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Fruit Recognition using Support Vector Machine based on Deep Features

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Abstract

Fruit recognition with its variety classification is a promising area of research. This research is useful for monitoring and categorizing the fruits according to their kind with the assurance of fast production chain. In this research, we establish a new high-quality dataset of images containing the five most popular oval-shaped fruits with their varieties. Recent work in deep neural networks has led to the development of many new applications related to precision agriculture, including fruit recognition. This paper proposes a classification model for 40 kinds of Indian fruits by support vector machine (SVM) classifier using deep features extracted from the fully connected layer of the convolutional neural network (CNN) model. Also, another approach based on transfer learning is proposed for recognition of Indian Fruits. The experiments are carried out in six most powerful deep learning architectures such as AlexNet, GoogleNet, ResNet-50, ResNet-18, VGGNet-16 and VGGNet-19. So, the six deep learning architectures are evaluated in two approaches, which makes 12 classification model in total. The performance of each classification model is assessed in terms of accuracy, sensitivity, specificity, precision, false positive rate (FPR), F1 score, Mathew correlation (MCC) and Kappa. The evaluation results show that the SVM classifier using deep learning feature provides better results than their transfer learning counterparts. The deep learning feature of VGG16 and SVM results in 100% in terms of accuracy, sensitivity, specificity, precision, F1 score and MCC at its highest level.

Keywords

Fruit Recognition, Convolutional neural network (CNN), Transfer Learning, Support vector machine (SVM), Deep Feature.

Cover Page Footnote

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1. Introduction

With the advancement of the lifestyle of human society, extra consideration has been paid towards the quality and variety of food we eat. Many real-life applications have used fruit identification systems, for example, store checkout where it may be very well utilized rather than manual scanner tags. Besides, it can be used as supportive appliances for blind people. Recognizing different types of fruits is a repeated chore in supermarkets, where the cashier has to define each item type that will determine its cost. The skilled farm labour in the horticulture industry is one of the most cost-demanding factors. Under these challenges, fruit production still needs to meet the growing demands of an ever-growing world population, and this casts a critical problem to come. A fruit recognition system, which automates labelling and computing the price, is the right solution for this problem. Since last two decades, many applications are reported for recognising the kind of fruits. But, in the meantime, no such advanced techniques are reported for recognition of Indian fruits. Therefore, this research is carried out to classify most popular Indian fruits with its varieties.

In this study, we consider five most popular Indian fruits, i.e. apple, orange, mango, pomegranate and tomato. We include the almost all varieties which are originated and cultivated in India. Table 1 illustrates the type and varieties of fruits.

This study includes 14 varieties of apple,9 varieties of mango,5 varieties of orange, 4 varieties of pomegranate and 8 varieties of tomato. Here we have not considered the fruit varieties which are neither cultivated in India nor available in the Indian market. Some fruit images are taken from the data set of Fruit-360 [1], i.e. Apple Red Delicious and five varieties of tomato such as Bumble Bee, Cherry Red, Maroon, Romanesco, Red Sweet Cherry & Sammarzano. The 40 kinds of fruits are shown in Fig. 1. The Apple varieties from Fig. 1: Sl.no. 1 to 14 shows Ambrosia, Camspur Auvli, Earley Fuji, Fuji, Gala, Golden1, Golden2, Golden Spur, Granny Smith, Green, McIntosh, Oregun Spur, Red Delicious and Scarlet Gala. The Mango varieties from Fig. 1: Sl. no. 15 to 23 shows Alphanos, Amrapali, Baiganpali, Dusheri, Himsagar, Kesar, Langra, Neelam, Suvernarekha. The Orange varieties from Fig. 1: Sl. No. 24 to 28 shows Bergamout1, Bergamout2, Bitter, Kinnow, Sweet. The Pomegranate varieties from Fig. 1: Sl no. 29 to 32 shows Arakta, Bhagwa, Ganesh, Kandhari. The Tomatoes varieties from Fig. 1: Sl. no.33 to 40 shows Tomato1, Tomato2, Bumble Bee, Cherry Red, Marron, Red Sweet Cherry, Ramensco and Sammarzano.

Table 1
Five most popular types of Indian fruits and their varieties.

Sl. No.	Fruits	Varieties
1	Apple	Ambrosia, Camspur Auvli, Earley Fuji, Fuji, Gala, Golden1, Golden2, Golden Spur, Granny Smith, Green, McIntosh, Oregun Spur, Red Delicious, Scarlet Gala.
2	Orange	Bergamout1, Bergamout2, Bitter, Kinnow, Sweet
3	Mango	Alphanos, Amrapali, Baigapali, Dusheri, Himsagar, Kesar, Langra, Neelam, Suvernarekha.
4	Pomegranate	Arakta, Bhagwa, Ganesh, Kandhari.
5	Tomato	Tomato1, Tomato2, Bumble Bee, Cherry Red, Maroon, Romanesco, Red Sweet cherry, Sammarzano.

In recent years, with the application of computer vision and machine learning, there has been an incredible advancement in the fruit industry. The inclusion of automated methods has been reported in different phases in the production chain. The fruit production consists of three phases: pre-harvesting, harvesting and post-harvesting. In the pre-harvesting stage, the on-tree detection and yield estimation have been done to predict the quantity of fruit. In the harvesting stage, the mature fruit has to be picked up from the tree to container. In the post-harvesting stage, the sorting is done as per fruit kind and quality. Most of the cases, computer intelligence with robotics are employed for on-tree detection and collection of fruits [2−6]. Again, for fruit classification computer vision [7,8], image processing [9], machine learning [10] techniques are widely used. Many researchers have also reported their work on the quality inspection of fruits [11−15]. The quality inspection is done by defect segmentation [16−20] and type of flaws appeared [21] on the surface of fruits. Some work has been done for identification of varieties of a particular type of fruits [22,23]. Although the machine learning techniques have made a great accomplishment on image identification, still it has some limitations such as restricted data handing capability, the requirement of segmentation & feature extraction [24].

The Faster R−CNN is used to detect the on-tree fruits namely apple, mango and almond. Each image

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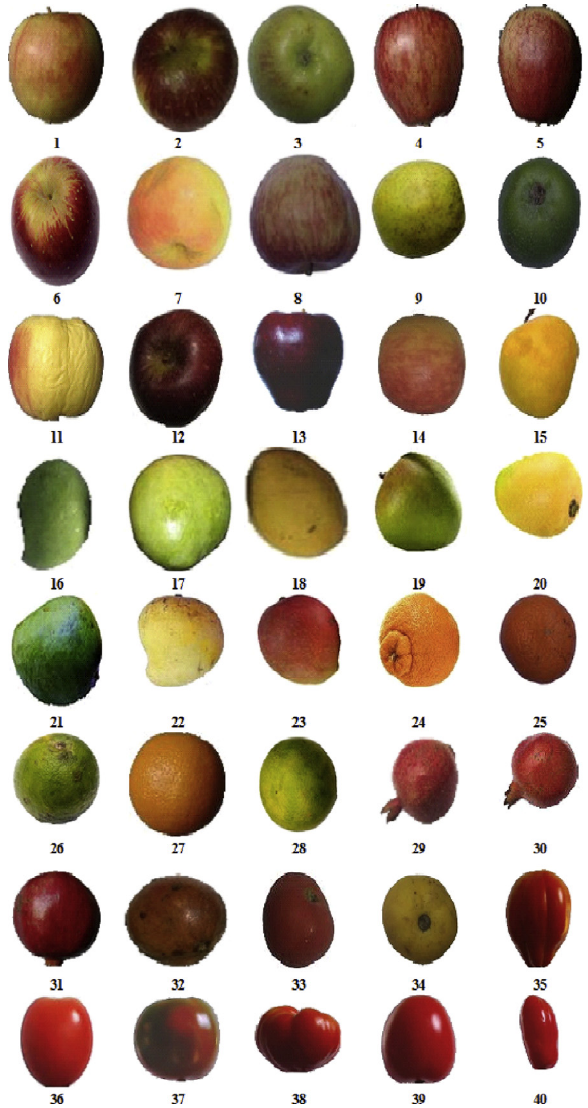

Fig. 1. Samples of 40 kinds of Indian fruits.

contains 100 to 1000 number of fruits, and in the case of mango & apple, it achieved an F1 score of more than 0.9 [2]. Besides, Faster R−CNN the fusion techniques are employed to detect the sweet pepper using RGB and near-infrared (NIR) images, leads to a novel multi-modal Faster R−CNN model. The approach is useful for the automated robotic platform and resulted in the F1 score of 0.837 [3]. An automatic non-destructive method is suggested for detection and counting of three varieties grapes. The approach develops an algorithm for correlation between on-tree counting of grapes & the actual harvested weight of grapes, results in co-efficient of correlation (R^2) 0.74 [4]. An image-processing method was suggested to detect on-plant intact tomato fruits accurately. This process consists of three steps. At the first step, pixel-based segmentation was conducted to roughly segment the pixels of the images into classes composed of fruits, leaves, stems and backgrounds. Blob-based segmentation was then conducted to eliminate misclassifications generated in the first step. At the third step, X-means clustering was applied to detect individual fruits in a fruit cluster. The developed method did not require an adjustment of the threshold values of each image for fruit detection because the image segmentations were conducted based on classification models generated by machine learning approaches. The results of fruit detection in the test images showed that the developed method achieved a recall of 0.80, while the precision was 0.88. Also, the recall of young fruits was 0.78, although detection of young fruits is complicated because of their small size and the similarity of their appearances with that of stems [5]. A review of on-tree fruit detection in robotics platform was carried out with limitations, findings and future direction [6]. The fruit classification based on colour, texture and shape feature with inclusion of principal component analysis (PCA) and support vector machine (SVM) is proposed. The methodology successfully classified 18 types of fruits and achieved 88.2% of accuracy [7]. Again, the same dataset is evaluated based on fitness-scaled chaotic artificial bee colony (FSCABC−FNN). The experimental results demonstrated that the FSCABC−FNN achieved a significant classification accuracy of 89.1% [8]. The application of image processing for analysis of fruit and vegetable is reviewed [9]. An approach of creating a system identifying fruit and vegetables in the retail market using images captured with a video camera is proposed [10]. The quality inspection technique is proposed for apple based on near-infrared images of surfaces [11]. The research reports the quantitative measurement of the performance of the system for verification of orientation and a combination of the four segmentation routines. The routines were evaluated using eight different apple varieties. The ability of the methods to find individual defects and measure the area ranged from 77 to 91% for the number of defects detected, and from 78 to 92·7% of the total defective area. In many kinds of research, the quality analysis of fruits is based on defect appearance on the skin with different prospective such as multivariate image analysis for skin defect detection of citrus [14], image analysis for blueberries [15] and machine vision and learning for golden delicious [16] and Jonagold apple [17]. In addition, the apple defect detection was reported based on the combination of lighting transform and image ratio methods [19] and hyperspectral imaging techniques [20]. Besides, defect detection, the type of flaws that appeared on the skin is also identified [21,24]. Again, different methodologies are reported for classification of varieties of fruits such as image analysis for tomato and lemon variety classification [22] and six-layer CNN model for classification of 16 different varieties of fruits [23].

In past few years, the CNN is applied in various fields such as object detection [25−29], image classification [30−33] and video classification [34]. In last couple of year many researches have been conducted for on-tree detection [35−37], classification [38−41] and grading [42,43] of fruits. As far as our investigation, almost no research has been done for Indian fruit recognition.

In this paper, a system based on deep CNNs is suggested for recognition of 40 kinds of Indian fruits. In this study, we use a dataset consisting of images of fruits captured by 13 Megapixel Smartphone camera with a white background in natural daylight. Later the images are processed by removing the background and resize to 227×227×3 dimension. The collected image dataset is used for classification purpose using six most powerful pre-trained deep learning networks such as AlexNet, GoogleNet, ResNet-18, ResNet-50, VGGNet-16 and VGGNet-19. Another approach is that the classification is done by SVM classifier using deep learning features. The performance of all classification models is evaluated using confusion matrix measures including accuracy, sensitivity, specificity, F1 score, Mathew correlation and Kappa coefficient (K).

The remaining of the paper is organised as follows. Section 2 includes details about image dataset. The proposed method is discussed in section 3. The experimental results and discussion are given in section 4. Finally, in section 5, conclusion and future scope are discussed.

2. Dataset

The dataset used to examine the performance of the suggested method includes images of 40 kinds of Indian fruits (Fig. 1). These images were obtained with13 Megapixel smartphone camera in natural daylight without shade. Each image in this dataset consists of 96dpi×96dpi resolution and three-channel (RGB) colour images. Table 2 lists the names and numbers of fruits kinds in this dataset. The image dataset is named as **Indian Fruits-40**. The dataset contains 23,848 numbers of images and makes available [44].

Table 2
Details of image dataset Established for Fruit Recognition.

Name of Fruits	Label	Varieties	Train	Test	Sub-Total
Apple	1	Ambrosia	492	62	554
	2	Camspur Auvli	576	61	637
	3	Earley Fuji	480	56	536
	4	Fuji	492	66	558
	5	Gala	421	64	485
	6	Golden1	550	53	603
	7	Golden2	515	53	568
	8	Golden Spur	460	116	576
	9	Granny Smith	495	63	558
	10	Green	420	55	475
	11	McIntosh	493	75	568
	12	Oregun Spur	480	59	539
	13	Red Delicious	491	63	554
	14	Scarlet Gala	430	64	494
Mango	15	Alphanos	665	100	765
	16	Amrapali	600	90	690
	17	Baiganpali	638	96	734
	18	Dusheri	500	66	566
	19	Himasagar	576	72	648
	20	Kesar	701	69	770
	21	Langra	640	88	728
	22	Neelam	640	58	698
	23	Suvernarekha	640	58	698
Orange	24	Bergamout1	410	37	447
	25	Bergamout2	576	52	628
	26	Bitter	562	51	613
	27	Kinnow	565	52	617
	28	Sweet	480	43	523
Pomegranate	29	Arakta	480	43	523
	30	Bhagwa	440	40	480
	31	Ganesh	493	44	537
	32	Kandhari	490	44	534
Tomato	33	Tomato1	540	49	589
	34	Tomato2	500	45	545
	35	Bumble Bee	738	67	805
	36	Cherry Red	492	44	536
	37	Maroon	376	33	409
	38	Romanesco	738	67	805
	39	Red Sweet Cherry	479	43	522
	40	Sammarzano	672	61	733
Grand Total					23,848

3. Methodology

In this study, we applied two approaches for recognition of Indian fruits, namely transfer learning and second by SVM using deep learning features.

3.1. Fruits Recognition based on transfer learning approach

Transfer learning is a machine learning approach that is restated as an outset to solve a different problem using the knowledge collected from an established model. The current study fine-tuned this by using pre-

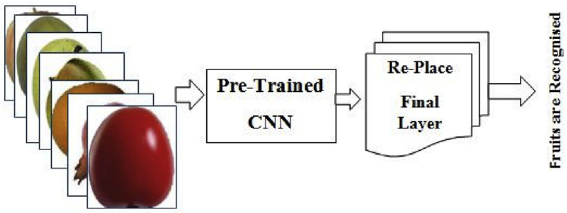

Fig. 2. Fruits Recognition based on Transfer Learning approach.

trained CNN models based on transfer learning. Fig. 2 illustrates the fruit recognition model based on transfer learning approach.

The approach introduced here is an unsupervised transfer learning as the source & domain is same, but source & target task is different. There are two steps in unsupervised feature construction method for learning of high-level features. In the first step, higher-level basis vectors b = {b1, b2,…bs} are learned on the source domain data by solving the optimization problem (1) as shown as follows,

$$\min_{a,b} \sum_i \left\| x_{si} - \sum\nolimits_j a_{si}^j b_j \right\|_2^2 + \beta \|a_{si}\|_1 \qquad (1)$$
$$s.t.\ \left\|b_j\right\|_2 \le 1\, \forall_j \in 1, \ldots.s$$

In this equation, a_{Si}^j is a new representation of basis bj for input x_{Si}, and β is a coefficient to balance the feature construction term and the regularization term. After learning the basis vectors b, in the second step, an optimization algorithm (2) is applied to the target domain data to learn higher-level features based on the basis vectors b.

$$a_{Ti}^* = \arg_{aTi} \min \left\| x_{Ti} - \sum_j a_{Ti}^j b_j \right\|_2^2 + \beta \|a_{Ti}\|_1 \qquad (2)$$

Finally, discriminative algorithms can be applied to $\{a_{Ti}^*\}$ with corresponding labels to train classification or regression models for use in the target domain.

3.1.1. Summary steps of transfer learning approach

The following steps summarize the transfer learning:

Step-1: Collection of fruit Image.
Step-2: Pre-processed the image, i.e. removes the background and resize to 227×227×3 dimension. Again, augmentation is used to fit the image size with the input size of the network.
Step-3: Load a pre-trained network. Replace the classification layers for the new task and train the network on the data for the new task.
Step-4: Classification is performed using the newly created deep model and measures the performance of the new network.

The similar approach is repeated for six most powerful CNN model, i.e. AlexNet, GoogleNet, ResNet-18, ResNet-50, VGGNet-16 and VGGNet-19.

3.2. Fruit recognition by SVM using deep learning features

Deep feature extraction is based on the extraction of features acquired from a pre-trained CNN. The deep features are extracted from fully connected layer and feed to the classifier for training purpose. The deep features obtained from each CNN network such as AlexNet, GoogleNet, ResNet-18, ResNet-50, VGGNet-16 and VGGNet-19 are used by SVM classifier. After that, the classification is performed and measures the performance of all classification models. The fruit recognition model using deep learning features by SVM classifier is shown in Fig. 3.

In the convolution layer, formats of enrolled channels are utilised. Each one channel is limited spatially (traverse along with height and weight) but enlarges with the complete deepness of input volume. The images that have, Height H, Depth D and Width W shading channels (i.e., H × D, W), the enrolled channels isolate an image width as W1=((W−F+2p))/(S+1), here F speaks to the spatially expands neuron estimate; p is the main part of zero paddings, and S is the size of way. Thus, the height is partitioned by H1=((H−F+2p))/(S+1); depth D1 is the extent of the number of channels K. For instance, an image having 28×28×3 (3 is for the shading channels), if the open field (or channel) has a size of 5×5×3 (altogether 75neurons + 1bias), a 5x5 window with profundity three moves along the width and height and produces a 2-D activation map.

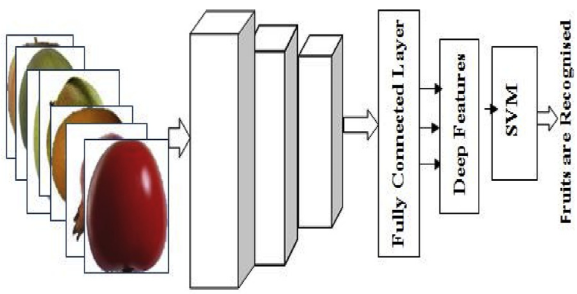

Fig. 3. Fruit Recognition by SVM Classifier using Deep Learning Features.

The Pooling Layer works individually above all the deepness portion for the input and rescales it extensional applying the MAX operation. It obtained the size of the volume of HDW and separates the image into W1=(W−F)/(S+1) as Width and H1=(H−F)/(S+1) as Stature and profundity D1 is same as the info D. After the calculation against each shading channels the MAX task is finished. In this way, the feature matrix is then diminished in POOLING layer.

3.2.1. Summary steps of deep learning approach

The following steps summarize the proposed deep feature extraction:

Step-1: Collection of fruit Image.
Step-2: Pre-processed the image, i.e. removes the background and resize to 227×227×3 dimension. Again, augmentation is used to fit the image size with the input size of the network.
Step-3: Features are extracted from fully connected layers and feed to the classifier for training purpose.
Step-4: Classification is performed using the deep features with the SVM classifier and measures the performance.

The similar approach is repeated for classification by SVM classifier using deep features of six most powerful CNN model, i.e. AlexNet, GoogleNet, ResNet-18, ResNet-50, VGGNet-16 and VGGNet-19.

4. Results and discussion

In this study, we examined the performance of classification models using six powerful architectures of deep neural networks for recognition of Indian fruits. The experimental studies were implemented using the MATLAB 2019a deep learning toolbox. All applications were run on a laptop, i.e. Acer Predator Helios 300 Core i5 8th Gen - (8 GB/1 TB HDD/128 GB SSD/Windows 10 Home/4 GB Graphics) and equipped with NVIDIA GeForce GTX 1050Ti. The measurement of performance of each classifier in terms of Accuracy, Sensitivity, Specificity, Precision, False Positive Rate (FPR), F1 Score, Matthews Correlation coefficient (MCC) and Kappa coefficient. The performance comparison of each classifier is in the following subsection. The confusion matrix measures are expressed in equations (3)−(10).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{3}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$FPR = \frac{FP}{FP + TN} \tag{7}$$

$$F1Score = 2 \times \frac{sensitivity \times Precision}{sensitivity + Precision} \tag{8}$$

$$\mathrm{MCC} = \frac{\mathrm{TP} \times \mathrm{TN} - \mathrm{FP} \times \mathrm{FN}}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}} \tag{9}$$

$$Kappa = 2 \times \frac{(TP \times TN - FN \times FP)}{(TP \times FN + TP \times FP + 2 \times TP \times TN + FN \times TN + FP \times FP + FP \times TP)} \tag{10}$$

4.1. Result based on transfer learning

In this section, we performed fine-tuning based on transfer learning using deep learning models from pre-trained CNN networks. For transfer learning, the training parameters such as minibatch size, validation frequency, maximum epoch and the initial learning rate was assigned as 64,30,5 and 0.001, respectively. Also, the stochastic gradient descent with momentum (SGDM) was chosen as a learning method. The performance score of eight parameters is given in Table 3 and Table 4. Note that, all the performance parameters are the average of 20 independent executions and their standard deviations.

As shown in Tables 3 and 4, AlexNet results in the highest value of accuracy, sensitivity, precision, F1Score, MCC and Kappa. Again, the lowest FPR is in AlexNet. Therefore, the performance of AlexNet is better in all sense. The second best and lowest performance results by ResNet50 and VGG16, respectively.

Table 3
Performance measures for deep models based on transfer learning in terms of accuracy, sensitivity, specificity and precision (best results in bold).

CNN model	Accuracy	Sensitivity	Specificity	Precision
AlexNet	**0.9760138779 ± 0.00495104203[a]**	**0.9735182114 ± 0.00496242021[b]**	**0.9993854680 ± 0.00012706250[c]**	**0.9750732822 ± 0.00458752295[d]**
GoogleNet	0.9737856590± 0.00420160427[a]	0.9712684222± 0.00404657729[b]	0.9993283024 ± 0.00010809523[c]	0.9731750487 ± 0.00319905632[d]
ResNet50	0.9759753275 ± 0.00390219116[a]	0.9732738412 ± 0.00388884525[b]	0.9993845906 ± 0.00009996608[c]	0.9750290182 ± 0.00367393900[d]
ResNet18	0.9737856590 ± 0.00420160427[a]	0.9712684222 ± 0.00404657729[b]	0.9993283024 ± 0.00010809523[c]	0.9731750487 ± 0.00319905632[d]
VGG16	0.9734926752 ± 0.00548890267[a]	0.9704918216 ± 0.00590022173[b]	0.9993208620 ± 0.00014068983[c]	0.9727529681 ± 0.00523201446[d]
VGG19	0.9748265225 ± 0.00560732125[a]	0.9721399842 ± 0.00569382258[b]	0.9993550296 ± 0.00014410468[c]	0.9743677792 ± 0.00440933249[d]

Means within a column the same letter(s) are not statistically significant ($p = 0.05$) according to Duncan's multiple range test (SPSS Version 26).

Table 4
Performance measures for deep models based on transfer learning in terms of FPR, F1 Score, MCC and Kappa (best results in bold).

CNN Model	FPR	F1Score	MCC	Kappa
AlexNet	**0.0006145321 ± 0.00012706250[a]**	**0.9735237095 ± 0.00493569688[b]**	**0.9733131025 ± 0.00496472242[c]**	**0.5079769884 ± 0.10155983972[d]**
GoogleNet	0.0006716977 ± 0.00010809523[a]	0.9710118043 ± 0.00426159205[b]	0.9709697781 ± 0.00401223659[c]	0.4622699325 ± 0.08618675703[d]
ResNet50	0.0006154095 ± 0.00009996608[a]	0.9731960441 ± 0.00404832293[b]	0.9730793465 ± 0.00398683638[c]	0.5071862088 ± 0.08004494717[d]
ResNet18	0.0006716977 ± 0.00010809523[a]	0.9710118043 ± 0.00426159205[b]	0.9709697781 ± 0.00401223659[c]	0.4622699325 ± 0.08618675703[d]
VGG16	0.0006791380 ± 0.00014068983[a]	0.9701647486 ± 0.00693724404[b]	0.9701596226 ± 0.00659383942[c]	0.4562600084 ± 0.11259287873[d]
VGG19	0.0006449704 ± 0.00014410468[a]	0.9721635506 ± 0.00552567955[b]	0.9720887371 ± 0.00539627815[c]	0.4836209795 ± 0.11502197764[d]

Means within a column the same letter(s) are not statistically significant ($p = 0.05$) according to Duncan's multiple range test (SPSS Version 26).

Table 5
Performance measures of SVM based on deep features of CNN model in terms of accuracy, sensitivity, specificity and precision (best results in bold).

CNN model	Accuracy	Sensitivity	Specificity	Precision
AlexNet	0.9979231518 ± 0.00095377488[b]	0.9979231518 ± 0.00095377488[b]	0.9999467475 ± 0.00002445581[b]	0.9979665487 ± 0.00092472566[b]
GoogleNet	0.9992272727 ± 0.00039981525[a]	0.9992272727 ± 0.00039981525[a]	0.9999801862 ± 0.00001025175[a]	0.9992346035 ± 0.00039521973[a]
ResNet50	0.9980739299 ± 0.00066547216[b]	0.9980739299 ± 0.00066547216[b]	0.9999506135 ± 0.00001706352[b]	0.9981027599 ± 0.00063980095[b]
ResNet18	0.9947859923 ± 0.00104360137[c]	0.9947859923 ± 0.00104360137[c]	0.9998663075 ± 0.00002675908[c]	0.9948799945 ± 0.00098940863[c]
VGG16	**0.9995681819 ± 0.00043561037[a]**	**0.9995681819 ± 0.00043561037[a]**	**0.9999889275 ± 0.00001116961[a]**	**0.9995740724 ± 0.00042796142[a]**
VGG19	0.9992500000 ± 0.00060849783[a]	0.9992500000 ± 0.00060849783[a]	0.9999807689 ± 0.00001560251[a]	0.9992599258 ± 0.00059585569[a]

Means within a column the same letter(s) are not statistically significant (p = 0.05) according to Duncan's multiple range test (SPSS Version 26).

Table 6
Performance measures of SVM based on deep features of CNN model in terms of FPR, FI Score, MCC and Kappa (best results in bold).

CNN Model	FPR	F1Score	MCC	Kappa
AlexNet	0.0000532525 ± 0.00002445577[b]	0.9979113241 ± 0.00097633093[b]	0.9978756994 ± 0.00098123957[b]	0.9573979846 ± 0.01956461238[a]
GoogleNet	0.0000198135 ± 0.00001025166[a]	0.9992265132 ± 0.00040026194[a]	0.9992090275 ± 0.00040906739[a]	0.9841491842 ± .00820133520[a]
ResNet50	0.0000493864 ± 0.00001706338[b]	0.9980689291 ± 0.00066721619[b]	0.9980297586 ± 0.00067658171[b]	0.9604908710 ± 0.01365070842[a]
ResNet18	0.0001336926 ± 0.00002675904[c]	0.9947385089 ± 0.00106810606[c]	0.9946544576 ± 0.00106704843[c]	0.8930459941 ± 0.02140720644[a]
VGG16	**0.0000110723 ± 0.00001116949[a]**	**0.9995675219 ± 0.00043655972[a]**	**0.9995583462 ± 0.00044521602[a]**	**3.29325E^{+13} ± 5.16121E^{+13}[b]**
VGG19	0.0000192308 ± 0.00001560251[a]	0.9992485172 ± 0.00061059544[a]	0.9992326775 ± 0.00062176155[a]	1.09775E^{+13} ± 3.37880E^{+13}[a]

Means within a column the same letter(s) are not statistically significant (p = 0.05) according to Duncan's multiple range test (SPSS Version 26).

Table 7
Accuracy (%) score of traditional image classification methods.

Methods	Bag-of-Feature	GLCM + SVM	HOG + SVM	LBP + SVM
Accuracy	88.70	97.3	85.2	96.2

4.2. Result based on deep feature and SVM

In this section, we used the fully connected layer for deep feature extraction, based on pre-trained CNN models of AlexNet, GoogleNet, ResNet50, ResNet18, VGG16 and VGG19. For each of these models, deep features were extracted from the layers fc6 in case of VGG16, VGG19 and AlexNet. Again, in case of ResNet50 & ResNet18 feature are extracted from fc1000 layer. And pool5-drop_7×7_s1 layer is used for feature extraction in case of GoogleNet. Then by using these features, SVM classifies the kind of the fruit. The performance scores of these experimental studies are given in Tables 5 and 6. Note that, the performance scores are the average of 20 numbers of independent executions results and their standard deviations.

As shown in Tables 5 and 6, VGG16and SVM results in the highest value of accuracy, sensitivity, precision, F1Score, MCC and Kappa. Again, the lowest FPR is in VGG16 and SVM. Therefore, the performance of VGG16 is better in all sense. The second best and lowest performance results by VGG19 and ResNet18, respectively.

4.3. Statistical analysis

To have a better comparison among the classification models, Post Hoc analyses were performed on the results obtained from 20 independent simulations of eight performance measurement parameter. It is observed from Tables 3 and 4 that all classification method based on transfer learning with consideration of eight performance measured parameter for fruit kind recognition is statistically insignificant to each other. It implies that all the classification models based on transfer learning have almost statistically equal performance (since superscript letters are identical column-wise).

Again, from Tables 5 and 6 it is observed that in terms of accuracy, sensitivity, specificity, precision, FPR, F1 score & MCC the deep feature of VGG16, VGG19 & GoogleNet with SVM perform the best (since superscript letters ‘a’ column-wise), AlexNet & ResNet50 (since superscript letters ‘b’ column-wise) perform moderate and ResNet18 (since superscript letters ‘c’ column-wise) perform worst. Again, according to Kappa all the classification models (since superscript letters ‘a’ column-wise) is in one class except VGG16 (since the superscript letter ‘b’ column-wise) and indicates VGG 16 has the highest score. With the above analysis, it establishes a complete implication that the deep feature of VGG16 and SVM perform best for Indian-40 Fruit recognition.

4.4. Comparison of accuracy score (%) with other image classification method

In image processing and machine learning approach, mostly bag-of-feature, HOG plus SVM, GLCM plus SVM and LBP plus SVM are applied for image classification. The accuracy score of those approaches is given in Table 7.

The accuracy score in the percentage of all executed methods and models are shown in Fig. 4.

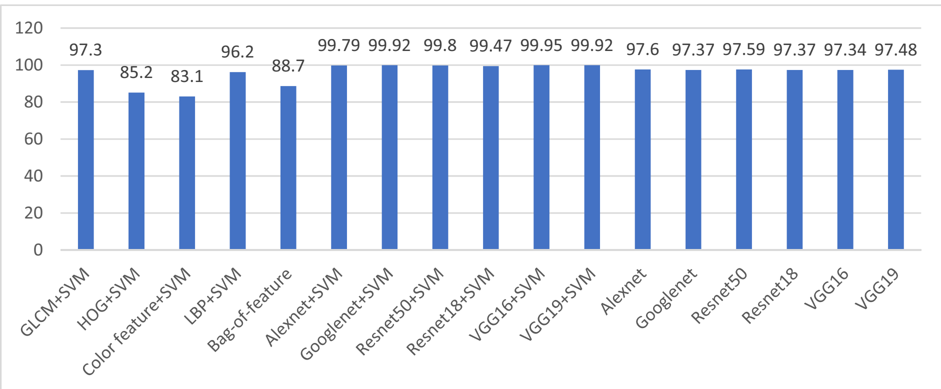

Fig. 4. Accuracy score (%) of all executed methods and models.

The accuracy score of traditional methods, transfer learning and deep feature based are noted below.

- The deep features plus SVM have better performance in terms of accuracy, sensitivity, specificity, precision, FPR, F1 score, MCC and Kappa compared to its transfer learning counterparts.
- The VGG16 feature plus SVM is statically superior among deep feature approach. It had 99.95% accuracy.
- No statically difference among the CNN models in the transfer learning approach concerning the confusion matrix measures.
- The bag-of-feature have accuracy 88.7% but, the training time required is very high, i.e. 60−70 min.
- Among the traditional image classification methods, GLCM plus SVM have the highest accuracy, i.e. 97.3%.

Hence, 40 kinds of fruits were classified successfully using VGG16 and SVM with an accuracy of 99.95%, which is better than the existing methods [45,46]. Based on image region selection and improved object proposals [45], five types of fruits were detected with a miss rate of 0.0377. Again, 9 types of fruits were classified using the six-layer convolutional layer and achieved 91.4% of accuracy [46]. So, considering the number of varieties of fruits and achieved accuracy is far better than the existing method.

5. Conclusion

This work analyses the performance results of deep feature extraction and transfer learning for recognition of Indian Fruit-40. This study carried out using six leading architectures of deep neural networks for both deep feature extraction and transfer learning. First, we compare the performance results of transfer learning models with consideration of eight measuring parameters. Results indicate that, although the classification models differ in value but, are not statistically significant. Then, we perform classification by SVM using deep features extracted from fully connected layers of CNN models. It shows that the performances of classification models are differing in numerical value with statistical significance. The evaluation results show that the SVM classifier using deep learning feature produced better results than the counterpart of transfer learning methods. In addition, the deep learning feature of VGG16 and SVM results in 100% in terms of confusion matrix measures including accuracy, sensitivity, specificity, precision, F1 score and MCC in its highest level. Further, VGG16 plus SVM classification model is statistically superior to other models. In future, one may develop application based on the smartphone for recognition of Indian Fruits with large and variety image dataset which could be of great benefit to the fruit industry and supermarket.

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