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Original Research Article

Smart Agricultural System Using AI

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Abstract

For many years, crop diseases have been among the major threats to food security, but their rapid identification remains difficult in many parts of the world due to a lack of necessary infrastructure. The purpose of this work is to develop a smart agricultural system that monitors the crops' diseases and suggests remedies for those diseases to the farmers using a deep learning algorithm called MobileNet. The system will work efficiently on smartphones and autonomous systems in real-time.

Keywords: Crop diseases, Deep Learning, Machine Learning, Artificial Intelligence and Smart system.

INTRODUCTION

According to the Food and Agriculture Organization of the United Nations (FAO), global food production must increase by 50% to meet the projected demand of the world's population by 2050 [1]. Based on a United Nations 2021 report, the number of people affected by hunger globally rose to as many as 828 million in 2021, an increase of about 46 million since 2020 and 150 million since the outbreak of the COVID-19 pandemic [2]. Nearly one in three people in the world (2.37 billion) did not have access to adequate food in 2020 - that's an increase of almost 320 million people in just one year [3]. With the Ukraine-Rassia war, all of these figures are expected to rise in 2022. David Beasley, head of the World Food Programme (WFP), stated that 10 countries are at the greatest risk of food insecurity across the globe [5]. These 10 countries were affected by conflict, economic crisis, and climate change. The fourth annual Global Report on Food Crises highlights that these 10 countries are: Yemen, the Democratic Republic of the Congo, Afghanistan, Venezuela, Ethiopia, South Sudan, Sudan, Syria, Nigeria, and Haiti. Also, the report stated that 61% of the South Sudan population was affected by a food crisis in the year 2020 [6]. Crop diseases are among the major threats to food security, but their rapid identification remains difficult in many parts of the world due to a lack of necessary infrastructure. Pests and diseases are responsible for 20 to 40% of global crop production losses each year, according to FAO [4]. Each year, plant diseases cost the global economy around $220 billion, and invasive insects around $70 billion [4]. Plants, which make up 80 percent of the food we eat and produce 98 percent of the oxygen we breathe, are under constant and increasing threat from pests and diseases, the United Nation's food agency, FAO, warned [7]. The United Nations General Assembly has declared the year 2020 as the International Year of Plant Health (IYPH). The year represents a once in a lifetime opportunity to raise global awareness about how protecting plant health can help to end hunger, reduce poverty, protect the environment, and promote economic development.

In this research we developed a smart agricultural system that monitors the crops' diseases, and suggests remedies for those diseases to the farmers using a deep learning algorithm called SSD Mobile Net. The system will work efficiently on smartphones and autonomous systems in real time.

In today's world, a lot of people are digitally connected through the internet and smart devices. In this work, we will be using SSD Mobile Net, a deep learning model widely known as light-weighted deep learning networks, to directly run-on smartphones. Deep learning algorithms are now doing an excellent job of recognizing, detecting, understanding, and performing a wide range of tasks in various industries. In the last decade, there has been an exponential rise in data

on the internet and huge improvements in GPU hardware. To perform detection and recognition tasks better, this algorithm was trained on a big GPU.

In recent years, Artificial Intelligence algorithms [8, 9] in the domain of computer vision have provided a lot of algorithms in food security systems [18, 19]. In their paper, Mohanty et al. [17] used the AlexNet and GoogleNet models, which have lower accuracy than MobileNet [20]. Due to the light weight of MobileNet, it is preferable to be deployed on a smartphone. In this work, we used MobileNet [11], which is fast, accurate, and light, and we annotated our own data with some plant diseases. In this work, we have an end-to-end pipeline that not only detects the plant diseases but also sends remedies to the farmer. There are various challenges present in object detection and recognition of plant diseases. Since most diseases look similar, they fall under intraclass challenges. Other challenges are partial occlusion, lower resolution cameras, inaccurate detections, and less annotated data. Keeping all of the challenges of this task in mind, we proposed a method to address the problem and perform the detection task as efficiently as possible.

LITERATURE REVIEW

Various methods are available for object detection tasks. Some of the popular algorithms are YOLO (You only look at once algorithm) [10], SSD (Single Shot Detector) [22], MobileNets [12], Retina Net [13], Faster R-CNN (Faster-Region based Convolutional Neural Networks) [14], R-FCN (Region-based Fully Convolutional Networks) [15]. Choosing the right object detector is an essential step for this research since speed, accuracy, and lightness of the model architecture are our priorities. Object detector models are categorized into two: the one-step object detection model and the two-step object detection model. YOLO [9], SSD [22], MobileNets [12], and Retina Net [13] are good examples of one-stage detectors. R-CNN, Fast RCNN [23], Faster R-CNN [14], and R-FCN [15] are also good examples of two-staged detectors. Compared to all the models, we chose the Single Stage Detector (SSD) MobileNet model since we opted for speed, accuracy, and, most importantly, due to its light weight architecture, which makes it run on smartphone devices efficiently.

Mobile Net ARCHITECTURE

The SSD MobileNet model is designed to be used in mobile applications and is Tensor Flow's first mobile computer vision model. MobileNet uses depth-wise separable convolutions. It significantly reduces the number of parameters when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks from two operations.

A depth-wise separable convolution is made

1. Depth-wise convolution
2. Point-wise convolution

Mobile Net is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and fast.

This convolution originated from the idea that a filter's depth and spatial dimension can be separated thus, the name separable. Let us take the example of Sobel filter, used in image processing to detect edges.

Depth-wise separable convolution: is a depth-wise convolution followed by a point wise.

1. Depth-wise convolution is the channel-wise spatial convolution. Suppose in the fig. 1, we have five channels; then, we will have 5 spatial convolutions.
2. Point wise convolution is the 1×1 convolution to change the dimension.

Depth-wise convolution: It is a map of a single convolution on each input channel separately. Therefore, its number of output channels is the same as the number of the input channels.

Point wise convolution: Convolution with a kernel size of 1x1 that simply combines the features created by the depth wise convolution. The main difference between MobileNet architecture and a traditional CNN instead of a single 3x3 convolution layer followed by the batch norm and ReLU. Mobile Nets split the convolution into a 3x3 depth-wise conv and a 1x1 point wise convolution.

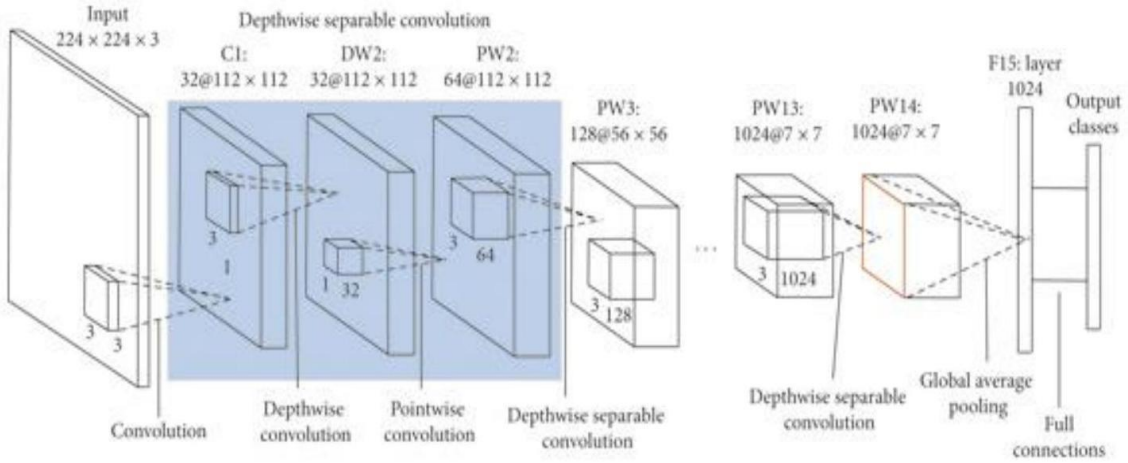

Fig. 1: Mobile Net Architecture

METHODOLOGY

In order to perform this task, we have proposed a pipeline shown in fig. 2.

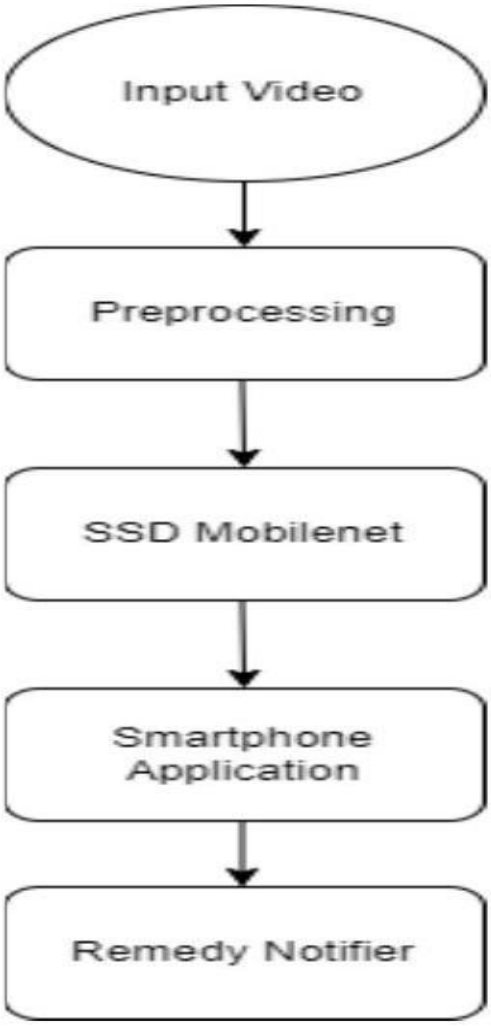

Fig. 2: Proposed pipeline

Pre-processing: In order to train a model we need to follow few pre-processing steps so firstly we perform data augmentation techniques to generate more data and each image is smoothened before training the model.

SSD MobileNet Object detection: In this step data set prepared in previous step is been used for training the model after model has trained it is deployed on smartphone.

Smartphone Application: Trained model is deployed in smartphone using filet library by building an android application. Every captured image through smartphone is saved in local storage and also syncs in cloud storage as backup. These images with output results are further used to make remedy suggestions report.

Remedy Notifier: The remedies of an identified disease can be sent to the farmers via an email or text messages using cloud functionalities.

RESULTS

In this section, we will discuss the results. The model is trained with four labels, namely Potato Early Blight, Grape Black Measles, Corn Common Rust, and Tomato Late Blight. Fig. 3 is the confusion matrix; Fig. 4 is the training and validation losses, and fig. 5 and fig. 6 are result outputs.

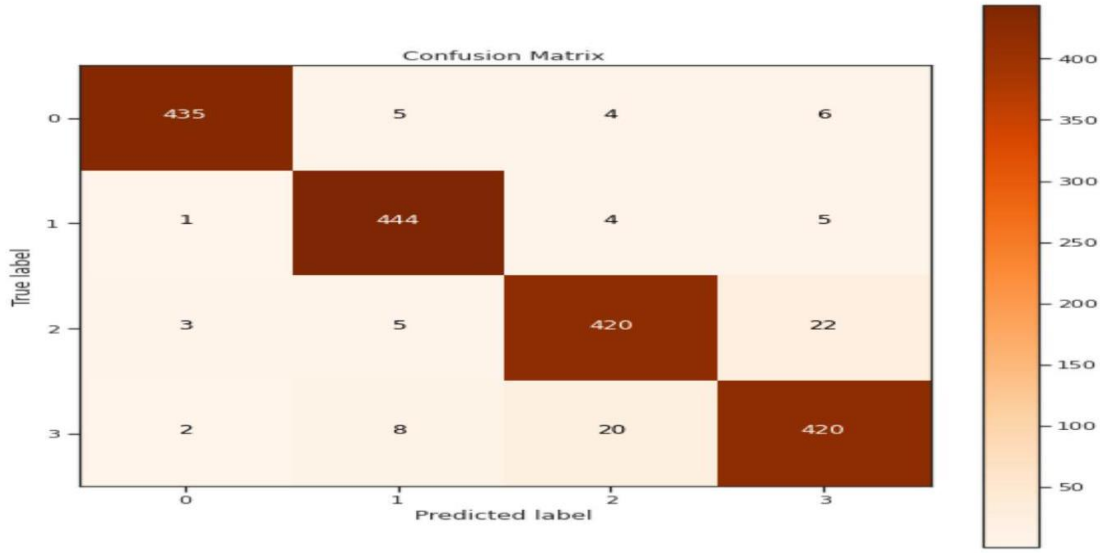

Fig. 3: Confusion matrix

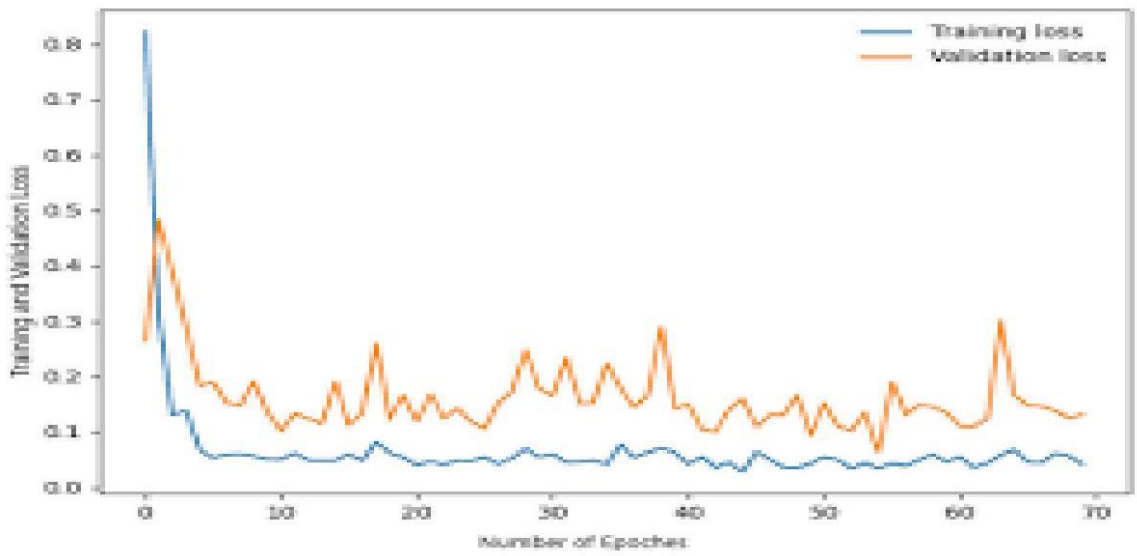

Fig. 4: Training curves and Validation loss

Fig. 3 is the confusion matrix of our trained model. A confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically supervised learning. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class or vice versa.

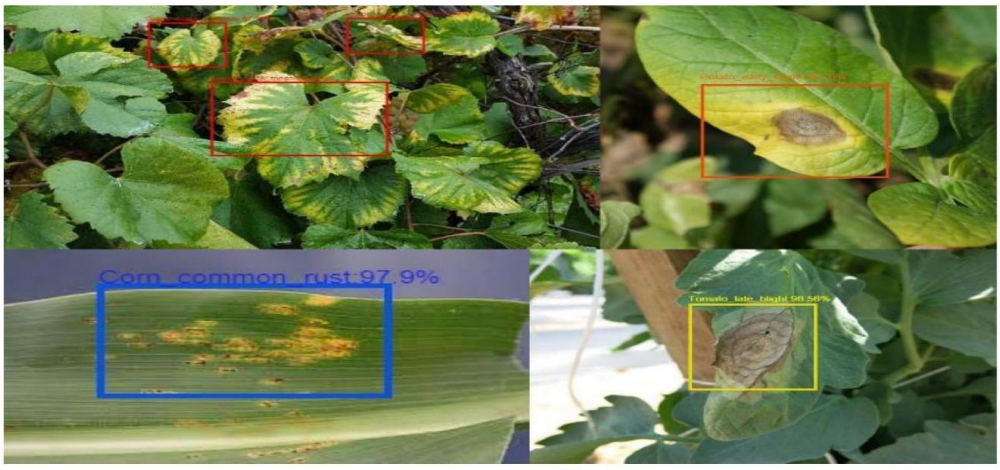

Fig. 5: detected Plant diseases

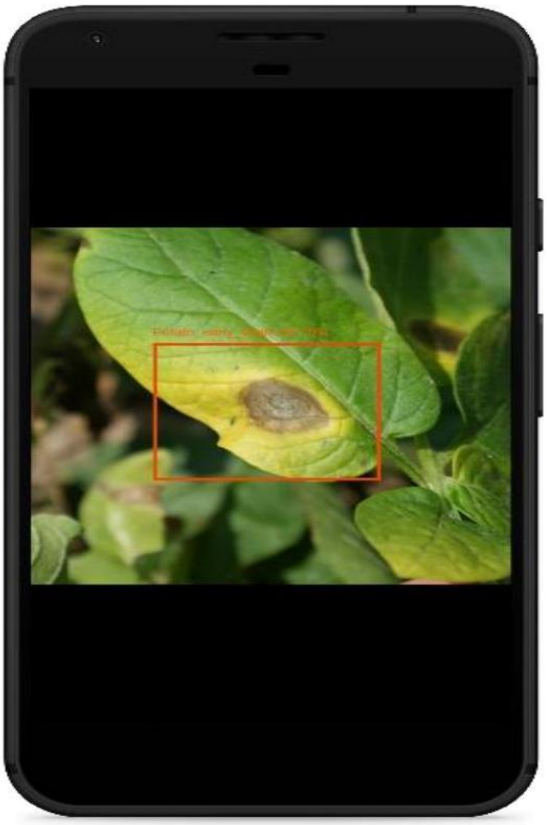

Fig. 6: Smart Phone Application Result

Discussion

Although this study has generated plant diseases solution for farmers, yet more advancement can be 'made. We have built a plant disease detecting application. The followings are potential recommendations for future work:

1. For detection and segmentation techniques, more custom classes should be added.
2. More data samples could be added, as well as extensive data augmentation techniques, to increase the model's accuracy because it has a significant likelihood of falling into infraclass recognition.
3. This program might use cloud computing to make it very scalable for treating different diseases.

CONCLUSION

In this work, we have developed an end-to-end solution for plant disease detection. We collect the data, annotate it, train the model, and deploy the trained model on a smartphone. A remedy notifier is also being developed to notify the farmers via email or text.

ACKNOWLEDGMENT

We acknowledge the several datasets that were used in this work. [21] Is one of the datasets we have used.

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