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Classification of Vegetables using TensorFlow

Om Patil[1], Prof. (Dr.) Vijay Gaikwad[2]
[1, 2] Department of Electronics Engineering, Vishwakarma Institute of Technology, Pune

Abstract**:** ***Recognition is one of the main areas in computer vision, it yields high-level understanding by computers, one of the most important areas in recognition is object recognition which is the process of finding a specific object in an image or video sequence [16]. This paper is purposing the glimpse of the recognition of a particular vegetable [17]. This is being implemented on the TensorFlow platform, which is making use of OpenCV as the main library database. TensorFlow [20] algorithm uses tensor as its basic unit of information. Firstly the given frame is converted into an image and differentiated into cubical parts from which the features are extracted, so to converged it into the data set[3]. Such data sets are encapsulated from every cubical unit, emerged as the whole bunch of values after traversing thoroughly through given frame. Having these values, the certain frame is categorized into one of the sets of images provided, at the conclusion side percentage-wise isolation of objects is done, and here the vegetables are being identified and corresponding action should be executed [6]. Highlighting the uniqueness of usage of this idea, would result into involution of more prominent ways of segregation of vegetables in a food production industry as per the requirement, in the territory wherein the only agriculture holds the backbone of economy [18]. The use of image processing techniques is of outstanding implication for the analysis of agricultural operations [16]. Vegetable and vegetable classification is one of the major applications that can be utilized in the supermarket to automatically detect the kind of the vegetable or vegetable purchased by the customer and to generate the costs for it. A simple android app has been developed to carry out this task [21] [23] [17].***

Index Terms: Tensor Flow, Vegetable classification. Inception-v3, Dataset, Classifier, Android app

I. INTRODUCTION

Vegetable classification is a difficult and important task in supermarkets since it is necessary for the cashier to know the categories of a particular vegetable in order to determine its price [17]. The packaging of the vegetable like other food products which has barcodes.The objective of this paper is to propose a novel vegetable classification system based on computer vision, with aim of solving this type of
problems [16]. First, we use merely a cell phone camera, getting rid of other complicated hardware. Second, the proposed classifier is expected to recognize as many types of vegetables as possible.

Different samples vegetable samples like Cucumbers, Tomatoes, Onions, Carrots, etc are considered in the work. Traders have warehouses where different varieties of vegetables are stored. Most vegetable dealers will sort the vegetables manually which results in high cost, subjectivity, tediousness and inconsistency associated with manual sorting [13]. Therefore, different apple varieties easily get mixed up during harvesting, storage and marketing.

Classification is a fundamental research work in the field of Agriculture and Botany. Up to now, it has been found that there are hundreds of thousands of species of vegetables [4]. People will get confused because they don't know the species of vegetables. Therefore, the design of a vegetable classifier will also bring ease to people's lives [1]. There are some challenges in vegetable classification, the background of vegetable image is complex, there is similarity between the different species of vegetables, so we can not just rely on a single feature, such as color, shape or texture to distinguish the species of vegetables[11] [8], and the same species of vegetables will be different because of the shape, scale, viewpoint and so on [9].

The idea is based on Martin Gorner's Hand-written digit recognition using Tensorflow for Poets [24] [20]. A similar procedure is followed for developing this android based system. The idea is to use computer vision, image processing and convolutional neural networks [12]. The convolutional neural network is an efficient recognition method which has been developed in recent years [2]. This network avoids the complex preprocessing of the image, and people can input the original image directly [7]. It uses the local receptive field, weights sharing and pooling technology and makes the training parameters greatly reduced compared to the neural network [13]. It also has a certain degree of translation, rotation and distortion invariance of the image. It has made great progress in the field of image classification [9]. TensorFlow [1] is the second generation of artificial intelligence learning system developed by Google, which supports the convolution neural network (CNN), recurrent neural network (RNN) and other depth of the neural network model, which can be used in speech recognition, image recognition and so on many machines deep learning field [20]. In

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this paper, we use the transfer learning technique to retrain the Inception-v3 [3] model of TensorFlow [1] on the vegetable category datasets [13] [11]. We implemented an effective vegetable classification model using a short training time and achieve a higher accuracy.

Transfer learning is a new machine learning method which can use the existing knowledge learned from one environment and solve the other new problem which is different but has some relation to the old problem. For example, we can apply the knowledge learned from the motorcycle problem to the study of bike problem [16]. Compared with the traditional neural network, it only needs to use a 784 small amount of data to train the model, and achieve high accuracy with a short training time [14].

This paper presents a unified approach that can combine many features and classifiers [3]. The training method implemented is efficient compared to traditional, where all features are simply concatenated and fed independently to each classification algorithm. We expect that this solution will endure beyond the problem solved in this paper.

II. RELATED WORK

About one year ago, a former embedded systems designer from the Japanese automobile industry named Makoto Koike started helping out at his parents' cucumber farm and was amazed by the amount of work it takes to sort cucumbers by size, shape, colour and other attributes. Makoto's father is very proud of his thorny cucumber, for instance, has dedicated his life to delivering fresh and crispy cucumbers, with many prickles still on them. Straight and thick cucumbers with a vivid colour and lots of prickles are considered premium grade and command much higher prices on the market. But Makoto learned very quickly that sorting cucumbers is as hard and tricky as actually growing them. "Each cucumber has different colour, shape, quality and freshness," Makoto says [19].

In Japan, each farm has its own classification standard and there's no industry standard. At Makoto's farm, they sort them into nine different classes, and his mother sorts them all herself — spending up to eight hours per day at peak harvesting times. "The sorting work is not an easy task to learn. You have to look at not only the size and thickness but also the colour, texture, small scratches, whether or not they are crooked and whether they have prickles. It takes months to learn the system and you can't just hire part-time workers during the busiest period. I myself only recently learned to sort cucumbers well," Makoto said. There are also some automatic sorters on the market, but they have limitations in terms of performance and cost, and small farms don't tend to use them. Makoto doesn't think sorting is an essential task for cucumber farmers. "Farmers want to focus and spend their time on growing delicious vegetables. I'd like to automate the sorting tasks before taking the farm business over from my parents" [19].

Makoto used the sample TensorFlow code Deep MNIST for Experts with minor modifications to the convolution, pooling and last layers, changing the network design to adapt to the pixel format of cucumber images and the number of cucumber classes [19]. Recently, a lot of activity in the area of image categorization has been done [5]. With respect to the produce fruit and vegetable classification problem, Veggie-Vision (Bolle et al., 1996) was the initial attempt of a supermarket produce recognition system [17].

Figure 1. Cucumber sorting machine.

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They used colour, texture and density (thus taking more information) features. Density is calculated by dividing weight with the area of the fruit. The reported accuracy was ≈ 95% when colour and texture features are combined, but top four responses are used to achieve such result. Rocha et al. (2010) presented a unified approach that can combine many features and classifiers [16]. The authors approached the multi-class classification problem as a set of binary classification problem in such a way that one can assemble together diverse features and classifier approaches custom-tailored to parts of the problem. They have achieved classification accuracy up to 99% for some fruits, but they fused three features [14], namely Border-interior classification (BIC), Color coherence vector (CCV), and Unser features and used top two responses to achieve them. Their method shows poor results for some type of fruit and vegetable such as Fuji Apple. Arivazhagan et al. (2010) combined the colour and texture features to classify the fruits and vegetables [10]. They used minimum distance classifier and achieved 86% accuracy over the dataset having 15 different types of fruits and vegetables [7].

Vegetable quality is oftentimes referred to colour, shape, mass, firmness, size and bruises from which fruits can be classified [6]. Lino et al. (2008) classified the lemons and tomatoes by the size and colour of the fruit. Peach fruits are recognized in (Liu et al., 2011) in a natural scene [16]. The red peach region is obtained first and then a matching expansion is used to recognize the entire region [18]. The potential centre point of the fitting circle is calculated by the intersection of the perpendicular bisector of the line on the contour [19]. Finally, the centre point and radius of the fitting peach circle are obtained by calculating the statistical parameters of the potential centre points. Variations in antioxidant profiles between fruits and vegetables are studied in (Patrasa et al., 2011) using pattern recognition tools [12]; classification was done based on global antioxidant activity, levels of antioxidant groups (ascorbic acid, total anthocyanins, total phenolics) and quality parameters (moisture, instrumental colour). Interrelationships between the parameters considered and the different fruits and vegetables were discovered by hierarchical cluster analysis (HCA) [7] and principal component analysis (PCA). Patel et al. (2011) presented the fruit detection using improved multiple features based algorithm [8]. They designed an algorithm with the aim of calculating different weights for different features like colour, intensity, edge and orientation of the input image. The approximate locations of the fruit within an image are represented by the weights of the different features [11]. They achieved the detection efficiency up to 90% for different fruit image on a tree, taken from different positions [16].

III. CONSTRUCTION OF VEGETABLES CLASSIFICATION MODEL

This section focuses on the construction process of the vegetable classification model. The construction process of the vegetable image classification model is divided into four steps: image preprocessing, training process, verification process and testing process [16] [1].

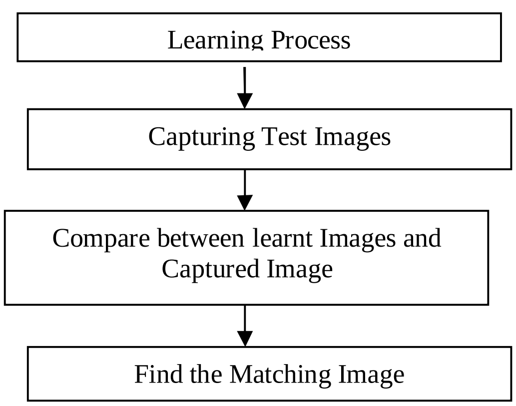

Figure 2. Steps involved in vegetable classification.

A. Image Preprocessing

The learning method of convolution neural network
belongs to supervised learning in machine learning, so in the image preprocessing step we need to label the data [14].

B. Inception-v3 Model

The main graph of Inception-v3 [3] model is shown in fig:

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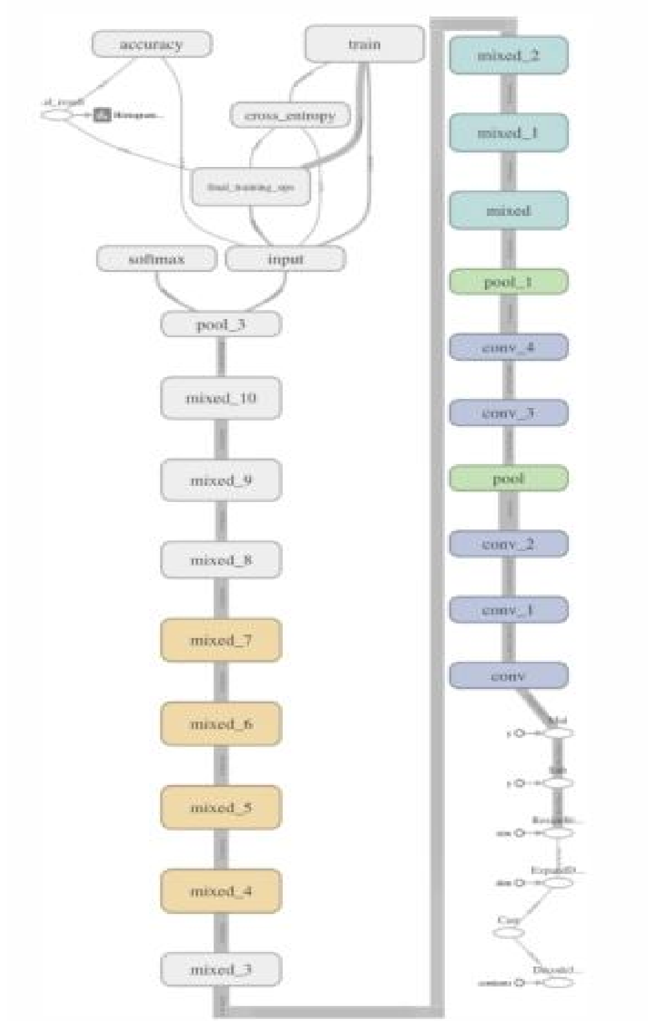

Figure 3. Main graph of Inception-v3 model.

C. Transfer Learning Based on Inception-v3 Model

Inception-v3 [3] network model is a deep neural network, it is very difficult for us to train it directly with a low configured computer, it takes at least a few days to train it. Tensorflow [1] provides a tutorial for us to retrain Inception's final Layer for new categories using transfer learning. We use the transfer learning method which keeps the parameters of the previous layer and removes the last layer of the Inception-v3 [3] model, then retrain the last layer [16]. The number of output nodes in the last layer is equal to the number of categories in the dataset [14]. For example, the ImageNet dataset has 1000 classes, so the last layer has 1000 output nodes in the original Inception-v3 model [16].

IV. IMPLEMENTATION

The main components in a TensorFlow system are the client, which uses the Session interface for communicating with the master [13], and one or more worker processes, with each worker process responsible for the arbitrating access to the computational devices and for executing graph nodes on those devices as instructed by their master [16] . We have both local as well as the distributed implementation of the TensorFlow interface. The local implementation is used when the client, the master, and the worker all run on a single machine in the context of a single operating system that processes. In our distributed environment, these different tasks are containers in jobs managed by a cluster scheduling system [14]. These two different modes are illustrated in Figure 5. Most of the rest of this section discusses issues that are common to both implementations, while Section 3.3 discusses some issues that are particular to the distributed implementation.

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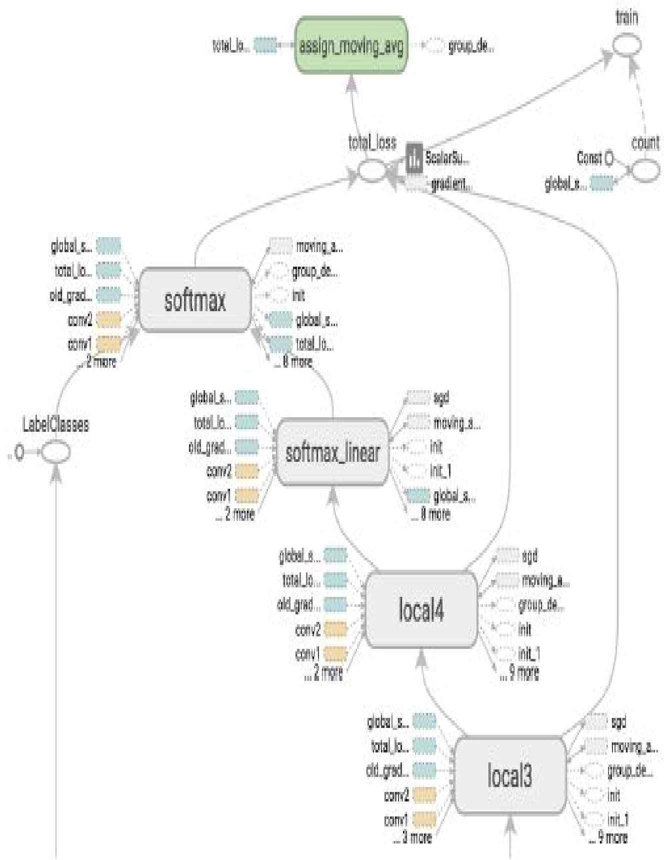

Fig. 4: Tensor Board graph visualization of a convolutional neural network model

A. Devices

Devices are the computational heart of TensorFlow. Device names are composed of pieces that identify the device's type, the device's index within the worker, and, in our distributed setting, an identification of the job and task of the worker (or localhost for the case where the devices are local to the process).

We have implementations of our Device interface for CPUs, and new device implementations for other device types can be provided via a registration mechanism. Each device object is responsible for managing allocation and deal location of device memory, and for arranging for the execution of any kernels that are requested by higher levels in the TensorFlow implementation.

B. Tensors

A tensor in our implementation is a typed, multidimensional array. We support a variety of tensor element types, including signed and unsigned integers ranging in size from 8 bits to 64 bits, IEEE float and double types, a complex number type, and a string type (an arbitrary byte array). Backing store of the appropriate size is managed by an allocator that is specific to the device on which the tensor resides. Tensor backing store buffers are reference counted and are deal located when no references remain [1].

V. EXPERIMENT

This experiment is based on the Inception-v3 [3] model of TensorFlow [1] platform, the hardware platform for training is HP Pavilion 15AB522TX with 2.4GHz Intel i5 6^{th} Generation processor, with 8GB RAM memory 1700MHz based on Windows 10 64 bit operating system. The system was then packaged as APK file and Android app was developed using Android Studio [21] [17]. The testing hardware used for the experiments is Sony Xperia X Plus smartphone with 4 GB RAM, powered by a Snapdragon Octa-core processor, operating on Android Naught OS. The experimental datasets are the four different vegetables. In this section, the following part is as follows: first, we make a simple introduction on the dataset; second, we introduce the process of the experiment in detail; then, we show the result of this experiment; finally, we verify the effectiveness of the method through the comparison experiment

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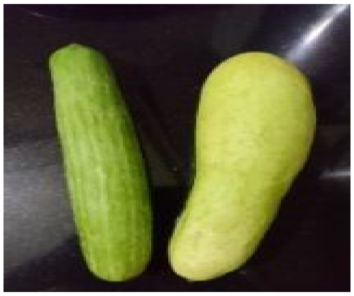
A. Dataset

Carrot



Cucumber

Tomatoes

Onions

Figure 5. Dataset.

B. Experimental Procedure

Image preprocessing has been used. For the vegetable dataset designed and taken by us, each of species has 1000 vegetable images, we only need to label the image in the dataset in case, the number of the vegetable images in some species is too small [2]. So in addition to label the image, we also need to add some 200 images to the species which contains few images to increase the dataset. Transfer learning based on Inception-v3 [3] model. We should keep the parameters of the previous layer, then remove the last layer and input the vegetable dataset to retrain the new last layer, the number of output nodes will be changed to 4 vegetable dataset.
The last layer of the model is trained by back propagation algorithm, and the cross-entropy cost function is used to adjust the weight parameter by calculating the error between the output of the softmax layer and the label vector of the given sample category [17].

VI. RESULTS

Figure 6 and figure 7 show the variation of accuracy and cross-entropy based on vegetable dataset [13]. The orange line represents the training set, and the green line represents the validation set.

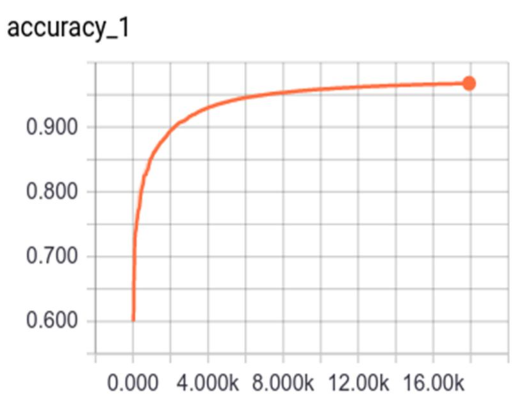


Figure 6. The variation of accuracy on the vegetable dataset.

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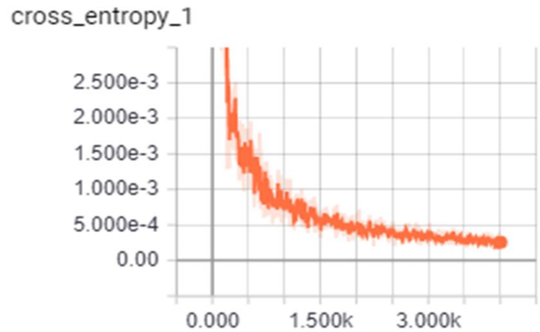

Figure 7. The variation of cross entropy on the vegetable dataset.

Following are the detected vegetables

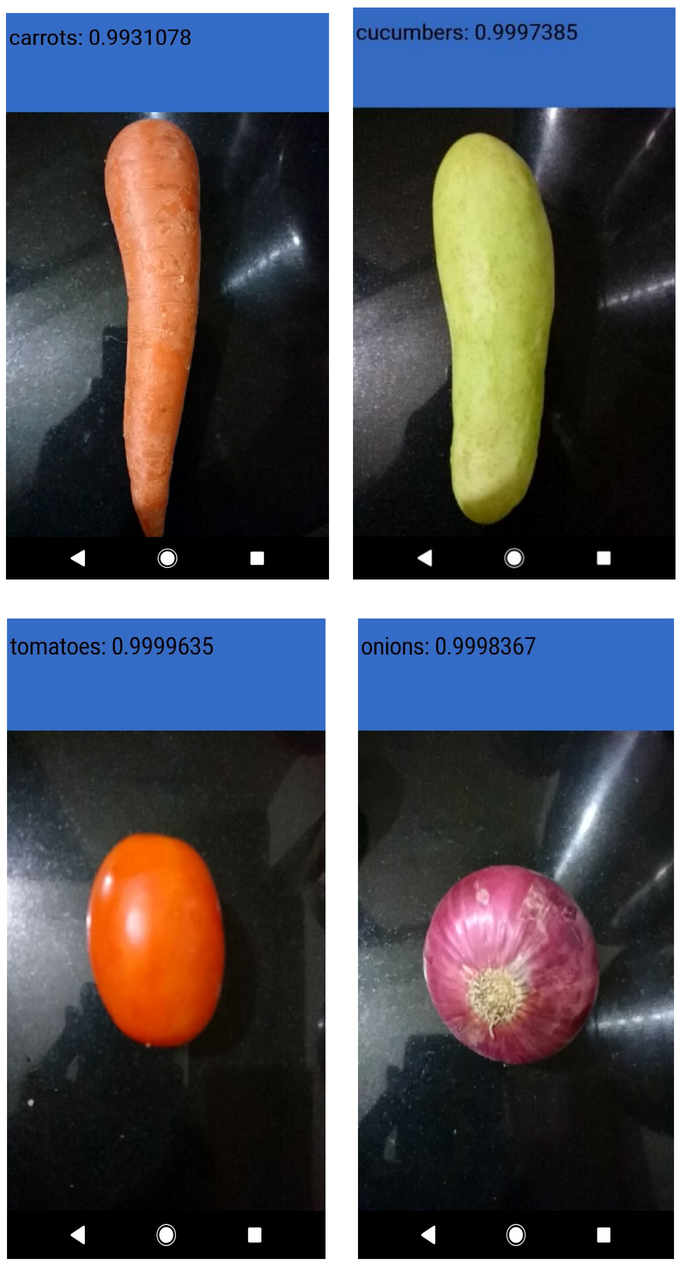

Figure 8. Testing results for detection of the vegetables.

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Figure 8 shows few screenshots of the android app where test samples are kept under mobile phone's camera frame and matched with the learnt images. The number displayed on the upper bar refers to the probability of detection of the vegetable generated by the algorithm.

Above screenshots show that the detection occurs in real-time and flawlessly. The accuracy of detection observed is 99% which gives user more reliable and convenient vegetable classification system. Figure 9 shows all the performance parameters including CPU size used, nodes, tensors and all the technical aspects of the system for users to know what is happening in the background while detection occurs.

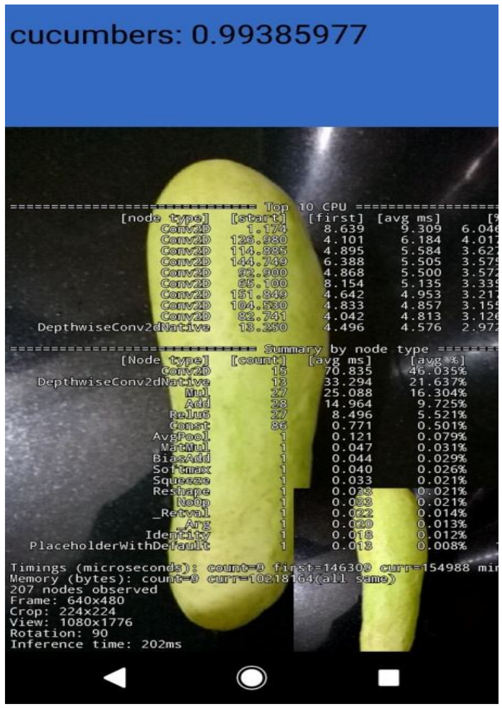

Figure 9. Performance Parameters for the App.

VII. CONCLUSION

This project is based on multiple physical parameters through comparing image histograms to find the best matching image. Our experimental results proved that this application shows accuracy with 99 % of identifying vegetables, the experiment shows samples of learnt images and tested images. Several computer vision and image processing approaches are used in the field of agriculture and food industry for vegetable classification and vegetable disease classification. Most of the work in this field using image processing is composed of the main three main steps (1) background subtraction, (2) feature extraction, and (3) training and classification. TensorFlow, a flexible data flow based programming model, as well as single machine and distributed implementations of this programming model.

In order to improve and enhance this application, there is some future work should be implemented, providing a user-friendly interface, and expanding the range of vegetables known by the application will increase the performance of the application. Adding multiple vegetables and increasing training dataset will surely improve the performance. The method is going to remain the same. We can surely make the advancement of the information and communication technology in the field of agriculture and food industry.

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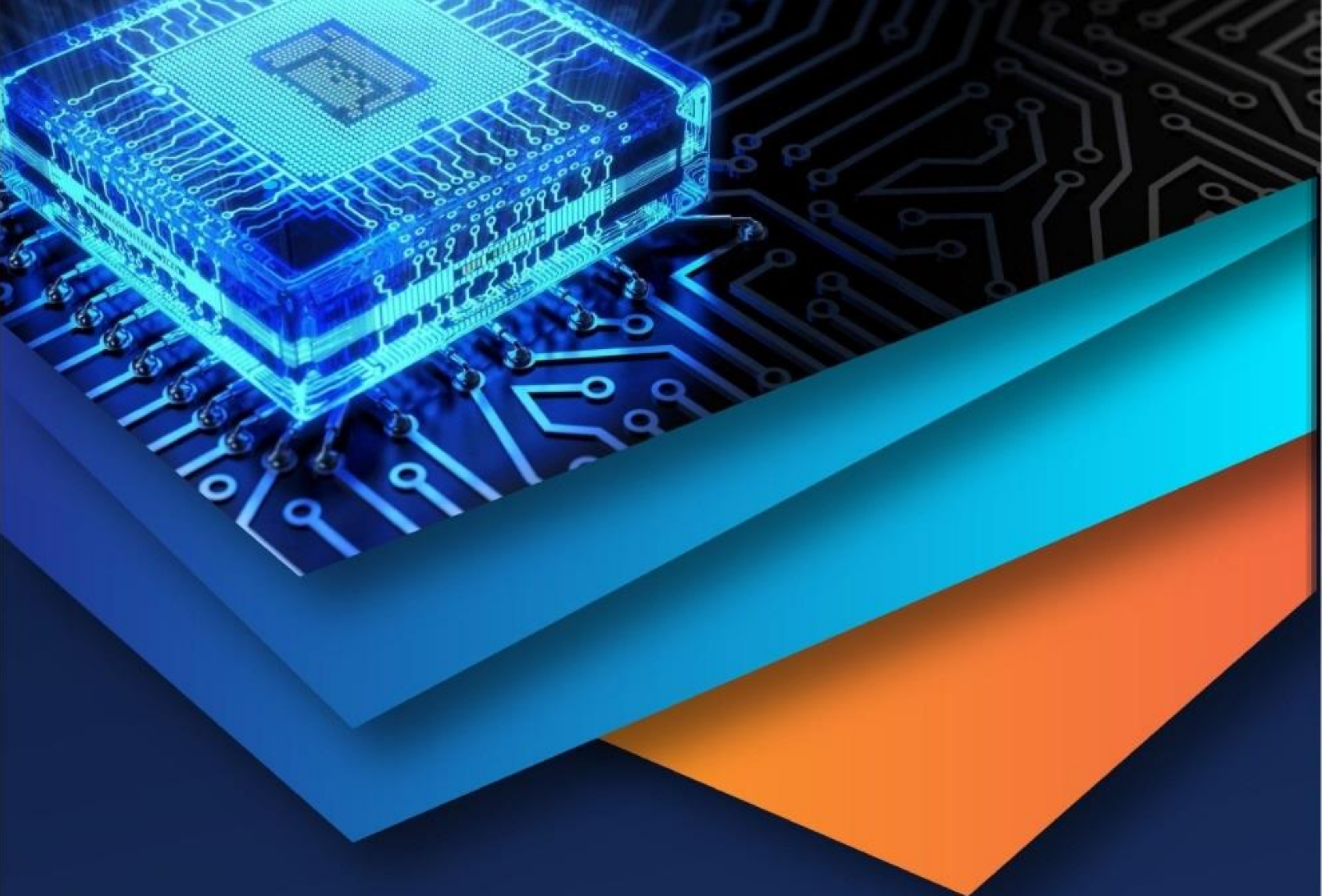
[24] https:/github.com/martin-gorner/tensorflow-mnist-tutorial



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