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Identification of Fruit Categories using a nine-layer Deep Convolutional Neural Network

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Abstract : Fruit category classification is essential for industrial, commercial and agricultural applications. This study proposes a novel framework for fruit category classification from images using Nine-layer Deep Convolutional Neural Network (9-Deep CNN). This model uses a dataset of 53,056 images of 79 different fruits. Image augmentation methods were used to enhance the dataset size to 1,06,650 images. Max pooling and stochastic gradient descent techniques were used to train the model. The 9-Deep CNN was trained for optimized hyperparameters such as batch sizes, training epochs, and dropouts. The experimental results show that the proposed fruit category classification model based on the 9-Deep CNN achieves an average accuracy of 99.56%. This accuracy is much greater than the accuracy of the state-of-art methods. Furthermore, 9-Deep CNN is tested for performance and reliability.
Keywords : Deep convolutional neural network, Fruit category classification, Hyperparameters, Transfer Learning.

1. Introduction

Automatic fruit recognition is a challenge as it is difficult to offer an accurate description of a category of fruit. Fruit classification can be used in factory production, supermarket sales points, fruit-picking robot and, dietary guidance [1]. A number of artificial intelligence methods are currently being used for agricultural image classification [2]. The decision tree is the most useful and simplest machine learning tool for classification. The Decision Tree is a tree-like graph structure, where all internal nodes indicate a test on an attribute, all branches denote an outcome of the test, and all leaf nodes hold a class label. The k-NN is a non-parametric supervised classification technique in machine learning. The k-NN method stores all existing cases and classifies new cases based on a distance value from labeled neighbors [3]. The logistic regression is another machine learning based classification algorithm for estimating the parameters of a logistic model. It predicts the probability of an

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outcome that can have only binary values. The Naive Bayes is a simple and powerful machine learning algorithm for predictive modeling based on Bayes' Theorem. The NB classifiers are extremely scalable, requiring a number of parameters linear in the number of variables in a learning task [4]. The Support Vector Machine is a supervised machine learning algorithm that can be used for either classification or regression tasks [5]. The SVM algorithm discovers the hyperplane in an N-dimensional space that distinctly classifies the data points.

The Deep neural networks is a subfield of machine learning techniques inspired by artificial neural networks. The Deep convolutional neural network is one of the deep neural networks which is applied for handling computer vision challenges [6]. Deep CNN is a normalized form of multilayer perceptron. Hyper-parameters are the variables that regulate the Deep CNN structure and training process. This includes activation function, training epochs, gradient descent, mini-batch size, dropout probability and learning rate [7]. To build an efficient image classification model using less number of images in training data, data augmentation is usually necessary to increase the classification performance of the Deep CNN. Deep CNN needs a large number of training data to achieve better performance. Image augmentation artificially generates training images through dissimilar methods of processing, such as image crop, flips, rotation, shifts, shear and zoom [8].

Transfer learning is a widespread technique in machine learning where pre-trained models are used as the beginning on image classification algorithms given the massive computational power that is necessary for them [9]. The most popular pre-trained models used for classifying images include AlexNet, Inception-V3, ResNet and VGG16 [10]. In this study, the performance of the proposed nine-layer Deep Convolutional Neural Network (9-Deep CNN) model has been compared with state-of-art machine learning and popular transfer learning techniques. The remaining part of the article is structured as follows: Section 2 reviews related works. Implementation procedures of the fruit category classification model are described in section 3. Section 4 presents the achieved results of the fruit category classification model and related discussions. Finally, section 5 holds the conclusions and future directions.

2. Related Works

The automatic classification of fruits through computer vision is a challenging job because of the several properties of various categories of fruits. Mostly fruit recognition techniques are a combination of different analysis methods based on color, shape, size, and texture. For instance, the author in [5] proposed a model for classifying fruit images using a multi-class kernel support vector machine and achieves a classification accuracy of 88.2%. In [11], the authors proposed and developed the K-NN and SVM model with a dataset of 178 images for recognizing different fruits. The authors in [12] proposed a hybrid classification model for classifying fruit images using an improved artificial bee colony and neural network approaches and achieves an accuracy of 89.1%. The authors in [3] introduced a fruit recognition technique using the nearest neighbor classification algorithm and different feature analysis methods. One more method was suggested by the authors in [13], which combines the features that are mined by the fitness-scaled chaotic artificial bee colony and biogeography-based optimization technique. The classification accuracy of the techniques was 89.5%.

Electronic nose technology is used in several fields, and frequently in the beverage production for classification and quality-control purposes. In [14], the author developed an Electronic nose classification model for fruits using different aroma data and artificial neural network with backpropagation. The classification accuracy of the model was 76.39%. The author of [15] used a Single-hidden layer feed-forward neural-network with Backpropagation and fractional Fourier entropy for the detection of fruit types. The model achieves the classification accuracy of 88.99 %. Another technique that was proposed by the authors in [16] used Biogeography-based optimization and feed-forward neural network techniques for fruit image classification. The model used 18 classes of 1653 chromatic fruit images. Overall, the classification accuracy using this approach was 89.11%. The authors in [1] proposed an approach for fruit detection using Faster Region-based CNN. The F1 score of the approach was 0.838 for the detection of sweet pepper. The model proposed by the authors in [17] is an approach that applies the multilayer perceptron optimized by an improved hybrid genetic algorithm with fractional Fourier transform for the need of classifying the different categories of fruits. The overall accuracy of the model was 89.59%.

Likewise, identification of fruit category from images can be achieved using a 13-layer convolutional neural network with data augmentation, max pooling, minibatch and stochastic gradient descent [8]. The overall accuracy of the method was 94.94%. Another approach based on a faster R-CNN framework for image-based fruit detection was proposed by the author in [18]. The F1-score of the model was 0.9 which was achieved for apples and mangoes. In [19], the author proposed a deep convolutional neural network for automatic yield estimation. The model achieves a 91% average testing accuracy on real images and 93% on synthetic images. The authors in [20] reviewed different research works that are based on computer vision techniques, applied to fruits and vegetables quality evaluation challenges. In [21], the authors developed the 9-layered deep convolutional neural network model with an augmented dataset of 61,486 images and optimized hyperparameters for recognizing different plant leaf diseases. The model achieved 96.46% classification accuracy. Recently, a deep neural network was developed in [22] for identifying fruits from images. This technique was implemented for 95 different classes of fruit images. The average accuracy of this method was 95.88%. In our study, the image based Deep CNN model were designed, trained and tested in order to present a fruit category classification. The following division explains the basics of the proposed 9-Deep CNN and the dataset.

3. Materials and Methods

In this section, the procedures of data pre-processing and training the 9-Deep CNN model for fruit category classification are described. Training and testing of all the models were performed with a python programming language with augmenter, Keras, OpenCV, Pillow, Scikit-learn, and Tensorflow libraries. The complete implementation process of all the models was performed using an NVIDIA DGX-1 GPUs. Fruit image data were downloaded and combined from the open datasets [8, 22]. Histogram representation of the original dataset is presented in figure 1.

Less number of training images may lead to overfitting. For enhancing the dataset size, the data augmentation techniques were used. Image flipping, gamma correction, noise injection, rotation, and scaling are the five types of image augmentation methods used. Finally, a dataset of 1,06,650 images was obtained with 1,350 images for each of the 79 fruit categories. Figure 2 shows the example images of the dataset.

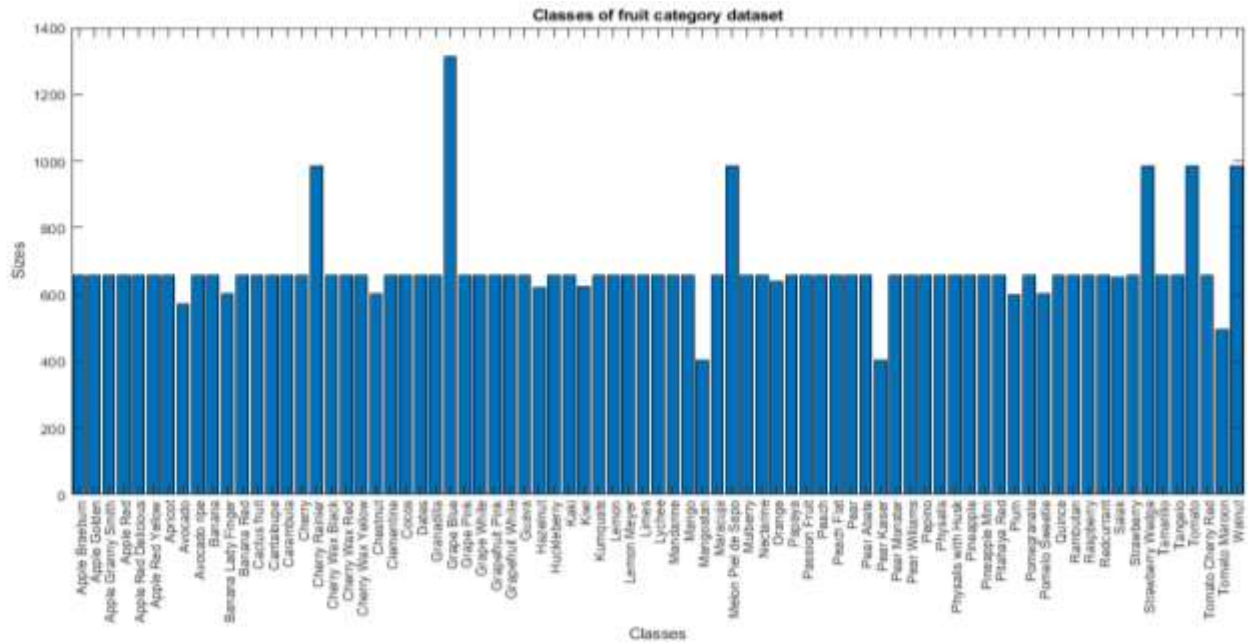
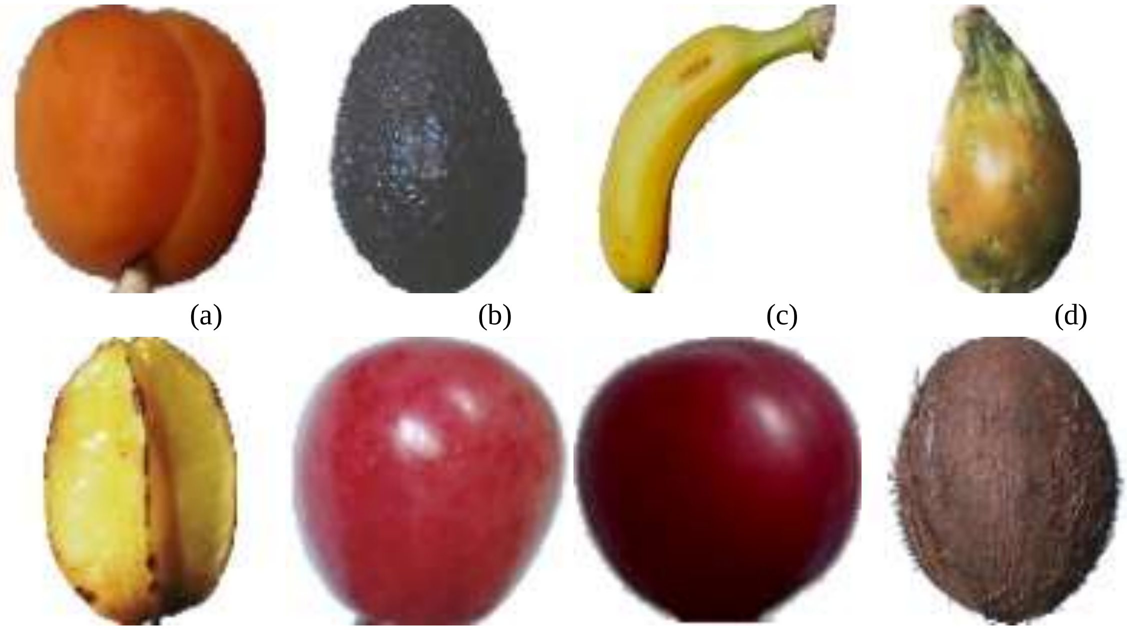


Figure 1: Classes of fruit category dataset



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 2: (a) Apricot, (b) Avocado ripe, (c) Banana Lady Finger, (d) Cactus fruit, (e) Carambula, (f) Cherry Rainier, (g) Cherry Wax Red, and (h) Cocos.

Training the 9-Deep CNN for making a fruit image classification model was proposed. The Keras architecture is considered as a beginning point, but it was modified to support the 79 classes. Figure 3 shows the layered structure of the Nine-layer Deep Convolutional Neural Network.

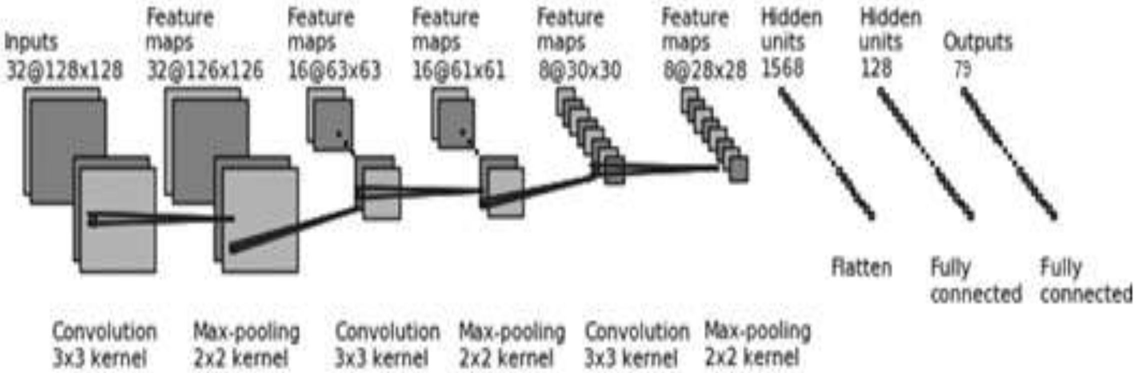


Figure 3: Architecture of the 9-Deep CNN Model

Three convolution layers, three max-pooling layers, and stochastic gradient descent methods were used to train the proposed 9-Deep CNN model. The training performance of the proposed 9-Deep CNN using augmented dataset and optimized hyperparameters is much higher than the other possible combination of hyperparameters and original dataset. The optimized hyperparameters values of the fruit image classification model using 9-Deep CNN are given in table 1. The training performance of the 9-Deep CNN is illustrated in figure 4.

Table 1: Hyperparameters value of the 9-Deep CNN for fruit image classification

Parameter	**Value**
Training epoch	1000
Learning Rate	0.01-0.0001
Mini-Batch Size	64
Dropout Probability	0.2
Pooling Layer	Max Pooling
Gradient Descent	Stochastic
Training Set	94800
Test Set	11850

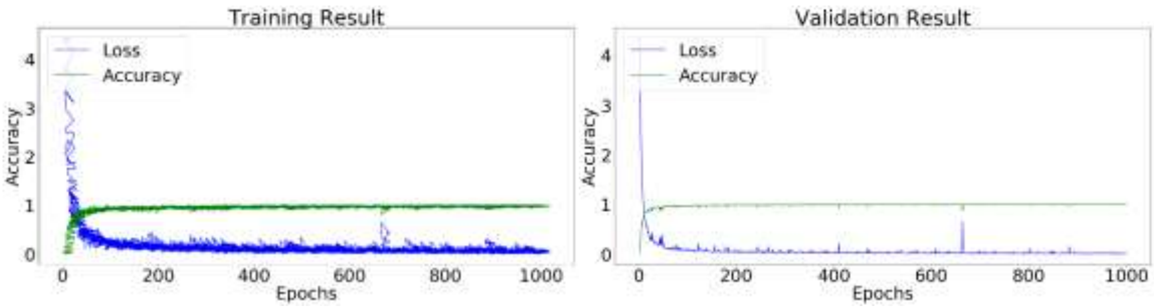


Figure 4: Training performance of the 9-Deep CNN for fruit image classification

Testing procedures of the proposed 9-Deep CNN model was initiated after the conclusion of the training procedures. Furthermore, the performance of the 9-Deep CNN model for fruit image classification was tested with unseen input images and the outcomes were compared with the commonly used machine learning and transfer learning algorithms in the succeeding section, which were fairly expressive.

4. Results and Discussions

The performance of the 9-Deep CNN was evaluated using the unseen fruit images in the test set. The training and testing split-ups of the augmented dataset was 94,800 and 11,850 images, respectively. Performance of the 9-Deep CNN for fruit image classification was compared with modern machine learning and transfer learning algorithms. Additionally, the succeeding testing processes are associated with respect to the performances of the 9-Deep CNN models. Finally, the results show that the 9-Deep CNN model is larger than all of the above-mentioned models. The confusion matrix derivations for Mango fruit of all the above algorithms are given in table 2. The derivations of the confusion matrix are True Positive (TP), True Negative (TN), False positive (FP) and False Negative (FN).

Table 2: Confusion matrix derivations of all the models for mango fruit

Model	**TP**	**TN**	**FP**	**FN**
Proposed	**150**	**11649**	**47**	**4**
Inception-V3	144	11578	93	35
VGG 16	139	11034	580	97
ResNet	136	10875	672	167
AlexNet	133	10637	815	265
SVM	118	10037	1086	609
KNN	110	9768	1210	762
LR	104	9243	1679	824
DT	99	8638	2145	968

The accuracy is the number of correct fruit image classifications that are made by the 9-Deep CNN model. The 9-Deep CNN reaches superior classification accuracy of 99.56%. Figure 5 shows the overall accuracy of all the models. The developed model achieved individual class accuracy between 97% and 100%. Figure 6 presents the testing accuracy of separate classes. The classification accuracy of all the models for mango fruit class was calculated by the equation (1):

$$\text{Classification Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} * 100 \quad (1)$$

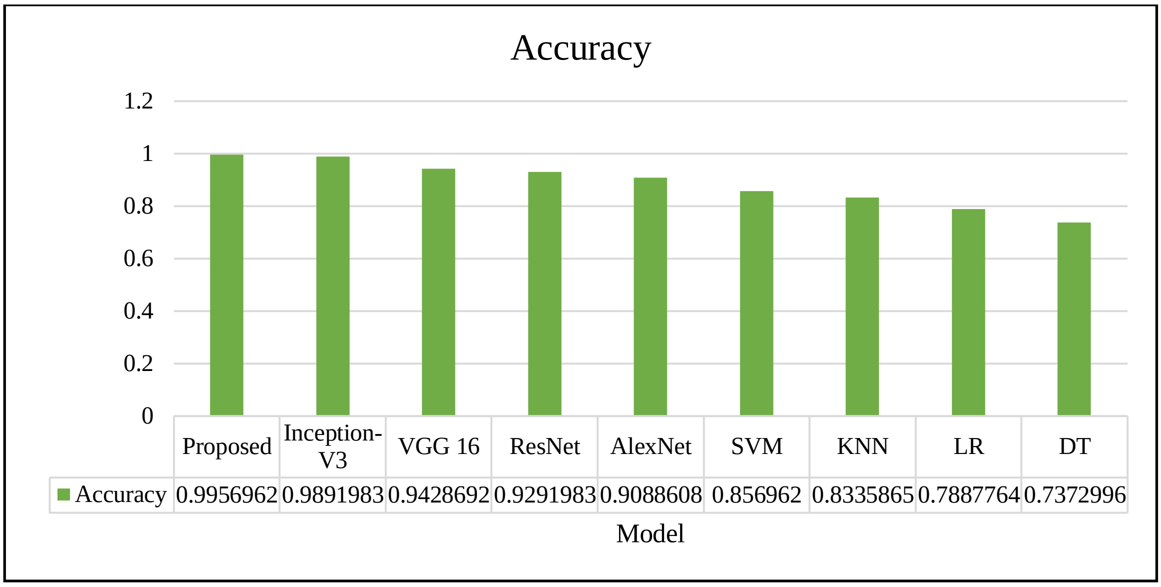


Figure 5: Overall testing accuracy of the different models.

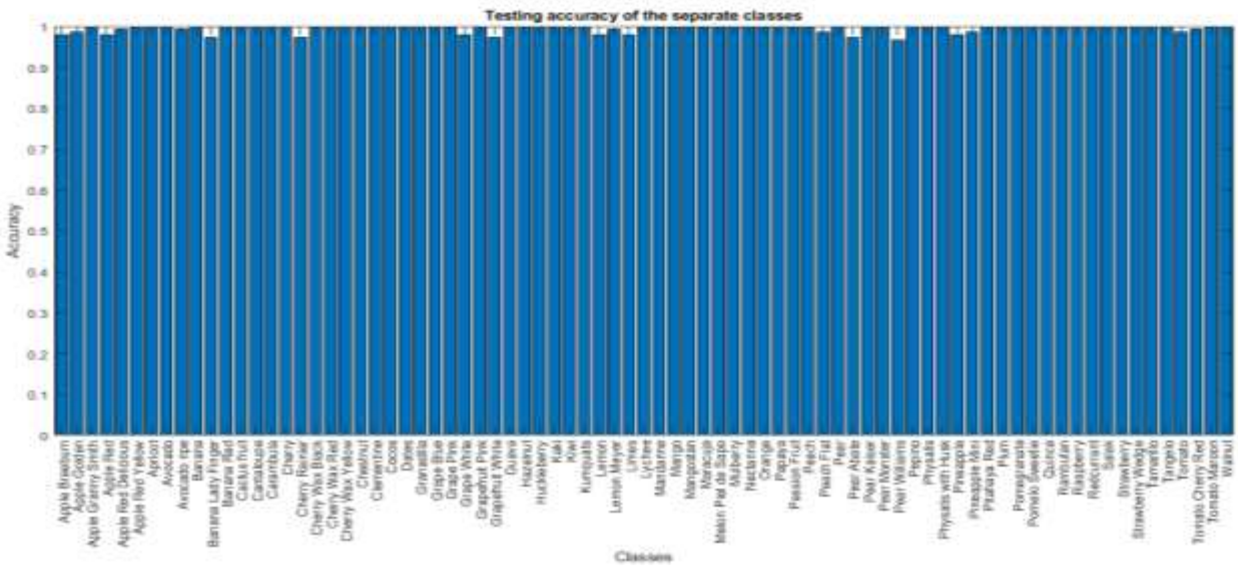


Figure 6: Testing the accuracy of the distinct classes.

Furthermore, the precision value for any individual class is defined as the TP is divided by the TP and FP value of the 9-Deep CNN model. Figure 7 illustrates that the proposed 9-Deep CNN model achieved greatly superior precision than all other methods. The range of the precision value of all the models for mango fruit are generated using the below equation (2):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad (2)$$

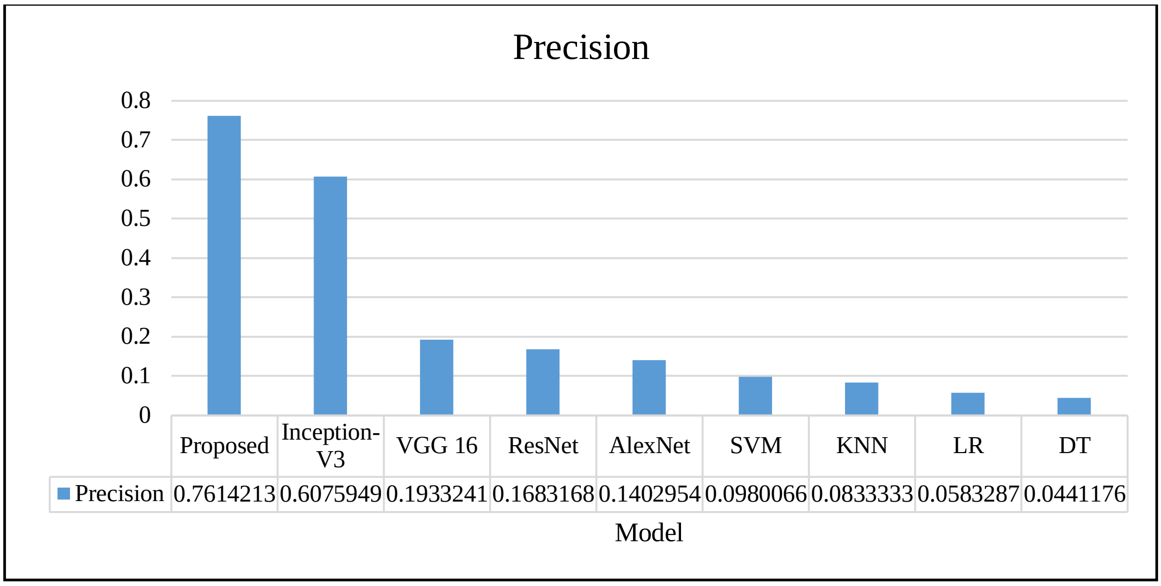


Figure 7: The Precision value of the different models.

Moreover, the recall of any individual class is defined as the TP divided by the TP plus FN. Figure 8 presents the proposed 9-Deep CNN model which has achieved a significantly greater value of recall compared to all other methods. The given equation (3) is used to compute the recall of all the models:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (3)$$

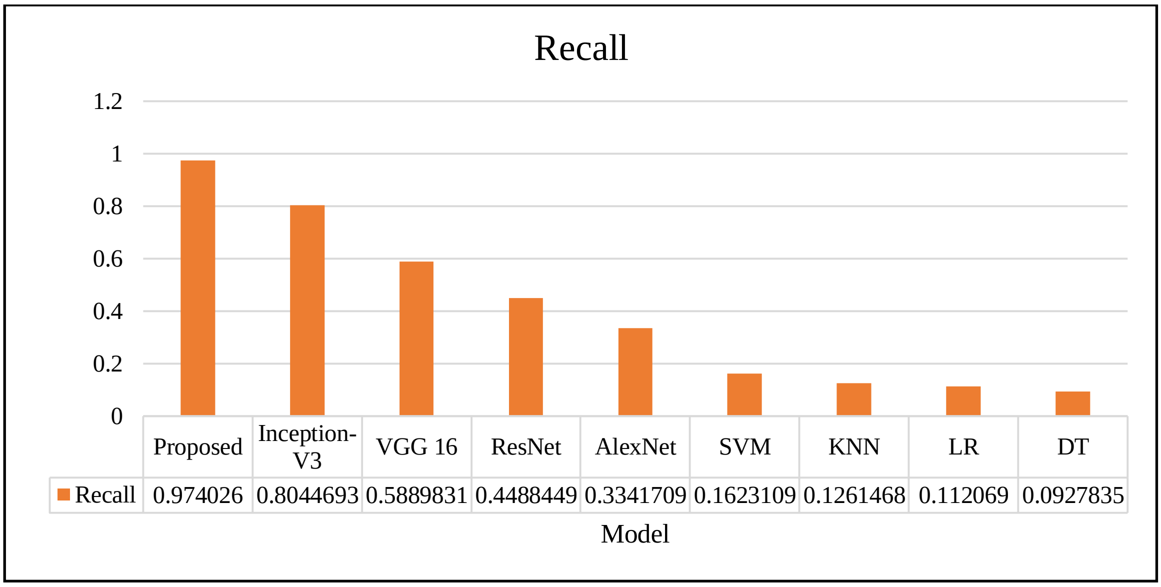


Figure 8: Recall value of the different models.

Likewise, the F1 Score is the harmonic mean amongst the precision and recall as well as important performance metrics for any classification algorithms. Figure 9 illustrates that the F1 Score of the proposed 9-Deep CNN model is superior to the other classification algorithms. The equation (4) is used to calculate the F1 Score:

$$\text{F1 Score} = 2\,\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (4)$$

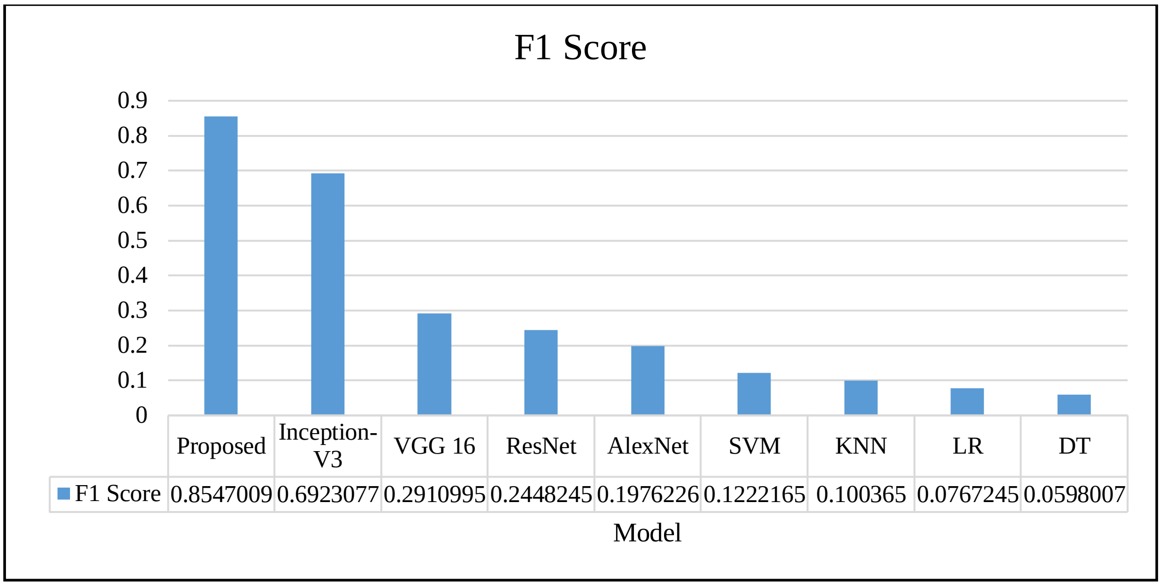


Figure 9: F1 Score of the different models.

Finally comparing the results of the proposed 9-Deep CNN model with the other transfer learning and machine learning systems for classification of fruits using images, it can be concluded that the proposed 9-Deep CNN model offers more improved outcomes than those of traditional machine learning and state-of-the-art transfer learning.

5. Conclusion

Deep learning is a current research method in computer vision and it knows how to handle the problems in fruits image classification. The 9-Deep CNN model was proposed to classify 79 different classes of fruits images. The training process of the 9-Deep CNN has used 94,800 images and optimized hyperparameters. The proposed model and all other models were tested with 11,850 of test set images. The proposed 9-Deep CNN model achieves an overall accuracy of 99.56%. The optimized hyperparameters and the augmented dataset had a bigger impact on the particular outcomes. Compared with other state-of-the-art techniques, 9-Deep CNN has greater performance and constancy. In future, a number of fruit image classes and counts will be increased. The most important goal of future work will be to extend the fruit category classification objective from a single fruit image to a multiple fruits image with improved classification performance.

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