

Care Green: Smart Android And IOT Detection and Prevention Mechanism for Crop Diseases*

Dr. Preeti Mishra

Professor, B.Tech CSE

Graphic Era Deemed to be University
Dehradun, India

dr.preetimishranit@gmail.com

Shivam Gupta

Student, B.Tech CSE

Graphic Era Deemed to be University
Dehradun, India

shivamguptasg1808@gmail.com

Garima Garg

Student, B.Tech CSE

Graphic Era Deemed to be University
Dehradun, India

ggarima163@gmail.com

Abstract—As professional agriculture engineers are responsible for the recognition of leaf diseases but by using intelligent systems they can be diagnosis in early stage also. A leaf disease diagnosis method that is implemented with the resources of a mobile phone application .The widespread distribution of smartphones among crop growers around the world with an expected 5 billion smartphones by 2020 offers the potential of turning the smartphones into a valuable tool for diverse communities growing food[1].It can be used both by amateur gardeners and by professional agriculturists for early detection of diseases. The recognition of a disease can be done by using dataset of 54,305 images (Plant Village Dataset) of diseased and healthy plants leaves collected under control conditions .The images cover 14 species of crops including: Apple, Grape, Soybean, Potato, Cherry, Tomato, Corn, Peach, Squash, Blueberry, Strawberry, Raspberry, Orange and Pepper. It contains images of 17 basic diseases,4 bacterial diseases,2 diseases caused by mold(oomycete),2 viral diseases and 1 disease caused by a mite. 12 crop species also have healthy leaf images that are not visibly affected by diseases. Out of 54,305 images 43,444 images used to train the model and rest used for validation .In Care Green preprocessing , augmentation ,feature extraction and detection engine is there. The main purpose of data preprocessing is to eliminate the noise in the image, so as to adjust the pixel values for that SRCNN model is used. It enhances the quality of the image. Data augmentation is a strategy that enables practitioners to significantly increase the diversity of data available for training models, without actually collection new data[2]. Data augmentation techniques such as cropping, padding, and horizontal flipping are commonly used to train large neural networks. .In feature extraction ,features of leafs are identified and using fine tuning technique some layers of the pre-trained model mobileNet v2 and inception v3 are trained from those features . The shape oriented feature extraction like Area, Color axis length, eccentricity, solidity and perimeter are calculated. Similarly the texture oriented feature extraction like contrast, correlation, energy, homogeneity and mean. Finally the detection engine to classify the leaf disease for that Adam Optimiser classifier is used and it also tells about the method to control from those diseases. Work till now is not satisfactory because low features were ignored due to which accuracy was not upto the mark and access time of using the application was high. The main contribution of Care Green is that it provides information about fertiliser according to standard unit which is used world wide.The accuracy was experimentally measured between 88% and 97% with loss 0.1607.

I. INTRODUCTION

Agriculture forms a vital part for every country economy. Farmers can grow variety of crops but diseases hamper the

growth of crops. One of the major factors responsible for the crop destruction is plant disease. Different plants suffer from different diseases and the main part of plant to examine the disease in leaf. The diseases on leaf can reduce both the quality and quantity of crops and their further growth. Through proper management strategies such as pesticides, fungicides and chemical applications one can facilitates control of diseases which results in better quality. The disease treatment may be delay because the professional agriculturists can't go to the locale to diagnose in good time. Relative to the person's vision, computer image processing technique take on some characteristics such as speediness, huge information and distinguish small diversity which can't be distinguished by person's eyes, so image classification technique can help farmers to judge the reasons and severity of crop diseases, and it takes on important theoretical and practical significance for improving the productivity of crops.So,above goal can be achieve through android application.Care Green application can be used in both Hindi and English language according to one's comfort.Android application has the feature firstly it detects the disease of leaf and then give description about those diseases and the methods to prevent from those diseases. Model is trained using concept of image preprocessing , image segmentation and feature extraction using SRCNN Model and CNN model having pre-trained model(mobilenet v2,inception v3) by applying fine tuning. Limitations of existing work:- 1. Low resolution features were ignored. 2. Accuracy was not upto the mark. 3. Access time was high. Our Contribution:- 1. Android application provides information about fertiliser according to standard unit which is used world wide. 2. No internet access is required ,so it can be use at any time. The rest of this paper is organized as follows. In section II related work is proposed. In section III the methodology of our work is explained . Then the architecture and the working of application is proposed in section IV. In section V the system software and the hardware required are introduced. Section VI presents the experimental results. Finally, conclusion of the paper.

II. RELATED WORK

Kawasaki et al. [3] proposed the use of deep CNN to distinguish healthy cucumbers from the infected ones by using

images of leaves. In this study, they used CNN to diagnose two harmful viral infections: MYSV (melon yellow spot virus) and ZYMV (zucchini yellow mosaic virus). The used dataset in this work consists of 800 images of cucumbers leaves (300 with MYSV, 200 with ZYMV and 300 nondiseased). Rotation transformations on images were used to enlarge the dataset. For this binary classification task, authors proposed CNN architecture which consists of three convolutional layers, pooling layers, and local contrast normalisation layers. The activation function used in this network is the Rectified Linear Unit (ReLU) function. The achieved accuracy of this study is 94.9% under a 4-fold cross-validation strategy.

Lu et al. [5] explored the use of CNN for the classification of rice diseases. They used 500 images captured in an experimental rice field to build a dataset used for training and validation purposes. AlexNet was the CNN architecture used to build a rice diseases classifier. Authors have compared the deep CNN with traditional machine learning algorithms. The overall accuracy of the deep model was 95.48% under 10-fold cross-validation. On the other side, the results of shallow models are: SVM achieved an accuracy of 91%, standard back propagation achieved 92% and Particle Swarm Optimization (PSO) achieved 88%.

Budihal [4] et al. in 2015 proposed work on detection of diseases in tomato leaf only using colour transformation and applying Otsu's threshold. Using this technique author is able to detect disease spot accurately. For GoogleNet, re-tuning improves the accuracy from 97.71 to 99.18% and similarly for AlexNet the re-tuning increases the accuracy from 97.35 to 98.66%.

Vijay Singh and A.K. Misra in 2017 proposed their work on automatic technique is used for detecting little leaf disease found in pine tree using image segmentation and soft computing techniques. From these techniques they are able to detect the symptoms of little leaf diseases.

Garcia et al in 2016 proposed their work by creating database for Identifying multiple plant diseases using colour histograms and pair wise based classifier as their techniques and from which they are able to identify multiple plant diseases using digital image processing.

Arivazhagan et al in 2013 proposed their work by doing color transformation method which is used for RGB images, and color transformation is followed by segmentation. From this, lesion area of leaf detected and classified crop disease using texture feature.

Revathy et al in 2015 proposed his work by using colour transformation and Otsu threshold techniques which are used to detect brown black colour spots from leaves. Able to detect only few diseases (which are having black spots).

Pujari et al in 2015 proposed work by considering cereals crop and fruit crops and their study is based on detection of fungal disease. They used Image processing statical method as their technique from which they are able to classifying fungal disease based on disease severity.

Shashank, Upendra and Abhishek in 2019 proposed their work on Crop Plant Disease Detection Using Image Processing

using K means classifier, Otsu threshold and SVM as their techniques and they are able to predict crop and leaf disease. Peifeng et al in 2017 develop an automatic diagnosis method to differentiate various wheat diseases only. By using embedded image processing system as his technique from which he is able to diagnosis wheat leaf rust disease.

Krishnan et al. in 2014 proposed his work by separating foreground and background images to detect Bacterial Leaf Scorch (BLS) of shade trees. For same K-means clustering segmentation is used as technique which from detect infected area of Bacterial Leaf Scorch (BLS) of shade trees is identified.

Babu and Srinivasa Rao in 2010 proposed his work on five diseases which effect on the plants like Early scorch, Cottony mold, Ashen mold, late scorch and tiny whiteness. For which clustering techniques and neural networks techniques are used and they are able to detect and classify the examined diseases.

III. METHODOLOGY

A. Image Acquisition

It is the initial state for the work flow series of image processing because as processing is practicable only with the help of an image. As pronouncement of leaf is based on the number of spots, their area, and their color features. These features are compared with predetermined limits (according to which model is trained) in order to select the emulate disease. Image acquisition involves the steps to obtain the plant leaf by capturing the high quality images through the camera or to select the image from the gallery itself. This image is in RGB (Red, Green, and Blue) form.

B. Image Preprocessing and Labelling

As the images are procure from the real field it may contain dust, spores and water spots as noise. Firstly, the label of images are provided i.e. the input images are categorized on the basis of the leaf structure (shape and size). After labelling, set one's sight on data preprocessing is to eliminate the noise in the image, so as to adjust the pixel values. It enhances the quality of the image. Prerequisite is there so that the image becomes well suited for a specific task. Image enhancement can be done at both spatial as well as a the frequency level of the image. Techniques such as median filter, histogram equalization, image smoothening, image sharpening, etc., can be used for performing image enhancement. Image smoothing is done using the filtering techniques. There are different types of filtering techniques available in image processing like median filter, average filter, Gaussian filter etc. Firstly image is converted from RGB format to Gray i.e. Scale Conversion this is done because color increases the complexity of the model as color images are often built of several stacked color channels, each of them representing value levels of the given channel and the inherent complexity of gray level images is lower than that of color images. After presenting a gray-level image model/method, in most cases it can be afterwards be extended to color images. That is a more natural path than introducing the complexity of dealing with

color images. Followed by scale conversion masking is to be done on that image. Image Masking is a process of graphics software like Photoshop to hide some portions of an image and to reveal some portions. It is a non-destructive process of image editing. Masking is the process that is underneath many types of image processing, including edge detection, motion detection, and noise reduction. Then bicubic interpolation is applied to the images as it helps in resize or distort the image from one pixel grid to another. Lastly background removal using BackgroundSubtractorMOG2 algorithm is there as Image Background Removal Service will help the image to look more creativity, more clean and sharp, giving the image into a new realistic background. BackgroundSubtractorMOG2 algorithm is a gaussian mixture based background segmentation algorithm and provides the stability even when there is change in luminosity and better identification capability of shadows in the frames.[1]

C. Image interpolation

An image $f(x,y)$ tells the intensity values at the integral lattice locations, i.e., when x and y are both integers. Image interpolation refers to the “guess” of intensity values at missing locations, i.e., x and y can be arbitrary. Here we used bicubic interpolation as it is an extension of cubic interpolation for interpolating data points on a two-dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbor interpolation.

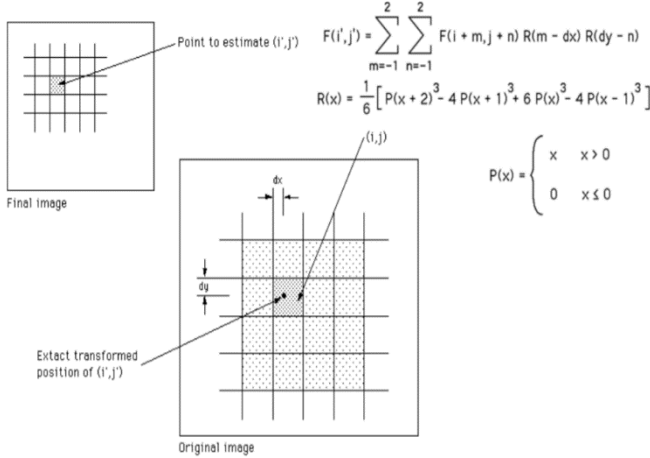


Fig. 1. Bicubic Interpolation

D. Image Augmentation

Image augmentation artificially creates training images through different ways of processing or combination of multiple processing, such as rescaling, random rotation, shear and flips, padding, etc.[2] An augmented image generator can be easily created using ImageDataGenerator API in Keras. ImageDataGenerator generates batches of image data with real-time data augmentation. It helps to increase the generalizability of the model. For Image augmentation image re-scaling is done

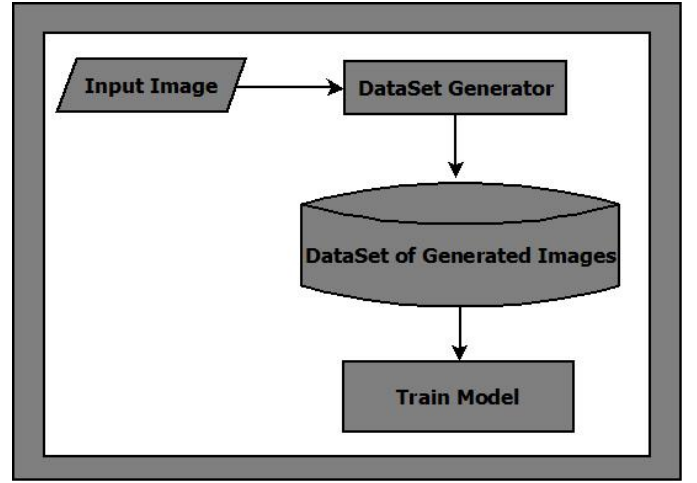


Fig. 2. Bicubic Interpolation

in which size of every image is converted to 255. It can be horizontally or vertically. The Flip Horizontally reverses the active layer horizontally, that is, from left to right. It leaves the dimensions of the layer and the pixel information unchanged. Some frameworks do not provide function for vertical flips. But, a vertical flip is equivalent to rotating an image by 180 degrees and then performing a horizontal flip.

E. SRCNN model

Super Resolution Convolutional Neural Network that takes the low-resolution image as the input and outputs the high-resolution one. The trained models are applied to the validation and test data within the dataset and show a 3-5 dB rise in image quality compared to image interpolation (bicubic), with all tested models performing within a 0.1 dB range. Difference maps indicate that edge sharpness is completely recovered in images within the scope of the trained model, with only high frequency noise related detail loss.

The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image.

$$MSE = \frac{\sum_M^N [I_1(m, n) - I_2(m, n)]^2}{M * N} \quad (1)$$

The mean-square error (MSE) and the peak signal-to-noise ratio (PSNR) are used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the lower the error.

Super-Resolution Convolutional Neural Network (SRCNN) is reviewed. In deep learning or convolutional neural network (CNN), CNN is used for image classification. In SRCNN, it is

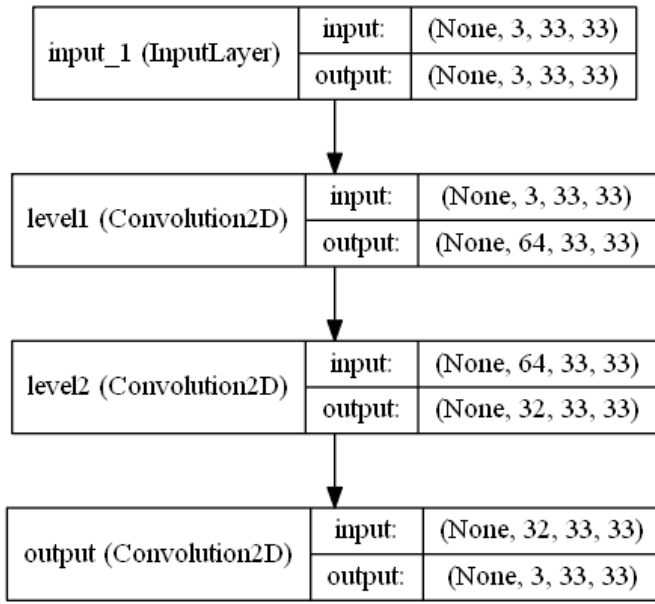


Fig. 3. SRCNN Architecture

used for single image super resolution (SR) which is a classical problem in computer vision.

In brief, with better SR approach, CareGreen get a better quality of a larger image even we only get a small image originally. From Fig. 3 with SRCNN, PSNR of 27.58 dB is obtained which is much better than the classical non-learning based Bicubic and sparse coding (SC).

F. Feature Extraction

It is the procedure of outlining a set of necessary features, or image characteristics that form the core element which when represented in an efficient or meaningful manner give the required information that is important for analysis and classification purpose. Feature extraction technique can be based on color, shape, or texture features. The most commonly used feature extraction technique is the texture extraction technique. The shape oriented feature extraction like Area, Color are calculated. Similarly the texture oriented feature extraction like contrast, correlation, homogeneity and mean. Color features are extracted by various methods, such as Color histogram, Color moments and Color structure descriptor. Grey Level Co-occurrence Matrix (GLCM) method is used for extraction of texture features. Now normalisation should be applied i.e. max-pooling.

Max pooling is a sample-based discretization process. The objective is to down-sample an input representation (image, hidden-layer output matrix, etc.), reducing its dimensionality and allowing for assumptions to be made about features contained in the sub-regions binned. This is done to in part to help over-fitting by providing an abstracted form of the representation. As well, it reduces the computational cost by reducing the number of parameters to learn and provides

basic translation in variance to the internal representation. Max pooling is done by applying a max filter to (usually) non-overlapping sub regions of the initial representation.

G. Classifier

Adam is a replacement optimization algorithm for stochastic gradient descent for training deep learning models. Adam is an adaptive learning rate method, which means, it estimations of first and second moments of gradient to adapt the learning rate for each weight of the neural network. N-th moment of a random variable is defined as the expected value of that variable to the power of n. More formally:

$$m_n = E[X^n] \quad (2)$$

where m=moment X=random variable

Adam has the advantages of two other extensions of stochastic gradient descent. Specifically:

- Adaptive Gradient Algorithm (AdaGrad) that maintains a per-parameter learning rate that improves performance on problems with sparse gradients (e.g. natural language and computer vision problems).
- Root Mean Square Propagation (RMSProp) that also maintains per-parameter learning rates that are adapted based on the average of recent magnitudes of the gradients for the weight (e.g. how quickly it is changing). This means the algorithm does well on online and non-stationary problems (e.g. noisy).

Adam Configuration Parameters

- alpha. Also referred to as the learning rate or step size. The proportion that weights are updated (e.g. 0.001). Larger values (e.g. 0.3) results in faster initial learning before the rate is updated. Smaller values (e.g. 1.0E-5) slow learning right down during training
- beta1. The exponential decay rate for the first moment estimates (e.g. 0.9).
- beta2. The exponential decay rate for the second-moment estimates (e.g. 0.999). This value should be set close to 1.0 on problems with a sparse gradient (e.g. NLP and computer vision problems).
- epsilon. Is a very small number to prevent any division by zero in the implementation (e.g. 10E-8).

IV. PRETRAINED MODELS

A. Inception_V3

Although Inception v3 can be trained from many different labeled image sets, ImageNet is a common dataset of choice. ... Only images from the training dataset are used to train the model and only images from the evaluation dataset are used to evaluate model accuracy. ImageNet, is a dataset of over 15 millions labeled high-resolution images with around 22,000 categories. ILSVRC uses a subset of ImageNet of around 1000 images in each of 1000 categories. In all, there are roughly 1.2 million training images, 50,000 validation images and 100,000 testing images[2]. Input size of model by default is 299*299 .

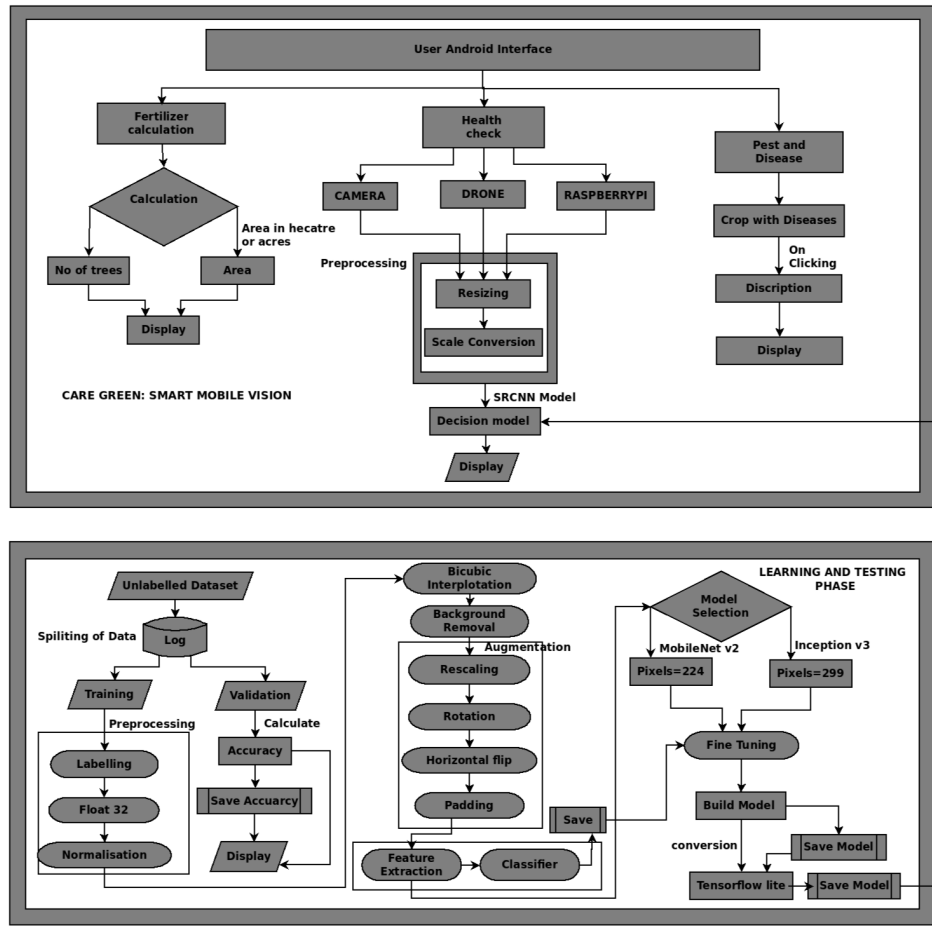


Fig. 4. Proposed Care Green Architecture

B. MobileNet_V2

MobileNet_V2 is a significant improvement over MobileNet_V1 and pushes the state of the art for mobile visual recognition including classification, object detection and semantic segmentation. Depthwise Separable Convolution is introduced which dramatically reduce the complexity cost and model size of the network, which is suitable to Mobile devices, or any devices with low computational power[3]. Input size of model by default is 224*224 .

C. ResNet 34

ResNet, short for Residual Networks is a classic neural network used as a backbone for many computer vision tasks. This model was the winner of ImageNet challenge in 2015. The fundamental breakthrough with ResNet was it allowed us to train extremely deep neural networks with 150+layers successfully. Each ResNet block is either two layers deep (used in small networks like ResNet 18, 34) or 3 layers deep (ResNet 50, 101, 152).

V. PROPOSED ARCHITECTURE

Firstly install the Care Green App then an android interface will appear which is splash screen of the android app. Then

an activity will appear which will have multiple sections in it. First and the top most section of the activity will have a collection of icons or button having different crops which is done by using the scroll bar. On clicking any icon from the scroll bar will display another activity which will show three buttons and some crop advisory on the same page. First button provide a feature to calculate the fertilizer required for the crops according to the crops growth some like apple, orange etc. requires fertilizer on the basis of count of trees while others such as pepper, strawberry ,etc depends on the area which may be in hectare or acres. Second button on the same screen will take the user to the list of crops. On clicking the name of the crop, user will see the list of diseases which can be present in that crop. On clicking the name of disease user will get a screen which will contain the information of the disease and gives the prevention measures and the treatment methods for that disease which can be in chemical and biological method. Third button on the screen is heath check. On clicking it ,user will see three option for the detection of the disease in the crop. Three options are first is using android phone camera, second is using drone to capture images of the leaf using controller which user need to install with Care Green App through which user can control the drone and capture

TABLE I
EXPERIMENTAL RESULTS (%) OF LEAF DISEASE DETECTION USING PLANT VILLAGE DATASET

Architecture	Validation Loss	Validation Accuracy	Training Loss	Training Accuracy	Overall Accuracy
Inception V3 Without DA	0.4051	0.7616	0.3878	0.8621	0.8118
Inception V3 DA	0.3872	0.8717	0.3502	0.8811	0.8764
Mobilenet V2 Without DA	0.2381	0.9223	0.2181	0.9353	0.9288
ResNet 34	0.1447	0.9544	0.4218	0.9624	0.9584
Mobilenet V2 DA (Proposed)	0.1607	0.9552	0.1007	0.9672	0.9612

TABLE II
PLANTVILLAGE DATASET

S.No.	Crop	Disease	No. of Images
1	Apple	Apple Scab	631
		Apple Black Rot	622
		Apple Cedar Rust	276
		Apple Healthy	1646
2	Grape	Grape Black Rot	1181
		Grape Black Measles (Esca)	1384
		Grape Leaf Blight	1077
		Grape Healthy	424
3	Peach	Peach Bacterial Spot	2298
4	Strawberry	Strawberry Leaf Scorch	1110
		Strawberry Healthy	457
5	Potato	Potato Early Blight	1001
		Potato Late Blight	1001
		Potato Healthy	153
6	Corn	Corn Gray Leaf Spot	514
		Corn Common Rust	1193
		Corn Northern Leaf Blight	986
		Corn Healthy	1163
7	Orange	Orange Huanglongbing (Citrus Greening)	5508
8	Tomato	Tomato Bacterial Spot	2128
		Tomato Early Blight	1001
		Tomato Late Blight	1910
		Tomato Leaf Mold	953
		Tomato Septoria Leaf Spot	1772
		Tomato Two Spotted Spider Mite	1677
		Tomato Target Spot Tomato Mosaic Virus	1405
		Tomato Yellow Leaf Curl	5358
		Tomato Healthy	1592
9	Squash	Squash Powdery Mildew	1836
10	Cherry	Cherry Powdery Mildew	1053
		Cherry Healthy	855
11	Blueberry	Blueberry Healthy	1503
12	Pepper	Pepper Bacterial Spot	998
		Pepper Healthy	1479
13	Soybean	Soybean Healthy	5091
14	Raspberry	Raspberry Healthy	372

image from the drone and can detect disease in the crop. Use of drone can be very helpful for the farmers having large fields and having difficulty in managing field and cover larger area using drone. To capture image from drone click on the button which is present on the controller in the android app image is captured through camera attached with the drone. User can also record videos (it will take the image in the form of frames) and that image will be store in the gallery of user's android phone and then user can upload image in the app which will be passed to the proposed model i.e., SRCNN Model and CNN Model and will display the result on the android screen where plant having any disease or not, if any disease is present then it will tell which disease is present. Third option is the use of IOT device i.e., Raspberry Pi. Raspberry pi have its own OS which is installed in the memory card attached to it. A machine learning code which

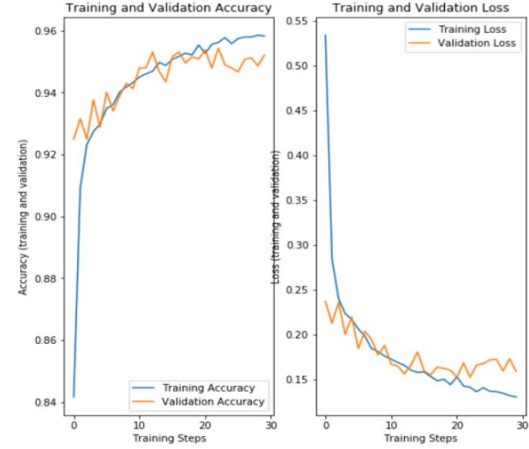


Fig. 5. Accuracy and Loss Graph

is written in python is present in the raspberry pi which is having a tensorflow lite model in it. A camera module is also attached to the raspberry pi. For the above things happen user firstly need to connect the raspberry pi to the android hotspot (whose IP address is stored in the python code in raspberry pi). Then login it using he login id which user used at the time of installing Raspberry pi Os after that go to the Work directory and run a command which will execute the python code which will capture the image from camera which is attached to the raspberry pi and then it will passed to the proposed model i.e., SRCNN Model and CNN Model and will display the result on the android screen where plant having any disease or not, if any disease is present then it will tell which disease is present.

VI. EXPERIMENTS AND RESULTS

A. Hardware Description

Care Green have been performed using the proposed approach in a machine having Ubuntu 18.04.3 LTS, Intel Core i5-5200U CPU @ 2.20 Ghz 8 GB RAM, 500 GB HDD having 2048 MB Nvidia GeForce 920M GPU.

The programs are coded using Python 3.7.3 and having libraries as follow :-

sys, keras-2.2.4, tensorflow-2.0.0, cv2, skimage, matplotlib-3.0.3, numpy-1.16.2, tensorflow_hub-0.7.0 to make use of some predefined functions.

For a better performance and faster results Care Green used system with GPU.

TABLE III
COMPARISON OF PROPOSED ARCHITECTURE WITH EXISTING WORK

Parameters	Amara et al. [8]	Barbedo et al. [14]	Brahimi et al. [4]	Wang et al.[13]	Proposed Architecture
Dataset	Banana Dataset(PlantVillage)	PlantVillage Dataset	PlantVillage Dataset	Apple Dataset(PlantVillage)	PlantVillage Dataset
No. of Species	1	14	14	1	14
No. of Classes	3	38	38	4	38
No. of images	3700	54306	54323	2086	54305
Preprocessing	Re	Re, Sg, PT, AT, Cr	Cr, Re	Re, Fl, Ro, Zo	Re, Fl, NR, Sg, BR
CNN Architecture	(Modified)LeNet	GoogLeNet	Inception V3	VGG16	MobileNet V2
Transfer Learning	No	Yes	Yes	Yes	Yes
Learning rate	0.001	N/A	0.001	0.001	0.001
Activation Function	Sigmoid	N/A	N/A	SGD	Softmax
Batch Size	10	N/A	20	N/A	64
Train - Test Ratio	60% - 40%	N/A	80% - 20%	80% - 20%	67% - 33%
Optimizer	SGD	N/A	N/A	N/A	Adam
No. of iterations	30	N/A	N/A	N/A	30
Overall Accuracy	0.9282	0.9935	0.9976	90.4	96.72

difference in the CNN Architecture and time usage can be reduced.

B. Description about Data Set

Care Green has been analyze through 54,306 images of plant leaves, which have a spread of 38 class labels assigned to them. Each class label is a crop-disease pair, and made an attempt to predict the crop-disease pair given just the image of the plant leaf. Approaches described in this paper, firstly resize the images to 224 x 224 pixels for MobileNet_v2 and to 299 x 299 pixels for inception_v3, and perform both the model optimization and predictions on these downscaled images. The details of the dataset are shown in Table II.

C. Description about Result

In this experiment, three state-of-the-art architectures (Inception v3 [21], MobileNet v2 [14], ResNet-34 [13]) are trained on the dataset described in the previous section. To train and evaluate the performance of these state-of-the-art CNN, we use a Python deep learning framework.

These three CNN architectures are trained for the plant diseases classification task using two different strategies. Two of these strategies are based on the transfer learning from pre-trained networks. The first transfer learning approach is used without data augmentation which consists of fine-tuning only the fully connected layers, while the rest of the network is used as a feature extractor.

On the other hand, the second transfer learning strategy which is used with data augmentation, fine-tunes all network layers and starts back-propagation optimisation from the pre-trained network. Using these two approaches, the CNN classifier tries to learn more specific features for plant diseases classification starting from pre-trained networks. All these 5 training configurations (2 CNN Architectures × 2 strategies + 1 ResNet Architecture) use the same hyper-parameters values (Optimizing Algorithm = Adam, Activation Fuction = Softmax, Learning Rate = 0.001, Batch Sizes = 64). The dataset is divided into 67% for training and 33% for evaluation.

Note: The accuracy from different CNN Architecture which is shown in Table I were obtained on the same above hyper-parameters and no. of epochs are reduced to 5 to show the

VII. DISCUSSION

In this section we will present some discussion on the practical application and advantages with our Care Green architecture. Then we compare the Care Green with some of the previously proposed techniques.

In Table III, following preprocessing and data augmented techniques are used: Re-Resize, Sg-Segmentation, PT-Perspective Transformation, AT—Affine Transformation (translations and rotations), Cr-Crop, Fl-Flipping, Ro-Rotation, Zo-Zooming, NR-Noise Removal, BR-Background Removal

A. Practical Application and Advantages

1) Application:

- **Increased business efficiency through process automation.** By using smart devices, they can automate multiple processes across your production cycle, e.g. irrigation, fertilizing, or pest control.
- **Enhanced product quality and volumes.** Achieve better control over the production process and maintain higher standards of crop quality and growth capacity through automation.

2) Advantages:

- **Data collection:** Data can be collected from large area from Drone in the form of video or as an image .If image is captured from video then frames will be made. Data is stored in gallery , and then that images are passed in model for the detection of disease.
- **Reduction of risks:** When farmers up-to-date information collected, they can understand what situation will be in the future, and they can predict some problems that may arise. Moreover, farmers may use data to improve their sales and change business processes.
- **Business goes automated:** Many business processes become automated and their efficiency is growing. Thus, farmers may pay attention to other important processes.
- **Higher quality:** Smart agriculture makes it possible to avoid challenges and remove all issues that may arise

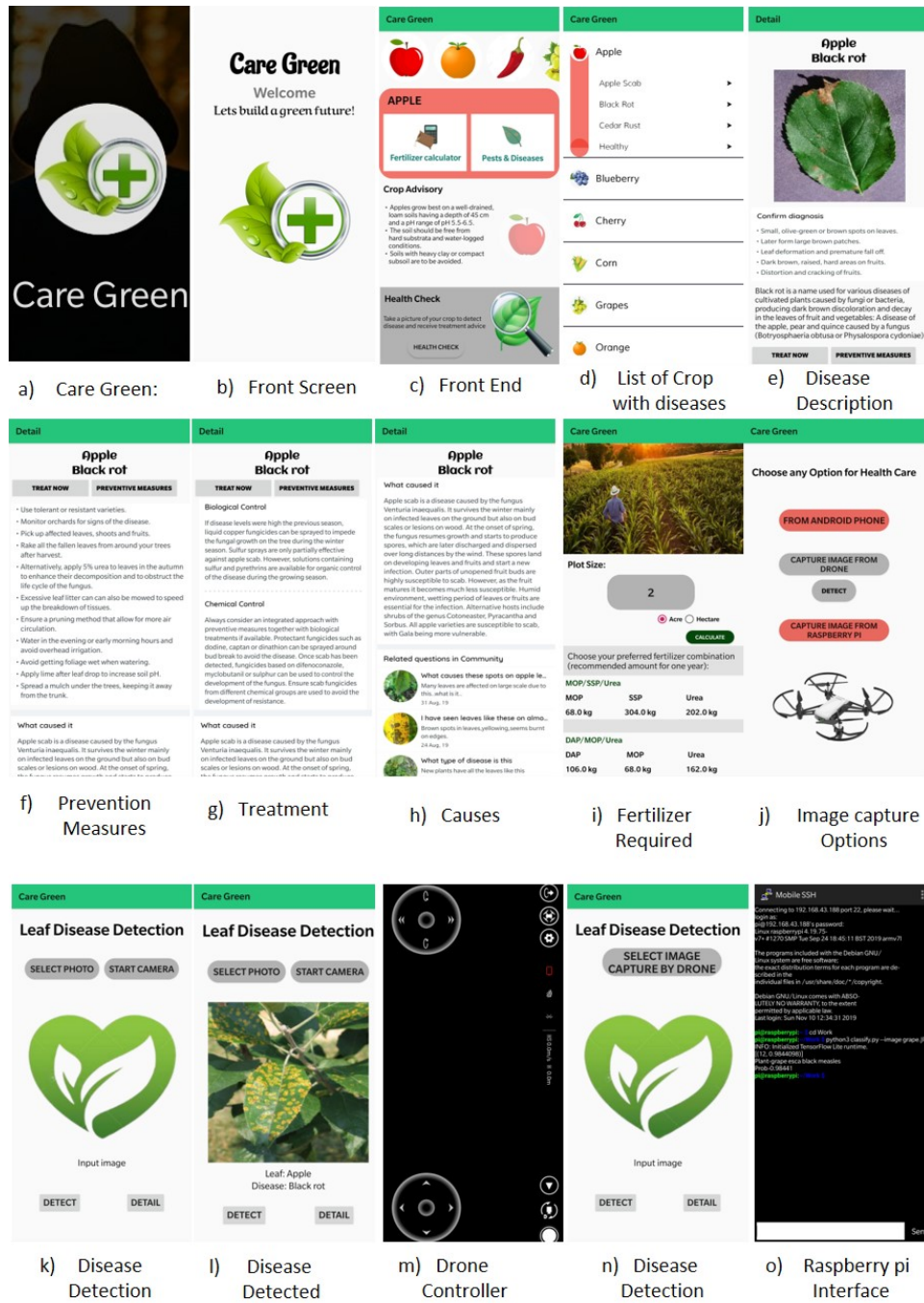


Fig. 6. Proposed Care Green Architecture

during farming processes. So the quality of the product is growing and consumers get a good product of high quality.

B. Comparison with Other Approaches

There is division of training dataset in two dataset with some x:y ratio. But this is not static. There is split of the dataset at every epoch rather than splitting it in start. Splitting of the dataset at every epoch and makes sure that training and

validation dataset is always different by shuffling dataset. This way, model's performance increases.

- val_loss starts increasing, val_acc starts decreasing. This means model is cramming values not learning.
- val_loss starts increasing, val_acc also increases. This could be case of over fitting or diverse probability values in cases where softmax is being used in output layer.
- val_loss starts decreasing, val_acc starts increasing. This is also fine as that means model built is learning and

working fine.

Inception V3 without DA(data augmentation): have the lowest training accuracy because of the highest validation loss and the training loss ,which effects overall accuracy.As data augmentation will help to train the model from every angle of image which will increase the accuracy.

Inception V3 with DA: To overcome the limitation of above proposed method data augmentation is done which will decrease the validation loss and training loss and improves the overall accuracy .But the accuracy was not satisfactory as in Inception V3 model size is 299*299 by default which occupies large space.

MobileNet V2 without DA: Accuracy given by Inception was not acceptable ,so new pretrained model is proposed which have 224*224 default size of model .This model even without data augmentation process gives the accuracy better than the Inception model with less validation loss and the less training loss.

ResNet 34 Overcome the limitation of MobileNet V2 without data augmentation ,without data augmentation only it improves the overall accuracy and the training accuracy but this model is used for small networks only as it is for two or three layers.

Mobilenet V2 with DA: Proposed in Care Green in which model is trained with data augmentation also i.e. model is trained with every angle of image so the accuracy can be improve with validation loss 0.1607 and the training loss 0.1007 which is the least losses till the proposed models.Even the overall accuracy is 96% at epoch of 30 only.

REFERENCES

- [1] An open access repository of images on plant health to enable the development of mobile disease diagnostics DavidP. Hughes 1,2,3 Marcel Salathe 4
- [2] Hughes, D., Salathe, M.: An open access repository of images on plant health to enable the development of mobile disease diagnostics, pp. 1–13 (2015)
- [3] Kawasaki, Y., Uga, H., Kagiwada, S., Iyatomi, H.: Basic study of automated diagnosis of viral plant diseases using convolutional neural networks. In: Advances in Visual Com- Fig. 6. Comparison table puting: 11th International Symposium, ISVC 2015, Las Vegas, NV, USA, 14–16 December 2015, Proceedings, Part II, pp. 638–645 (2015)
- [4] Brahimi, M., Boukhalfa, K., Moussaoui, A.: Deep learning for tomato diseases: classification and symptoms visualization. Appl. Artif. Intell. 31(4), 1–17 (2017)
- [5] Lu, Y., Yi, S., Zeng, N., Liu, Y., Zhang, Y.: Identification of rice diseases using deep convolutional neural networks.Neurocomputing 267, 378–384 (2017).
- [6] R. Kaur, M. Kaur : A Brief Review on Plant Disease Detection using in Image Processing.
- [7] Sujatha R*, Y Sravan Kumar and Garine Uma Akhil: Leaf disease detection using image processing. k-means clustering algorithm 671-672.
- [8] Amara, J.; Bouaziz, B.; Algergawy, A. A deep learning-based approach for banana leaf diseases classification. Gesellsch. Inf. Bonn 2017, 79–88.
- [9] Ferentinos, K.P. Deep learning models for plant disease detection and diagnosis. Comput. Electron. Agric. 2018, 145, 311–318. [CrossRef]
- [10] Fuentes, A.; Yoon, S.; Kim, S.; Park, D. A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors 2017, 17, 2022. [CrossRef]
- [11] Cruz, A.C.; Luvisi, A.; De Bellis, L.; Ampatzidis, Y. X-FIDO: An effective application for detecting olive quick decline syndrome with deep learning and data fusion. Front. Plant Sci. 2017, 8, 1741. [CrossRef] [PubMed]
- [12] Brahimi, M.; Arsenovic, M.; Laraba, S.; Sladojevic, S.; Boukhalfa, K.; Moussaoui, A. Deep learning for plant diseases: detection and saliency map visualisation. In Human and Machine Learning; Zhou, J., Chen, F., Eds.; Springer International Publishing: Cham, Switzerland, 2018; pp. 93–117. ISBN 978-3-319-90402-3.
- [13] Wang, G.; Sun, Y.; Wang, J. Automatic image-based plant disease severity estimation using deep learning. Comput. Intell. Neurosci. 2017, 2017, 1–8. [CrossRef] [PubMed]
- [14] Jayme Garcia Arnal Barbedo; Plant disease identification from individual lesions and spots using deep learning