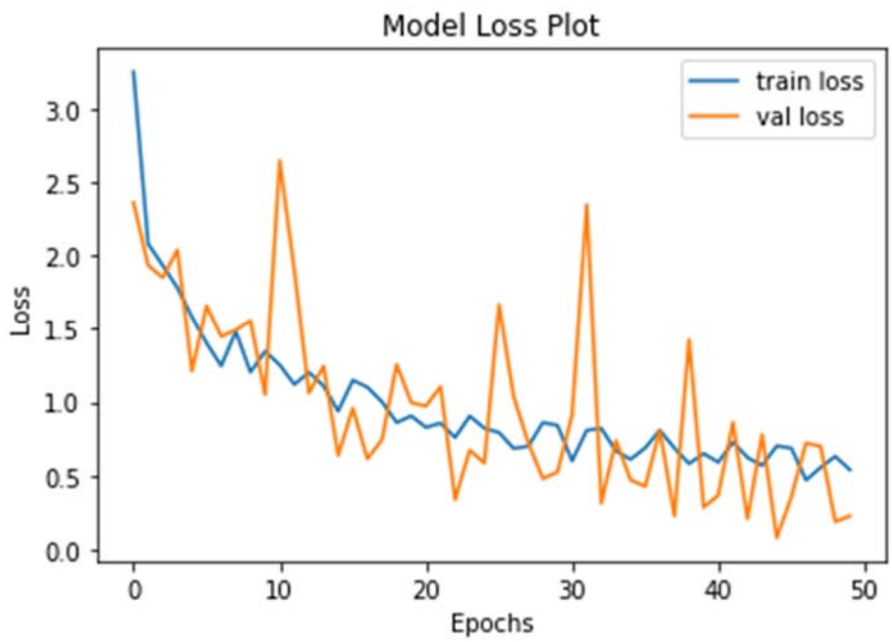
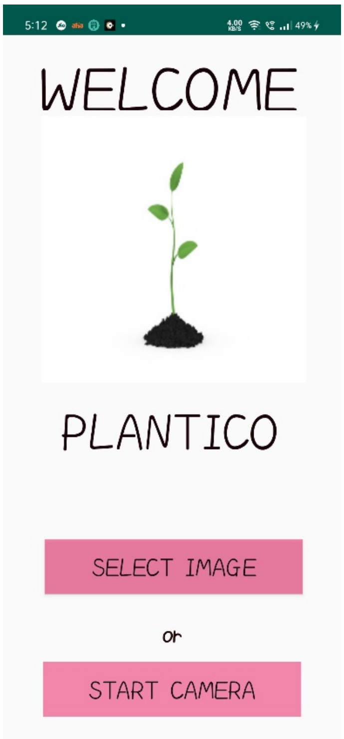


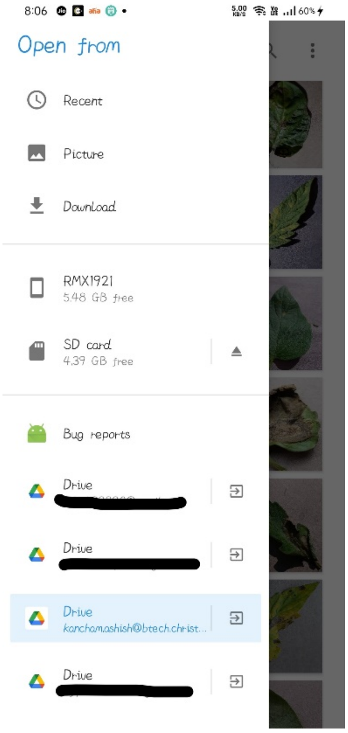
Fig. 5. Loss of the trained model

5.2. *Mobile Application*

The home page of the mobile application is shown in Fig. 6 (a). There are two options available for the user. One is the user can upload a photo from the device (see Fig. 6 (b)) and the second one is the user can use real-time detection using a camera (see Fig. 6 (c)). If the input leaf is diseased, the 'name of the disease' is automatically displayed (see Fig. 6 (d)) with a 'know more' option which will redirect the user to the remedy page (see Fig. 6 (e)) or if the input leaf is healthy, it will be displayed 'Healthy Leaf' (see Fig. 6 (f)) or if the input leaf is not within the 38 classes of 14 crops, it will display an error message (see Fig. 6 (g)).

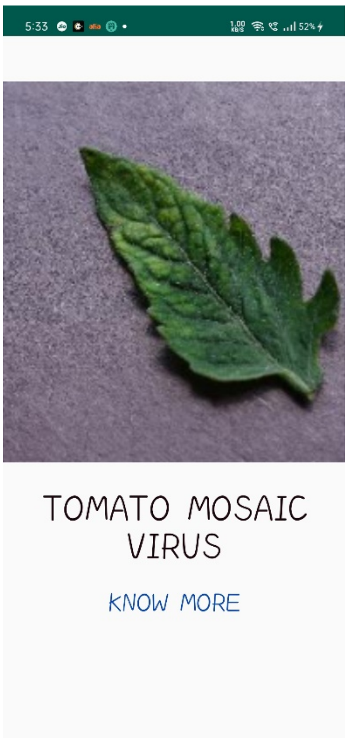


(a)

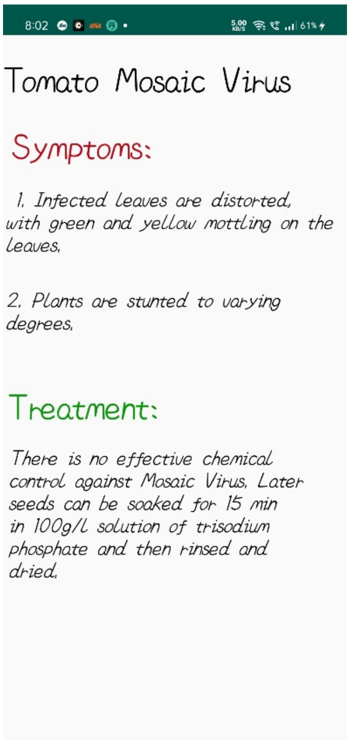


(b)

(c)



(d)



(e)

(f)

(g)

Fig. 6. Working of the mobile application

6. Conclusion

The main aim of this paper is to build a mobile application that can identify diseases and suggest remedies for the identified diseases. For this, firstly, a CNN model was built using MobileNetV2 architecture with the help of a dataset that contains 38 different classes of diseases belonging to 14 crops. The model is trained for 50 epochs with a batch size of 32 using adam optimizer. The model achieved an accuracy of 98.69% and a loss of 0.5373. After obtaining the trained model, the model is converted into a TensorFlow lite file using a converter. Then the converted file was deployed in Android Studio, where the application interface was developed. An APK file was generated from the Android Studio and it can be shared to any android device and can be installed. The application developed is fast, lightweight and achieving great results. In future work, some optimization techniques will be employed on the application. Also, with sensors employed on the field, with the help of IoT, the sensor statistics will be integrated with the application thus providing customized data to the farmer.

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