International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-12, October 2019

Development of Feature Based Classification of Fruit using Deep Learning

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Abstract*: Fruit classification is a challenging task in image processing. Computer vision based classification method is agile and rigorous compared to human based approach. In this paper, a method is developed for feature classification using deep learning. The region with their own characteristics is classified based on deep learning convolutional neural network technique. Traditional method for diagnosis of fruit involves visual observations by experts. The interference of environmental factors needs to be considered during diagnosis process. Datasets such as VOC, PASCAL, ImageNet etc. are easily available that are used for training of several different types of objects. The proposed model introduces two pre-trained networks; AlexNet and GoogLeNet. For faster and optimized training, Rectified linear unit (ReLu) is used that maintain positive value and map negative values to zero. The model learns to perform classification directly from images. Neural network architecture is used for implementation of deep learning. Error in deep learning is minimized compared to machine learning. The high end GPU's reduces the training time. A transfer learning technique is proposed to retrain the network that is capable of performing new recognition task.

***Keywords* : Classification, Deep learning, Convolutional Neural Network, GoogleNet, AlexNet**

I. INTRODUCTION

Traditional method for diagnosis of fruit involves visual observations by experts that are time consuming and having probability of human error. The interference of environmental factors needs to be considered during diagnosis process. Deep learning based method involved data sets such as PASCAL, VOC, ImageNet etc. that are easily available for training of several different types of objects. The purpose of classification is to find the characteristics of objects on the sample fruit image at corresponding pixels in the image. The algorithm identifies the most likely class to which pixel belongs. A particular pixel is labelled as apple or pomegranate, etc. The process involves identification of all the pixels in the image that belongs to apple and so on. In case of supervised classification, prior information is gathered such as area, eccentricity, etc. and applied to determine the identity and location of these features on the image.

Revised Manuscript Received on October 30, 2019.
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The statistical and geometrical parameters are calculated from these features and creating a series of template that represents these patterns. The templates are nothing but training parameters and their characteristics used to guide classification process. Each pixel is compared with each template and is assigned to class whose properties are nearest to it.

II. PREVIOUS WORK

Image is an important media of information source for human communication and understanding. In order to achieve better result, artificial intelligence based application is introduced in image processing [1]. In Convolutional neural network, semantic segmentation is important in high level computer vision applications. The prediction of labelled variables is independent from each other [2]. The region based active contour often fails for images having inhomogeneous intensity. Machine learning algorithms are more capable of handling inhomogeneous intensity of images [3]. The image is restored by introducing the cost function that enhances the contrast and consists of information loss term [4]. The fruit surface defects are classified using Radial Basis Probabilistic Neural Network. The attributes of defected area are extracted by manipulating gray level co-occurrence matrix [6]. It has been observed that convolutional neural network (CNN) detects mangosteen defect with an accuracy of 97% [7]. The fruit quality depends on the defect type and its size also fruit size and its skin color. The fruits maturity and grading into their relevant category are attained by developing pattern recognition system. The system involves two stages. First of all training and then recognition of pattern by using back propagation diagnosis model [8]. A multi-level thresholding algorithm improves the segmentation response and reduces the processing time. Then region of interest is analyzed for identification of defects in fruit surface [9]. Computer vision based automatic inspection system for determining the olive oil quality uses difference in superficial texture for assessment of defects in IR picture and color assessment in CIELab [10]. The classification process is affected by uneven illumination, jitter and dew. A unified convolutional neutral network centered on matrix based convolution neural network is implemented to overcome this challenge [11]. CNN requires large amount of datasets to facilitate feature extraction and classification. This problem is overcome by employing transfer learning that involves a pre-trained CNN. The datasets are sufficient for classification later optimized explicitly to provide a consistent result [12]. The external properties such as shape, size and color aid for quality inspection of fruits.

The local feature extraction process describes the object recognition for rapid quality inspection [13]. A deep convolutional neural network improves the image classification accuracy.
The classification framework is independent and minimizes the loss between class similarity and within class variance [14]. Deep learning classification is very challenging for high precision diagnosis. The classification accuracy for GoogleNet is observed to be 94.5% for two classes [15].

III. METHODOLOGY

The database of fruit is created that consists of samples from laboratory and real field conditions. The proposed model introduces two pre-trained networks; AlexNet and GoogLeNet. GoogLeNet is 22 layers deep pre-trained convolutional neural network. The network is trained on either Places365 or ImageNet datasets. The network trained by ImageNet datasets classifies images into 1000 categories. On the other hand the network trained by Places365 dataset classifies images into 365 categories. The network learns different feature representations for a wide range of images. For both the networks the image input size is 224-by-224. In AlexNet there is no any fixed pattern. Based on experiment, the convolutions for each layer are decided. This involves convolutional layers then max pooling and finally a few dense layers. The filter has no standard size. VGG introduces a standard filter size of (3×3), by employing max pooling after 2 convolutions. In VGG, the filter size is (3×3), and max pooling is introduced after each 2 convolutions. After the completion of each max pooling, the number of filters is doubled. It is observed that VGG network is far deeper than AlexNet. Training data includes inputs and targets. The raw data directly fed into the network that learns the features naturally. Feature detection layer involves convolution and pooling. The convolution approach activates the certain features from the images. The pooling reduces the number of parameters required by the network to learn. Features used to classify the image are area and eccentricity. The area illustrates the number of pixels in the defected regions that is returned as a scalar. The shape contour used to calculate the area i.e. feature surrounded by the closed polygon.
Area of polygon is calculated as given in [5]

$$A_{Polygon} = \sum_{i \, \varepsilon \, contour} (x_i + x_{i-1}) \; (y_i - y_{i-1}) \tag{1}$$

$$Area_{ellipse} = \pi * (a * b) \tag{2}$$

where a & b represent the major and minor axes of ellipse. In case the shape having interior holes, which is the case for shape generated by pore and particle analysis, the area is calculated in the same manner and subtracted from the area of surrounding contour. Another feature extracted is eccentricity that having same second moment as region and return a scalar value. It is measured by taking the ratio of foci distance and major axis of ellipse. The value of eccentricity lies between 0 and 1. An ellipse is a circle if the eccentricity value is 0. Similarly, an ellipse represented as line segment if its value is 1. The CNN architecture moves to classification after feature detection. The last layer of network requires softmax function for classification output.

IV. RESULT

In Fig. 1, the Deep Network Designer Network is illustrated. Fig. 2 shows the classification of apple using AlexNet. Then apply the curve fitting that allows of fitting a variety of curves and surfaces to the data through a bilateral interface. It performs smoothing custom equation, interpolation, linear and non-linear regression of defected region of image. The analysis removes the outliners and display confidence interval and its residuals. Further it visualizes the curves and surface, and compares multiple fits.

Table- I: Result of Sample Classification

S. No.	Classification of Samples		
	Sample	*Accuracy (%)*	*Classification Network*
1	Apple	99.9	GoogleNet
2	Pomegranate	100%	GoogleNet
3	Strawberry	100%	GoogleNet
4	Apple	99.8%	AlexNet
5	Pomegranate	99.1%	AlexNet
6	Strawberry	99.3%	AlexNet

In Fig. 3 and Fig. 4, the classification of pomegranate and strawberry are shown using AlexNet. Fig. 5 represents the error histogram of the trained network. There is a close relationship for R equals to 1 and 0 for random relationship. It means that the data fitting is quite specific. In Fig. 5, the number of vertical bars represents Bins observed on the graph. The total error ranges from -0.2222 to 0.1968. The difference of targets and outputs is nearly 0.07622 that is nearly zero. Each bin has a width of :

(0.1968-(-0.2222))/20 = 0.02095.

The vertical bar denotes the number of samples from dataset, which lies in a particular bin.
Fig. 6 represents, the performance curve of training, validation and testing returned by the function train. Error is minimized by introducing more epochs for training. It is observed that the error is increased for the validation datasets in case of overfitting the training datasets. The best performance is achieved from the epoch with low validation error. In Fig. 7, the Training State of network is described. Fig. 8 shows the change in one dynamic variable that affects others. The performance over the range of operating condition is analyzed for selection and sizing of sample of defected apples.

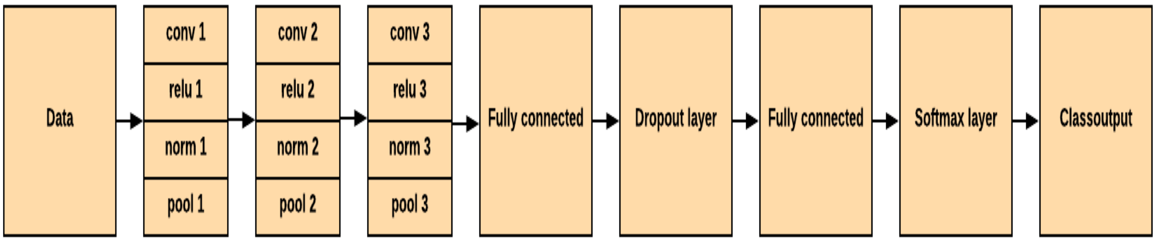
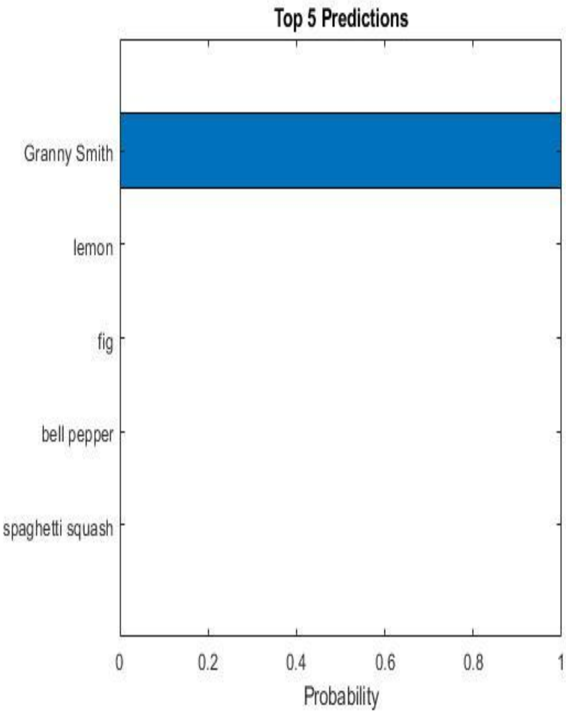


Fig. 1.Deep Network Designer Network

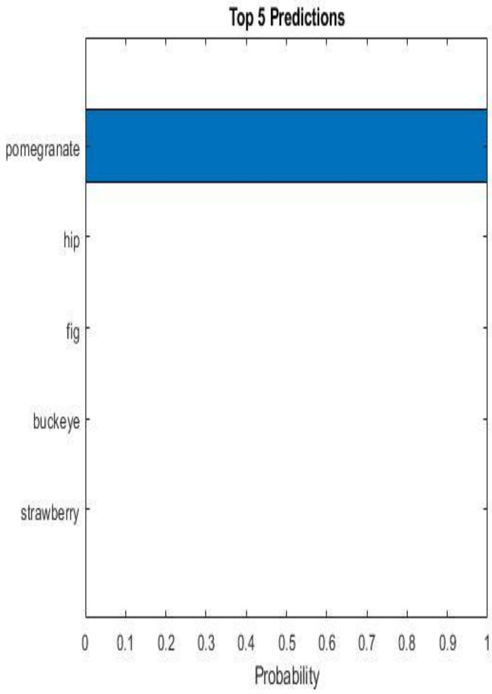
(a)



(b)

Fig. 2 (a) Input apple sample, (b) Classification of apple

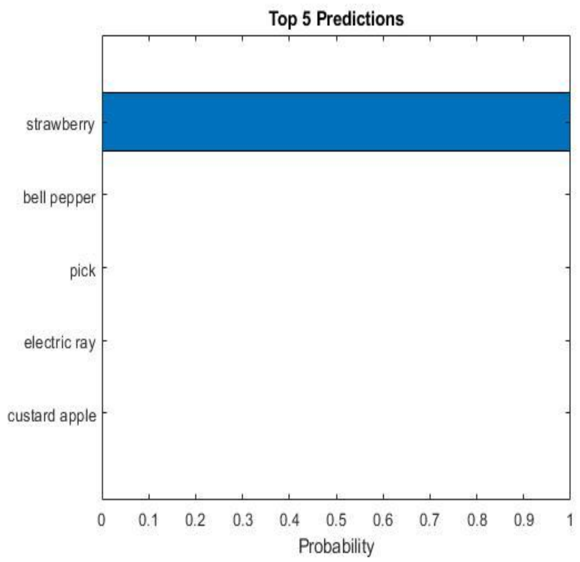
(a)



(b)

Fig. 3 (a) Input pomegranate sample, (b) Classification of pomegranate

(a)



(b)

Fig. 4 (a) Input strawberry sample, (b) Classification of strawberry

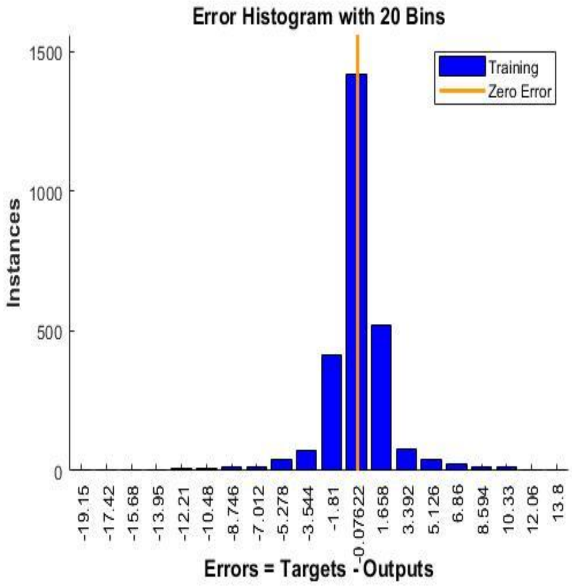


Fig. 5 Error Histogram

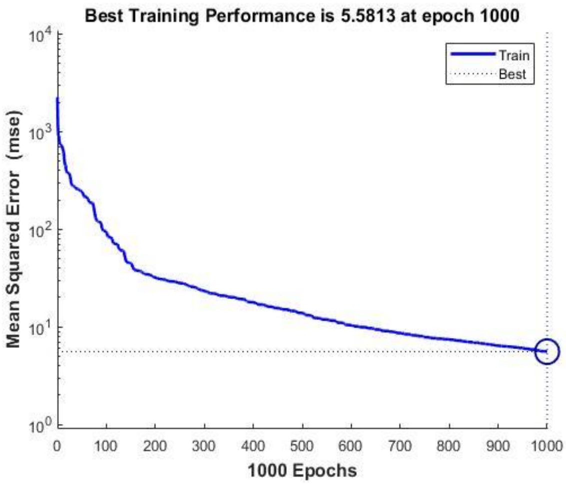


Fig. 6 Performance curve

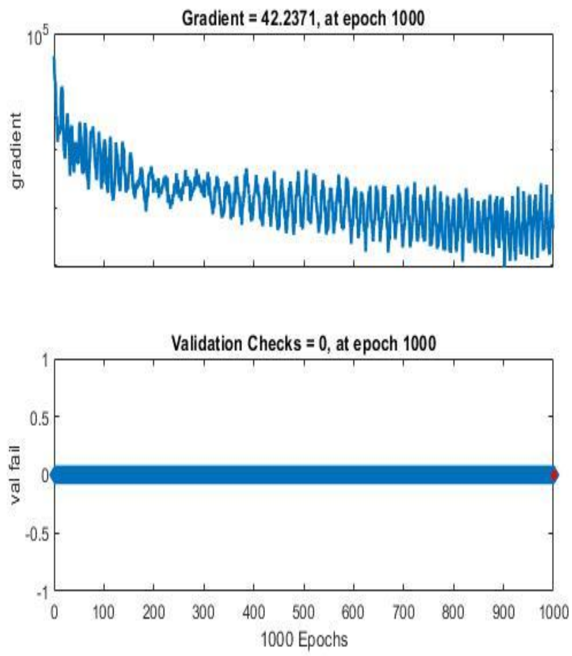


Fig. 7 Training State

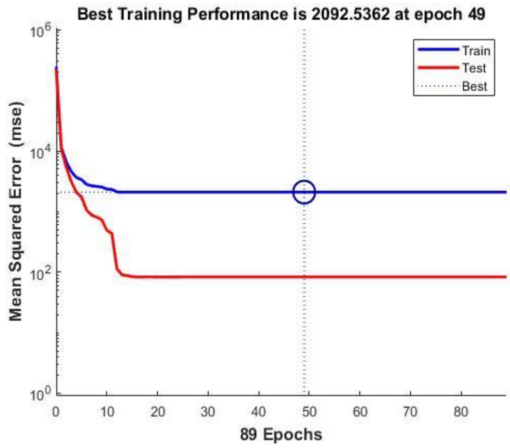


Fig.8 Performance curve

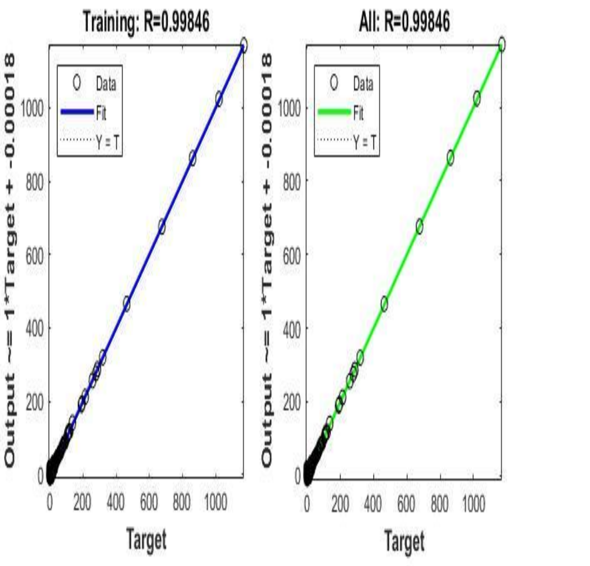


Fig.9 Regression plot

Retrieval Number L28041081219/2019©BEIESP
DOI: 10.35940/ijitee.L2804.1081219
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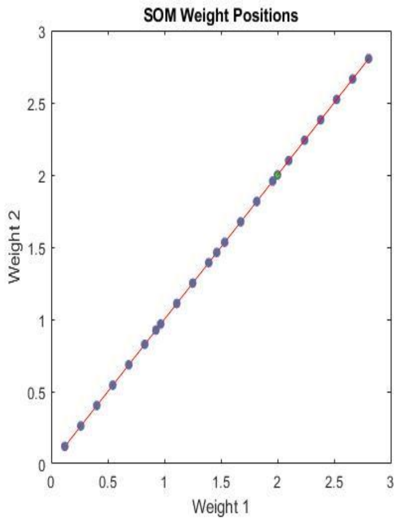

Fig. 10 SOM Weight Position

The next step is network validation by generating a regression plot as shown in Fig. 9 that represents the relationship between the output and the target. The best training of the network is achieved for equal outputs and targets. At first the response of the trained network is calculated for all the inputs in the data set and then extracting the outputs and targets. The dashed line represents the target. It is the difference of desired result and outputs. The solid line shows linear regression between outputs and targets for the best fit. For R = 1, there is perfect linear relationship between the outputs and targets. If R tends to zero depicts no linear relationship between outputs and targets.

V. CONCLUSION

In the proposed method, the training data directs a good fit. The value of R is found large during validation and testing. The scatter plot represents the data points having poor fits.
Fig. 10 represents the self-organizing map that respond similarly to certain type of input pattern for different parts of the network. The network is trained to produce a low-dimensional and distinct representation of the input space of the training samples. SOM operates in two modes training and mapping. The mapping automatically classify new input vector.

VI. RESULT AND DISCUSSION

Fruit classification based on deep learning is observed time saver and more accurate compared to traditional method. The pre-trained networks, AlexNet and GoogleNet achieved the better results. The training data are observed as a good fit. During the experimental observations, it is noticed that larger value of R shows the best result. The pretrained network classifier extracts informative features that are already learned and use them to learn a new network. Table 1, represents the classification accuracy of Apple 99.9%, Pomegranate 100% and Strawberry 100% using GoogleNet. On the other hand classification accuracy for Apple 99.8%, Pomegranate 99.1% and Strawberry 99.3% observed using AlexNet. It is observed that GoogleNet shows better result compared to AlexNet. In future, more work need to done for the fruit defect detection based on deep learning. Computer vision based fruit defect identification will bring a revolution in the fruit industry.

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