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AN EFFICIENT FRUIT IDENTIFICATION AND RIPENING DETECTION USING CNN ALGORITHM

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ABSTRACT

This system proposes an improved multi-task cascaded convolutional network-based intelligent fruit and ripening detection method. This method has the capability to make the Automated Robot work in real time with high accuracy. Moreover, based on the relationship between the diversity samples of the dataset and the parameters of neural networks evolution, this paper presents an improved augmented method, a procedure that is based on image fusion to improve the detector performance. The chloroplast is responsible for providing the green color in the plant. Where as the chromoplast its various types of colors in the plant. There is a change from Green to yellow color in most of the fruit. This is due to the overgrowth of the chromoplast by replacement of the chloroplast hence there is feeding of the green color and prominence of the yellow color. The change of color of unripe green fruit from green to red is because of the transformation of chloroplast to chromoplast because in immature stage chloroplast is green in color while on maturation the chloroplast disappears and chromoplast containing carotenoids which impart red color.

KEYWORDS: *Kaggle dataset, Feature Extraction, Pooling, Fruit Maturity, Image Processing,MTCNN*

I.INTRODUCTION

Fruits are common food consumed by human since prehistoric era. They make important nutritional contribution to human well-being because of their high nutritive value. It is need to ensure the quality of fruits that are consumed in any places. To do this, a fruit detection system can be established that can recognizes various types

of fruits from images that are captured by any digital camera or smart phone from various places. This system will help us to check the quality of fruits and also help us to develop a robotic harvesting system from orchards. To develop the system, machine learning techniques have used in this system. Accurate and efficient fruit detection is of critical importance for a machine.

Object detection and recognition is a demanding work belonging to the field of computer vision. Objects in the images are detected and recognized using machine learning models when trained on a sufficient number of available images. When applying deep learning models in this task when we have a large number of training images, the accuracy of object recognition is improved. This concept motivates us in developing such a model which can recognize a fruit and predicts its name. There may be a variety of applications of fruit recognition in agricultural work when we are to recognize thousands of fruit images in a less amount of time. It

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can also be applied in automating the billing process at a fruit shop where the model can recognize the fruit and calculate its price by multiplying with weight.

In this paper, we will recognize the fruit where the Convolutional Neural Network will predict the name of the fruit given its image. We will train the network in a supervised manner where images of the fruits will be the input to the network and labels of the fruits will be the output of the network. After successful training, the CNN model will be able to correctly predict the label of the fruit.

Different fruit detection schemes are developed till now using different techniques or algorithms like Deep Learning, Artificial Intelligence, etc., This paper proposes an improved multi-task cascaded convolutional network-based an Efficient fruit identification and ripening detection method. This method will detects the fruits from the images and identify the name of the fruit by using MTCNN model. Based on the training images this can be done and this paper also detects the ripeness of the fruit based on the color of the fruit. Generally in many of the fruits there will be a change from green to yellow and green to red. So based on this the model will check for the ripeness after detecting the fruits. It will display whether it is ripe or unripe at the fruit itself.

II. LITERATURE SURVEY

Several fruit detection schemes are introduced till now but they are lacking in response and accuracy. By trying various models , In paper [1] proposes a Multi-Task Cascaded Convolutional Networks Based Intelligent Fruit Detection for Designing Automated Robot.Their work discussed the CNN technique and image processing i.e., when an image is uploaded the fruits are detected surrounding the fruits by a square box, and the accuracy of this is 100 images can be detected in 80 seconds In the same year paper [2], proposes A fruits recognition system based on a modern deep learning technique. The accuracy of the fruit detection is shown by plotting a graph.

III. DATASET DESCRIPTION

The data is taken from Kaggle, the dataset used here is Fruit 360 with training set and testing set. The main datasets used are Apple,Orange and Strawberry.In these datasets there are nearly 1000 images which can be training images or diversity samples.

IV. METHODOLOGY

4.1 MTCNN Model

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

Fruit and Ripening Detection Using MTCNN Model

The MTCNN model or algorithm can be applied to fruits inorder to identify the fruit and also ripeness of the fruit.The developer need to import multiple modules such as Tensorflow,Numpy, Pandas, Matplotlib,etc., After importing all necessary packages, uploading the fruit images will be done.

4.2 Architecture

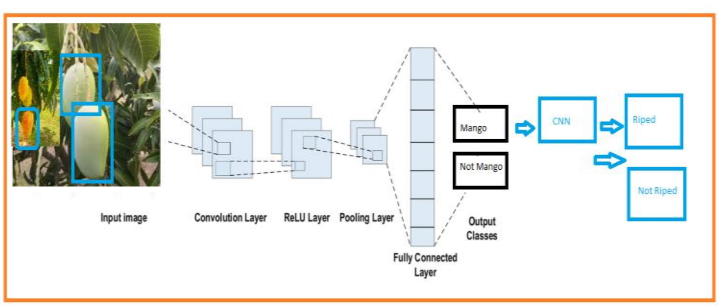

Fig1:Workflow Architecture

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Steps involved in this implementation

1) **Feature Extraction**: CNN compose of multiple layers and first layer define for feature extraction and this features will be extracted from given input image dataset or any other multidimensional dataset.
2) **Feature Selection**: Using this layer features will be selected by applying a layer called pooling or max polling.
3) **Activation module**: using this module RELU will be applied on input features to remove out unimportant features and hold only relevant important features
4) **Flatten**: This layer will be define to convert multidimensional input features into single dimensional input array
5) **Dense**: This layer can be used to connect one layer to other layer to receive input features from pre vious layer to new layer to further filter input features in next layer to get most important features from dataset to have best prediction result.

V. IMPLEMENTATION AND RESULTS

There are 3 modules used in this implementation:

1. Upload Full Train Image Dataset
2. Generate & Load MTCNN Model
3. Upload Test Image & Fruit Detection

After completing of the design the model will look like below:

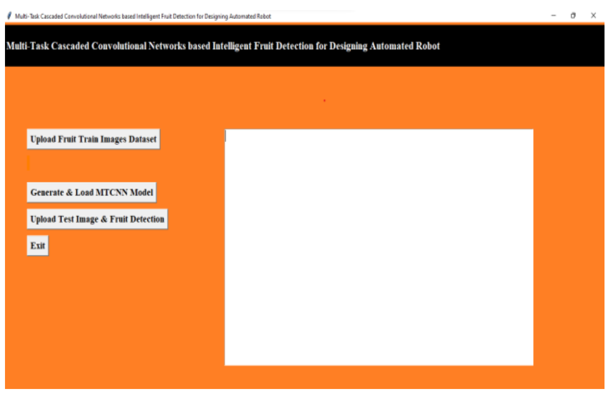

Fig2:Model View

In above screen click on 'Upload Fruit Train Images Dataset' button to load dataset

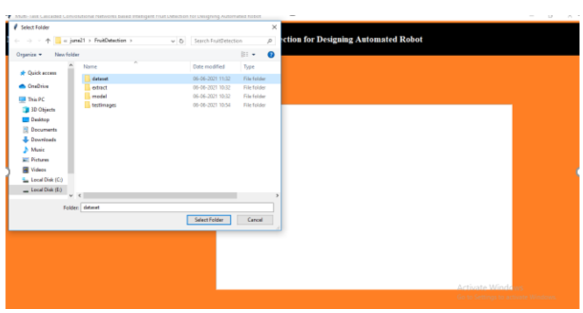

Fig3:Uploading dataset

After successful uploading of dataset generating and loading of MTCNN model will be done.In this we will get TPR and TNR which means MTCNN prediction on test data is 100% and false prediction rate is 0% and in below graph we can see MTCNN accuracy and loss.

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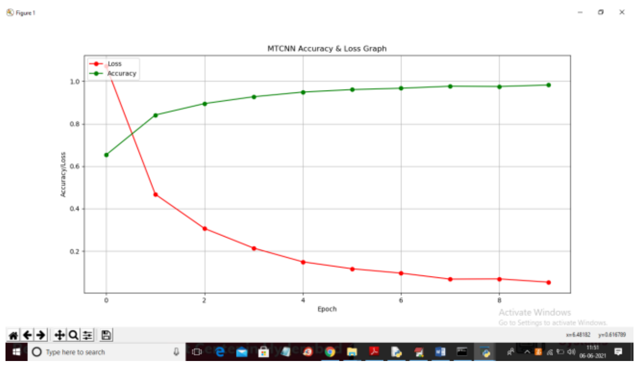

Fig4:MTCCNN accuracy graph

In above graph x-axis represents MTCNN epoch and y-axis represents accuracy and loss value and in above graph red line represents loss and green line represents accuracy and with each increasing epoch we can see loss value decrease and accuracy get increase closer to 100%. Now close above graph and then click on 'Upload Test Image & Fruit Detection' button to upload test image and then get fruit detection output.

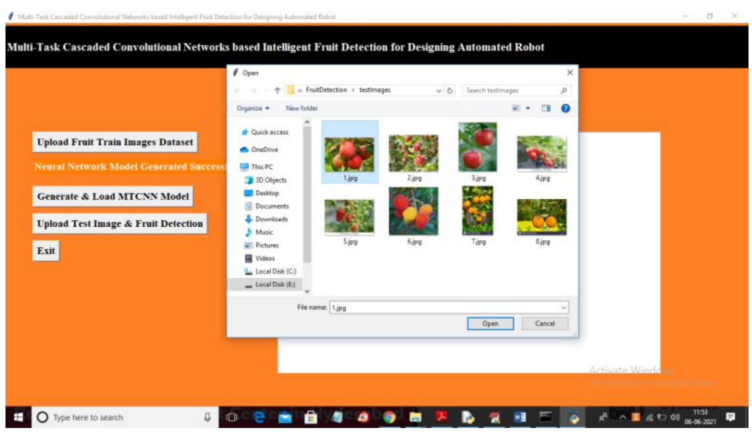

Fig5:Uploading Test Image

In above screen selecting and uploading '1.jpg' image and then click on 'Open' button to get below result

Fig6: Fruit and ripening detection

VI . CONCLUSION

In this paper work, An efficient fruit and ripening detection using convolutional neural network is proposed. By training the fruit data to the model fruit detection will be done and the accuracy is also shown by representing it in a graphical way,it is plotted using a package called Matplotlib. By this graph we can know the number of detected fruits and loss. And also the ripening is detected based on the color of the fruit. Therefore this model can be implemented in real-time environment which is very useful for farmers to harvest etc.

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