iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 8 Issue: VIII Month of publication: August 2020

DOI: https://doi.org/10.22214/ijraset.2020.31003

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 8 Issue VIII Aug 2020- Available at www.ijraset.com

Recognition of Fruit and Grading automatically using Machine Learning

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Abstract: This paper presents an automatic fruit recognition system for classifying and identifying fruit types. The work exploits the fruit shape and colour, to identify each image feature. The proposed system includes three phases namely: pre-processing, feature extraction, and classification phases. Fruit recognition and grading in automatic way is considered as challenging task due to similarities between various types of fruits and external environmental changes. In this paper, fruit recognition and grading based on Deep Convolution Neural Network along with keras is proposed. Due to the limitations of previous approaches as had limited dataset and not considered external environmental changes. The final decision was totally based on a fusion of all regional classification using probability mechanism. The results of carrying out these experiments demonstrate that the proposed approach is capable of automatically recognize the fruit name with a high degree of accuracy.
Keywords: DCNN, Keras and Feature extraction

I. INTRODUCTION

Automatic recognition of fruits includes the domains i.e. computer vision and machine learning. This is a work similar to that of classifying images according to their content or detecting objects in natural images but with a more precise and practical use case in mind. Automated harvesting is an emerging field that utilizes computer vision and machine intelligence in order to gather useful information about the growth and ripeness of fruits and vegetables, and other aspects of farming. Computer vision is also utilized in picking and sorting of fruits and vegetables. In this paper, an efficient and less resource intensive approach for automatic fruit classification is proposed. The lightweight nature of the proposed method makes it suitable for embedded devices and single-board computers like the Raspberry Pi. Furthermore, popular techniques for automated fruit recognition are also compared with the proposed method.

Nowadays, process automation plays an important role in industries. Many automatic highly efficient methods are developed to use in producing and checking processes. The topic of digital image processing has found many applications in the field of automation. In computer vision and pattern recognition, shape matching is an important problem of which is defined as the establishment of a similarity measure between shapes and its use for shape comparison. A by-product of recognition task might also be a set of point identical between shapes. Shape matching which is intuitively accurate for humans is a needed job that is not solved yet in its full generality. Its applications include object detection and recognition, image registration, and content based retrieval of images. Fruit recognition and classification systems can be used by many real life applications. Such as a supermarket checkout system where it can be used instead of manual barcodes, and as an educational tool to enhance learning, especially for small children and Down syndrome patients. It can assist the plant scientists, where shape and colour values of the fruit images that have been computed can assist them do further analysis on variation in morphology of fruit shape in order and can help them understand the genetic and molecular mechanisms of the fruits. Also, it can be used as aiding tool for eye weakness people which can aid them in shopping as a mobile application. As Fruits play main role in day to day life, grading of fruits is necessary in evaluating agricultural produce. The present existing technology is also used for fruit quality managing purpose but they are not more effective. There are some disadvantages like less reliability, less efficiency and less accuracy. That’s why it is necessary to develop a new technology for fruit classification those consist of high accuracy. Analysing the vision is a general characteristic of our brain. Due to advancement in vision based computing capabilities and as algorithms can understand images and videos, systems can be prepared now which understand what we are looking at and what actions we need to perform. Many machine vision algorithms are available for agricultural applications too.

A. Problem Statement

In existing traditional system, farmer can't identify the actual price for their fruits as there is lack of automatic efficient fruits grading system. The existing systems also has some problems like it is time consuming manual process, third party involvement in between customer and farmers the sellers sell the item with almost three fold of the original price as farmer don’t have proper fruits grading system.

B. Objectives

The main goal of our project is to automatic classify and grade the fruits. In order to attain the goal, the following objectives have been framed:

1) To develop an efficient automatic system to classify the fruits based on external appearance.
2) To develop an accurate fruit grading system.
3) To predict the accuracy of the developed system through validation method.

C. Proposed System

To overcome the problems we are developing the new technique for fruit quality assessment and classification .To identify degree of maturity, quality of product, analyse, classify and identify the fruit images which are selected and send into the system based on colour, shape, size and features of fruits. We propose automatic fruit recognition and grading method based on Convolution Neural Network as it is having more accuracy than any other machine vision method in recent years.

II. LITERATURE SURVEY

Preprocessing fruit images is a crucial initial step performed before image analysis. Many preprocessing methods are available in the literature, which use some algorithm to improve the quality of the fruit image through noise removal (Thangam *et al.*, 2009; Zelelew, 2008). This step is vital during defect detection and fruit grading processes. Fruit images are often affected by impulse noise, which degrade image quality and obscure information required for accurate defect detection.

Fruit images are often degraded by the presence of impulse noise, which is an area of research work that has attracted many researchers (Mélange *et al.*, 2011; Mohammad *et al.*, 2011; Hao *et al.*, 2012). This section presents a brief discussion on the various techniques available to remove impulse noise from digital images.

Several methods have been proposed to solve this problem and they include adaptive filter (Manikandan *et al.*, 2004; Kalavathy and Suresh, 2011), multistate median filter (Chen and Wu, 2001), weighted median filter (Yang *et al.*, 1995) and switching median filters (Ping *et al.*, 2007). Vector directional filters uses directional image vectors during de-noising (Lukac, 2004).

Variations to vector directional filters are the weighted vector direction filter which implement a tracking algorithm to identify the varying signal and noise statistics. Peer Group Filters (PGF) that uses statistical properties of accumulated distances for vector median filtering has also been proposed (Smolka, 2008). This algorithm switches between vector median and the original central pixel.

Hsu *et al.* (1993) presented an adaptive separable median filter as a post filter for removing the blocking effects which generally originate from lower- bit-rate image transmission.

Sun *et al.* (1994) used a switching scheme for median filtering to eliminate impulse noise in images. The switching procedure is based on the local measurements of impulses which are called desired detection. A median and weighted median based desire detector was developed and the significant properties were discussed. Investigation exhibited that the filtering arrangement capitulates an output image which is significantly improved than those of median, weighted median and most favorable stack filters.

Chen and Wu (2001a) proposed the use of median based switching schemes, called multi-state median (MSM) filter. By using uncomplicated thresholding logic, the output of the MSM filter was adaptively switched surrounded by those of a grouping of center weighted median (CWM) filters that have different center weights.

In the same year, Chen and Wu (2001b) also devised a novel adaptive operator that was based on the differences between the current pixel and the outputs of center-weighted median (CWM) filters with varied center weights to remove impulse noise. Extensive simulations show that the proposed scheme consistently works well in suppressing both types of impulse noise (salt and pepper and random) with different noise ratios. This work of Chen and Wu (2001b) improved the work of center weighted median filter by including more threshold values. Similarly, Zhang and Karim (2002) used a Laplacian edge detector and the detected edges were preserved during noise removal.

Wang and Zhang (1999) proposed algorithms that performed noise removal in two steps. The first step detected the noisy pixels, while the second step replaced these corrupted pixels using median filters. Uncorrupted or clean pixels were left untouched.

Dong *et al.* (2007) proposed a new impulse detector based on the differences between the current pixel and its neighbors aligned with four main directions for impulse noise detection. The result was then combined with a new directional weighted median (DWM) filter for noise removal.

Kang and Wang (2009) developed a de-noising algorithm that used a rank-order-based switching median filter to solve the problems posed by threshold selection in the conventional switching median filter.

Xu *et al.* (2009) applied adaptive fuzzy switching filter that adopted a fuzzy logic approach for the enhancement of images corrupted by impulse noise. In order to achieve optimal detail preservation, the algorithm used maximum- minimum exclusive median method to estimate and handle the corrupted pixels.

Esakkirajan *et al.* (2011) designed a modified decision based unsymmetrical trimmed median filter algorithm for the restoration of gray scale and color images that are highly corrupted by salt and pepper noise. This algorithm replaced the noisy pixel using a trimmed median.

A video directional weighted median filter with suitable color correction to remove random valued impulse noise from color video sequences was proposed by Bhupender *et al.* (2013). The switching median technique was utilized to protect noise free pixels from filtering so as to avoid blurring of frames. The threshold used for identifying isolated noisy pixels was made adaptive based on the local statistics of the current pixel component.

An image feature is a descriptor of an image, which can avoid redundant data and reduce the effects of noise and variance. In computer imaging, feature detection, extraction and selection are vital for image analysis and interpretation. Feature detection is a low-level image processing application. For an image, the feature is the “interest” part in image. In the pattern recognition literature the name feature is often used to denote a descriptor.

Within the field of feature extraction there are many areas of specialization. The techniques for these different specializations can vary substantially. Research into automated feature extraction from digital images dates back to the seventies and since that time, technology has improved and commercial access to imagery has continued to expand. Feature extraction and selection are based on the mathematical selection, computation and manipulation of image features with high efficiency, robustness and invariance (Lichun *et al.*, 2009).

Interest in automatic feature extraction has increased significantly since the advent of digital imagery and the possibilities associated with electronic processing. Baltsavias, *et al.*, 2001; Gruen, *et al.*, 1997; 1995). In addition, several commercially available photogrammetric workstation systems cited in the review by Plugers (1999) now incorporate some automated feature extraction capability. Other companies such as Definiens (2003) and Visual Learning Systems (VLSI, 2003) are developing software specifically targeted at feature extraction.

Repeatability is the desirable property of a feature detector (Padmavathi, 2012). Many approaches, such as principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, non-parametric weighted feature extraction, wavelet transform and spectral mixture analysis (Lu and Weng, 2007) may be used for feature extraction, in order to reduce the data redundancy. The common aim of all these techniques is to detect and extract features hidden inside an image so as to improve the classification performance.

Feature extraction and selection are considered as the important tasks that allow the determination of the most relevant features for fault detection in fruit images. Extracting and selecting suitable features are critical steps for successfully implementing a defect classification system. In general, this research work considers color and texture features of mango fruit during defect detection, which are described in the following sections.

Color is one of the most important features of images. Color features are defined subject to a particular color space or model. For the colour feature extraction the first step is segmentation. For the segmentation the choice of the colour space is also vital. A number of color spaces have been used in literature, such as RGB, LUV, HSV and HMMD (Stanchev *et al.*, 2003). Various popular colour spaces have been described in Table 2.2 (Cheng *et al.*, 2001; Gonzalo, 2005).

A number of important color feature extraction methods have been proposed in the literatures, including color histogram (Jain and Vailaya, 1996), Color Moments (CM) (Flickner *et al.*, 1995), Color Coherence Vector (CCV) (Pass and Zabith, 1996) and color correlogram (Huang *et al.*, 1997). Table 2.3 provides a summary of different color methods excerpted from the literature (Zhang *et al.*, 2012), including their strengths and weaknesses.

Texture is a very useful characterization for a wide range of images. It is generally believed that human visual systems use texture for recognition and interpretation. In general, color is usually a pixel property while texture can only be measured from a group of pixels (Haralick, 1979). Based on the domain from which the texture feature is extracted, they can be broadly classified into spatial texture feature extraction methods (STFEM) and spectral texture feature extraction methods (SpTFEM). For STFEM, texture features are extracted by computing the pixel statistics or finding the local pixel structures in original image domain, whereas SpTFEM transforms an image into frequency domain and then calculates feature from the transformed image.

Fruit disease identification is generally viewed as an instance of image classification. Recent years have encountered lot of activities in the area of using image classification for defect detection (Qiabao *et al.*, 2009; Katyal and Srivastava, 2012; Zheng and Lu, 2012). Classification methods attempt to partition pixels into different classes using different methods and it is being used by many different researches. Kotsiantis (2007) and Kotsiantis *et al.* (2006) provide detailed discussion on the various algorithms available for classification. Wei *et al.*(2005) on the other hand, focused on providing a review of machine-learning methods and analyzed several state-of-the-art machine-learning methods for automated classification and disease detection in food products.

While classification is a well-studied problem, its usage on defect detection has been found only in the last few decades (Catlett, 1991; Chan and Stolfo (1993a, 1993b).

Cubero *et al.* (2011) presented some modern developments in the field of the inspection of the interior and outside quality of fruits and vegetables. Similarly, Gomes *et al.* (2012) also presented an appraisal of the major publications in the last ten years with admiration to innovative technologies and to the spacious application of systems of visual inspection in the sectors of exactitude farming and in the food manufacturing.

Dubey and Jalal, (2012d, 2013), Dubey (2013) and Dubey *et al.* (2013), proposed a framework for fruit recognition and defect detection. The study considered 15 types of fruits and vegetables for recognition. The system performed defect detection using three steps, namely, region of interest segmentation, feature extraction and classification.

The system used improved sum and difference histogram as texture feature along with color features to train multi-class Support Vector Machine (SVM). The segmentation or region of interest extraction was performed using simple threshold approach (Li, Wang and Gu, 2002; Mehl *et al.*, 2002).

Janik *et al.* (2007) conducted a study to compare the performance of Partial Least Squares (PLS) regression analysis and ANN for the prediction of total anthocyanin concentration in red-grape homogenates from their visible- near-infrared (Vis-NIR) spectra. The proposed method combined the advantages of the data reduction capabilities of PLS regression with the non- linear modeling capabilities of ANN. ANN with PLS scores required fewer inputs and was less prone to over-fitting than using PCA scores.

Kim *et al.* (2009) designed technologies of color imaging and texture feature analysis that is used for classifying citrus peel diseases under the controlled laboratory lighting conditions.

A total of 39 image texture features were determined from the transformed hue (H), saturation (S) and intensity (I) region-of-interest images using the color co-occurrence method for each fruit sample. The model using 14 selected HSI texture features achieved the best classification accuracy, which suggested that it would be best to use a reduced hue, saturation and intensity texture feature set to differentiate citrus peel diseases.

Kumar *et al.* (2012) proposed a method for detecting infected citrus using airborne hyperspectral and multispectral imaging. This work used a hyperspectral imaging software (ENVI, ITT VIS) during image analysis. The infected areas were identified using image-derived spectral library, mixture tuned matched filtering (MTMF), spectral angle mapping (SAM), and linear spectral unmixing. The experimental results showed that the accuracy of the MTMF method was greater than the other conventional methods. A similar work was previously done by Polek *et al.* (2007).

Simoes *et al.* (2001) investigated on the applicability of color classification using an artificial neural network in the fruit-sorting domain. Further this approach was used for the segmentation of colored images represented by the RGB color system. Jointly with color analysis, shape analysis was done to generate a robust and real time system. The model was tested for orange classification according to a Brazilian standard and was able to provide fruit classification under less restricted visual conditions.

Boonmung *et al.* (2006) proposed an approach for quality inspection of orange fruit using color and texture features. Input image was segmented using histogram based thresholding technique to identify whether the portion of image was defective or non-defective.

Mercol *et al.* (2008) presented an automatic orange classification system that used visual inspection to extract features from images. Several data mining algorithms were used to classify the fruits in one of the three pre-established categories. These were five decision trees (J48, Classification and Regression Tree (CART), Best First Tree, Logistic Model Tree (LMT) and Random Forest), three artificial neural networks (Multilayer Perceptron with Backpropagation, Radial Basis Function Network (RBF Network), Support Vector Machine) and a classification rule. The results were encouraging due to good accuracy achieved and low computational costs.

Rasekhi *et al.* (2011) developed a comprehensive algorithm to combine image processing and neural network techniques for sorting orange fruits into size groups (Small, Medium and Large). RGB colour features were extracted and fed to a back propagation network model with a number of training functions including variable learning rate back propagation (MLP-GDM), resilient back propagation (MLP-RP) and scaled conjugate gradient (MLP- SCG) were used for ANN modelling. The results showed that the multi-layer perceptron with RP and SCG transfer functions had the least error.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 8 Issue VIII Aug 2020- Available at www.ijraset.com

III.SYSTEM DESIGN

A. System Architecture

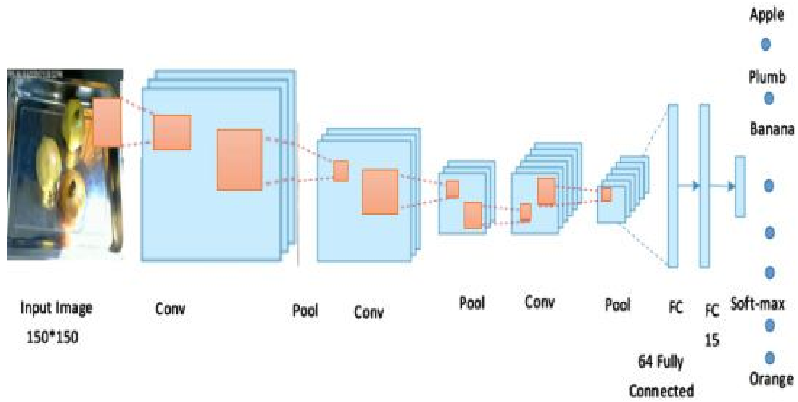

Fig. 1 Architectural diagram for Fruits classification and Grading using CNN

In this project we proposed two-track deep neural network model architecture. The first track consists of deep convolution neural network with max-pooling to enhance system ability, whereas the second track comprised of fully connected layers. The network has four layers of hidden neurons (three convolutional-pooling and one fully connected), apart from a final dense layer of output neurons (the input is not considered as a layer). The input contains 150×150×3 neurons, representing the RGB image. The first convolution-pooling layer uses a local receptive field (convolutional kernel) of size 3×3 with a stride length of 1 pixel to extract 32 feature maps, followed by a max. pooling operation conducted in a 2×2 region, the second and third convolution-pooling layers use the same local receptive field (kernel) resulting 64 and 128 features maps respectively whereas other parameters remain unchanged. The fourth layer is fully-connected layer with 64 ReLU (rectifier linear unit) neurons and the output layers have SoftMax neurons that corresponding to the various categories of fruits.

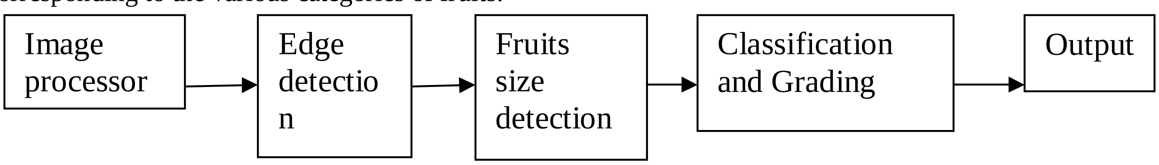

Fig. 2 Functioning of Fruits Classification and Grading Process

The figure 2 depicts the architectural diagram for fruits classification and grading. First the user has to give the

1) *Image datasets to image processor*: The image datasets of fruits is taken as the input to the system for image processing process for identification. In image processing, image segmentation can be defined as a "process of partitioning a digital image into multiple segments" (sets of pixels, also referred to as super pixels). The goal of image segmentation is to simplify and / or change the representation of an image, which is more meaningful and easier to analyze.
2) *Edge detection:* Edge detection process consists of external appearance identification of fruits which includes colour, texture; etc. as colour is most visually striking feature of any image it pays an important role in classification and grading system and also to identify defective fruits from normal fruits. Most of the existing system defines maturity of fruits by comparing its colour with the existing predefined reference colours. Colour models are divided into several models like HIS, HSV, JPG, RGB, etc. Texture and shape features used to classify fruits with Neural Network as classifier.
3) *Fruits size detection*: Fruits size is also one the most important parameter to measure the quality of fruit, larger the fruit, better it is. Larger fruits attract even more prices. It is difficult to measure fruit's size due to its natural irregularities. For size feature extraction, different size measures, which are most commonly used, are area, perimeter, weight, height (length), width and volume.
4) *Classification and grading:* The classification and grading process is carried out after analysing all the external parameters of the fruits.
5) *Classified and graded fruit:* After the classification and grading process of fruit output finally the last step is the classified and graded fruit is the output.

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B. Sequence Diagram

A sequence diagram represents interaction diagram which indicates about how each processes works among each other and the order of working process. It also up brings the construction of a message in a sequence or scenario.

A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are sometimes called event diagrams or event scenarios.

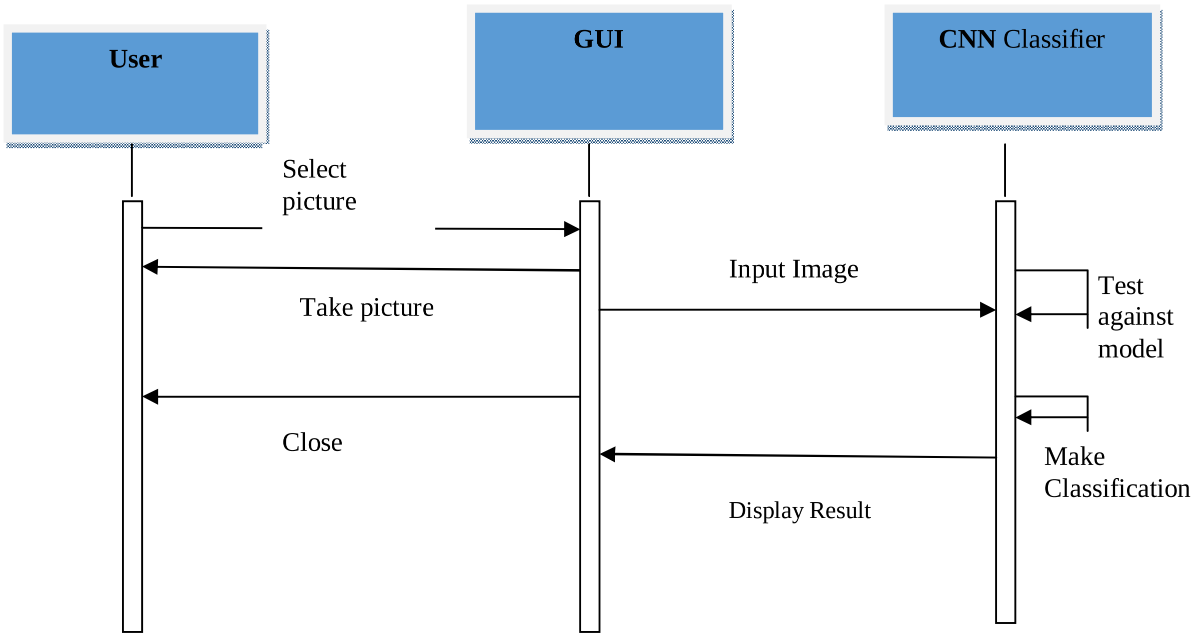

Fig. 3 Sequence Diagram

Figure 3 illustrates the interaction between the elements on the parallel axis. The objects shown are the user, GUI (front end) and CNN Classifier (developed system). The vertical axis represents time proceedings.

1) User selects the picture for testing and then sends it to the classifier in the sequence.
2) The classifier tests the image, then classifies the image and then sends it to the display.
3) User can see the result and closes the application.

IV. RESULTS AND SCREENSHOTS

Fig. 4 Screen showing sample fruits image datasets

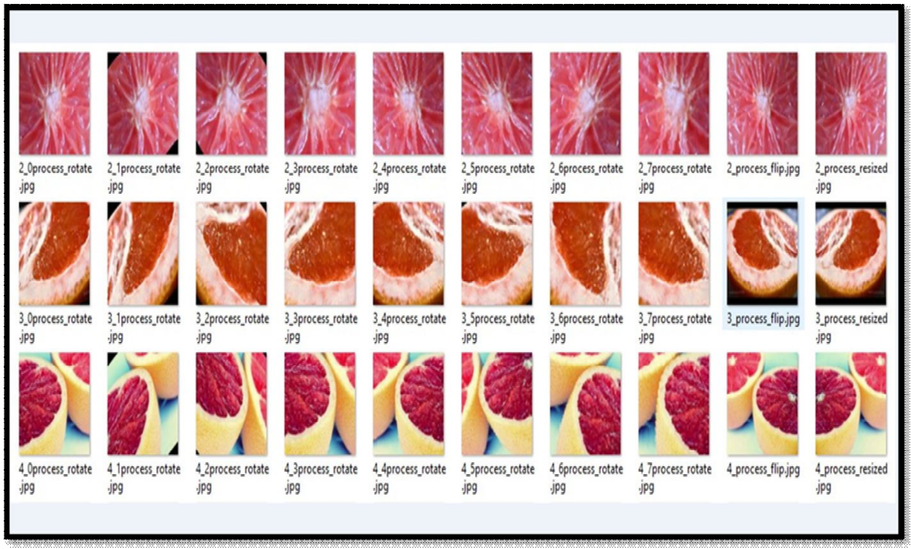

Fig. 5 Screen showing the pre-processing of fruits images

Fig. 6 Result Displayed for Orange fruit

The figure 6 shows the output screen of the proposed system. It contains interface for choosing the test images and uploading the test images. Here we have constraint that only one image is tested at a time.

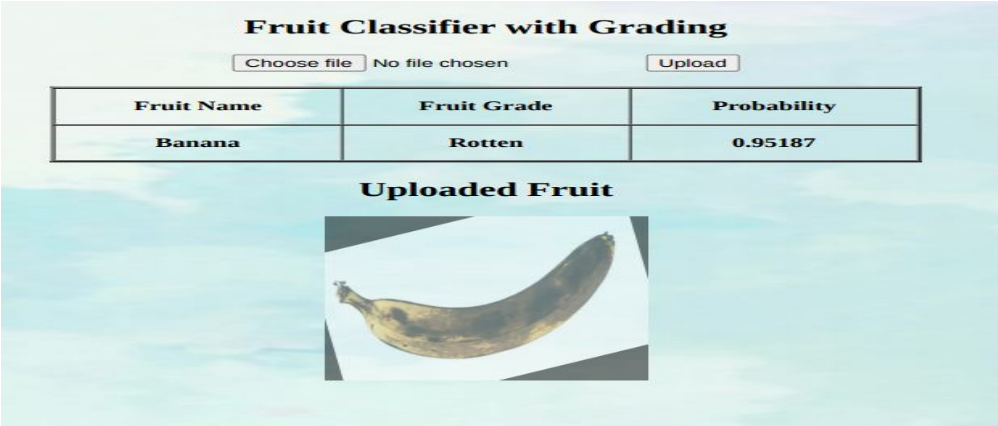

Fig.7 Result displayed for rotten banana

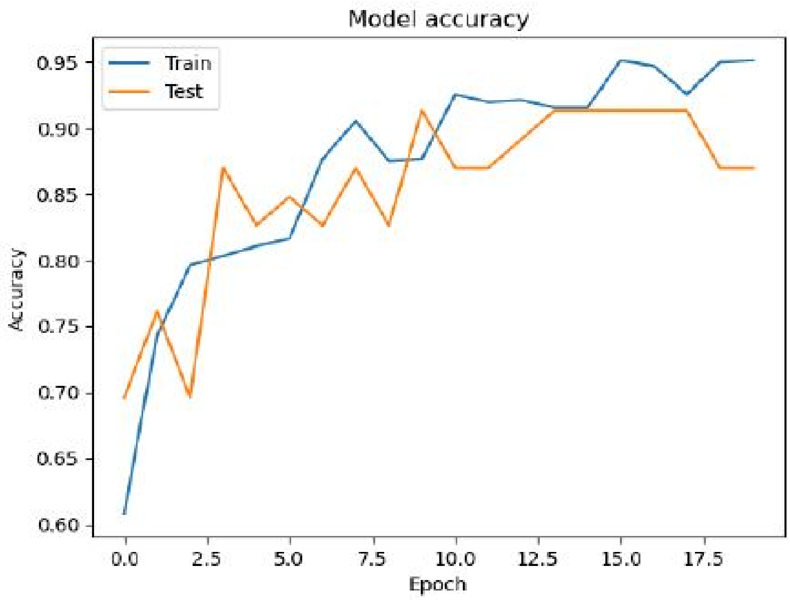

Fig. 8 Model Training and testing accuracy (%)

From the plot of accuracy we can see that the model could probably be trained a little more as the trend for accuracy on both datasets is still rising for the last few epochs. We can also see that the model has not yet over-learned the training dataset, showing comparable skill on both datasets. The figure 8 shows the model training and testing accuracy graph.

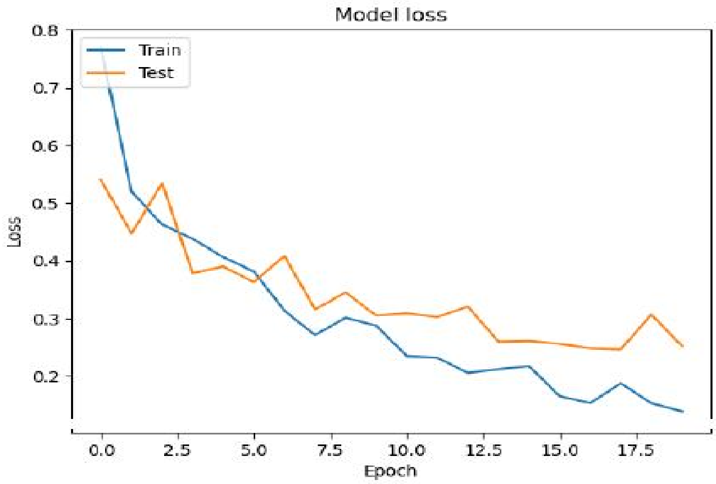

Fig 9: Model loss

From the plot of loss, we can see that the model has comparable performance on both train and validation datasets (labelled test). If these parallel plots start to depart consistently, it might be a sign to stop training at an earlier epoch.

V. Conclusion

This section summarizes and concludes the contributions made by our project. Fruits classification and grading process using automated machine vision systems made accurate, rapid, objective and efficient results over manual work. External properties like fruits colour, size, shape, texture are very important attributes for fruits classification and grading process. The outcome shows the availability of low cost hardware and software which replaces the manual work of fruits classification and grading using automated machine vision systems.

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