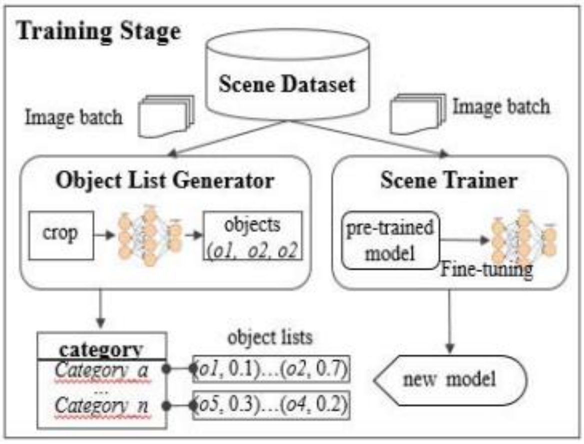
Fresh and Rotten fruits Classification

Abstract—In this paper, we are implementing the technique to scan the farm and to classify the fresh and rotten fruits. It will give the details about the location of fresh fruits and rotten fruits. With the help of that, one can pluck fresh fruits on time. Convolution Neural Network is used for this purpose. It will classify the fresh fruits from the farm and will make the list of the location.

Keywords—Scene recognition, Convolution Neural Networks, MobileNetV2

I. INTRODUCTION

From the ages, fruits are essential part of the healthy living. Picking up fresh fruits from the farm before they get rote is very difficult job. If one rotten fruit get in contact with the fresh fruit, fresh fruit will also get rotten. Hence, one must pluck before it gets rote.



In the big farms it is very time-consuming task to classify fresh and rotten fruits.

Figure 1: The proposed Convolutional Neural Network architecture

Artificial Intelligence has been witnessing a monumental growth in bridging the gap between the capabilities of humans and machines. [1] Researchers and enthusiasts alike, work on numerous aspects of the field to make amazing things happen. One of many such areas is the domain of Computer Vision. The agenda for this field is to enable machines to view the world as humans do, perceive it in a similar manner and even use the knowledge for a multitude of tasks such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. The advancements in Computer Vision with Deep Learning have been constructed and perfected with time, primarily over one algorithm — a Convolutional Neural Network (CNN). Figure 1 shows the basic architecture of the CNN with basic building blocks.

In deep learning, a convolutional neural network (CNN, or ConvNet) [2] is a class of artificial neural network (ANN), most applied to analyse visual imagery. CNN is a type of Artificial Neural Network effective in areas such as image recognition and classification.[3] Multilayer perceptron usually means fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "full connectivity" of these networks makes them prone to overfitting data. Typical ways of regularization, or preventing overfitting, include penalizing parameters during training or trimming connectivity. CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble patterns of increasing complexity using smaller and simpler patterns embossed in their filters. Therefore, on a scale of connectivity and complexity, CNNs are on the lower extreme.

II. CNN ARCHITECTURE

A light weight deep neural network structure named MobileNets is proposed which is constructed by depthwise separable convolution. MobileNets strikes a delicate balance between the recognition accuracy and the network parameters, which make it possible to use in mobile devices [4]. In 2018, MobileNetV2 is obtained based on the structural improvement of the MobileNet. It retains the simplicity MobileNets, significantly improves its accuracy, and reaches the advance level of classification and detection application for mobile application. Figure 2 shows two types of convolutional blocks in MobileNetV2.

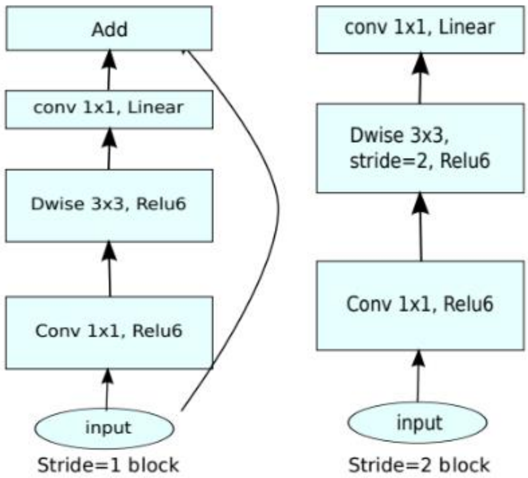


Figure 2: Convolutional blocks in MobileNetV2

It is based on an inverted residual structure where the residual connections are between the bottleneck layers [5]. The intermediate expansion layer uses lightweight depthwise convolutions [6] to filter features as a source of non-linearity. The architecture of MobileNetV2 contains the initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers.

III. DATASET, EXPERIMENTAL SETUP AND RESULTS

A. Dataset

A dataset was picked [7] which consisted of different quantities of fresh and rotten apples, bananas, and oranges. Google Colaboratory (Colab) is used to write the code and this data set is uploaded in the Colab. Figure 3 represents different types of fruits and their fresh and rotten quantities.

train samples of fresh apple: 1693

train samples of rotten apple: 2342

train samples of apple: 4035

train samples of fresh banana: 1581

train samples of rotten banana: 2224

train samples of banana: 3805

train samples of fresh orange: 1466

train samples of rotten orange: 1595

train samples of oranges: 3061

Figure 3: Represents quantities of fresh and rotten fruits

B. Experimental setup and results

For the experiment, a code for the classification of fruits is written in the Google Colab and along with the code, dataset is also uploaded in the Google Colab. Code has the call function used and due to that data set is automatically called and inputs are taken automatically. After that, classification is done according to the code and final value is given as the output to next component.

Results shows increase in accuracy with the use of the CNN model. There is rise in the accuracy and fall in the number of errors or loss. Figure 4 shows the comparison between different types of architecture and figure 5 shows results of accuracy and loss from the experiment.

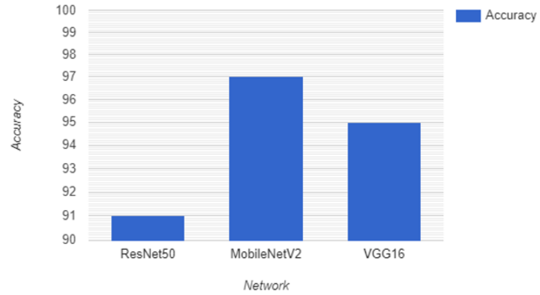


Figure 4: Comparison of different CNN architectures

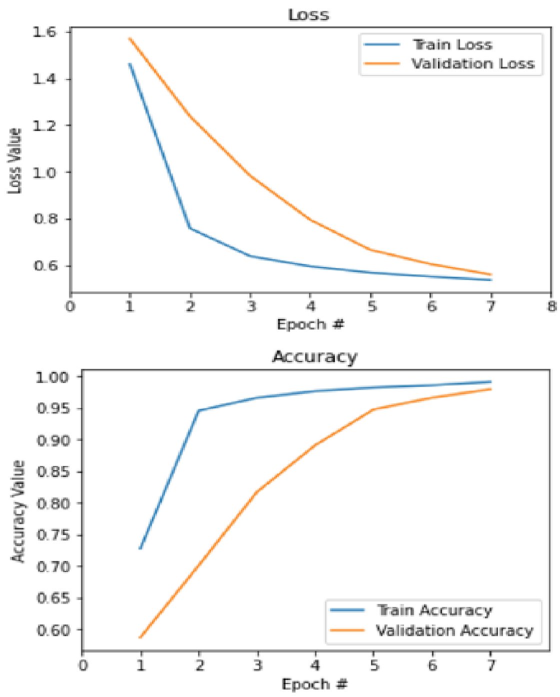


Figure 5: Results from the experiments performed. (Accuracy and Loss)

IV. CONCLUSION

This paper shows the work done with the use of Convolutional Neural Networks using MobileNetV2 architecture for classification of fruits. In this paper, we saw about CNN in detail, its basic block diagram, then regarding MobileNetV2 architecture. Then details are given about dataset, what does it contains and how to use it, then experimental setup Is explained and ends with the expected results. The results shows that there is rise in accuracy and fall in errors with the use of MobileNetV2 architecture with compared to others. The future studies can be focused on the direction of increasing speed of CNN for the maxpool and how to use ConvNet for small data source.

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