Feature Based Fruit Classification using Machine Learning Algorithms: A Comparison

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Abstract: Classification of fruits into different categories on the basis of their species, quality, size or shape is an aspect which the research community are trying to automate for over a decade. Due to limitations of manual process of segregation of fruits into their required respective class, the development of such smart systems is highly required. In this paper, based color and edge feature, three species of fruits including apples, bananas, and oranges are segregated into their respective classes using machine learning algorithms. For these three types of fruits, for the dataset development, total of 9600 images were acquired. To evaluate the performance of the machine learning based algorithms, five parameters including accuracy, Jaccard score, precision, recall, and F-1 Score are evaluated and compared to determine the best suitable algorithm for classification of fruits. Four machine learning algorithms and the traditional convolutional neural network (CNN) based classification models were used for classification of fruits into their respective classes. From the results it was observed that Decision Tree and Random Forest based models were best suited for classification of fruits with a high accuracy of 98.47% and 98.63% respectively.

***Index Terms* – Smart Agriculture, Fruit Classification, Machine Learning, Image Processing, Human Computer Interaction**

I. INTRODUCTION

Classification is one of the industrial process which has tremendous applicability. Agricultural industry is one such industry where classification process is highly required. Classification of fruits and vegetables into different categories based on their types, quality can be essential at a market store for customers to make informed decision. During harvesting, of fruits and vegetables, they can be segregated into different categories to put proper marketing price to increase the profit of the farmers. Due to improper handling of these agricultural products, bruises can be introduced during post harvesting storage or transportation. This can result in deterioration of the quality of products. Classification can play an important role in segregating these products on the basis of the health. Amount of water content in fruits and vegetables are also an important aspect based on which condition for storage of agricultural products can be planned so as to increase their shelf life. Earlier, these classification process were manual in nature but had their limitations. Therefore, there arose a need for the development of computer vision based automated system for the holistic classification of agricultural products. This classification can be performed for segregation, bruise or decay detection, and disease identification in fruits and vegetables. With the advent of new technologies, development of such system is reaching reality. However, there are still many issues that need to be addressed before making the system fully automated. Another major advantage for using such automated classification of multiclass fruit or vegetable classification is for selection of items by the visually impaired persons where it can be used for supportive applications. However, the fruit classification using computer vision-based system is difficult for majorly two reasons [1]: Texture, shape, and color of various fruits are similar and each fruit has various varieties, and in a single class of fruits, the variation depending upon their stage of development is very high.

Amalgamation of image processing and machine learning has contributed immensely towards development of system for classification models. There are three major imaging system that finds application in image processing techniques in vision based system. These techniques include Visible Spectrum-Near Infrared Image (VNIR) Processing, thermal imaging (TI), and hyperspectral imaging (HSI) systems. VNIR operates in visible spectrum range and the images acquired follow the three channel based RGB model. Thermal imaging technique captures the heat generated by the object and develops the corresponding heat map. HSI based imaging system captures the spectral information content of the object. In this paper, VNIR based spectrum is used to develop the dataset. For the development of the dataset apples, bananas, and oranges are considered. For each category of fruit, from online available repository of Fruit360, 500 images are acquired. Using the image augmentation techniques, the sample size is increased from 500 to 3200 for each fruit category. This resulted in the total sample size of 9600 images in visible spectrum. For classification of these fruits into their respective classes, from each sample, two categories of features including color and edge are extracted. The color feature is quantified by extracting the amount of red and green color component present in the sample. For quantifying the edge feature, two edge detection algorithms including canny edge and Laplacian edge detection model are considered. Once the features are extracted, classification models are employed to classify these fruits into their respective classes.

For classification model, machine learning and neural network based models are approached in this paper. For machine learning based model, support vector machine (SVM), random forest (RF), decision tree (DT), and K-nearest neighbour (KNN) based algorithms are used. Furthermore, for neural network based classification model, the traditional convolutional neural network (CNN) based classification model is developed. The architecture for CNN based classification model consist of two convolutional layers to generate the feature map and for evaluating the probabilistic distribution of sample belonging to a particular class a dense layer is formed. Two hidden layers are used in the dense layer for evaluating the probability distribution of the sample.

The flow of this paper include four section where the first section provides the introduction and motivation towards the work performed in this paper. The second section presents a similar work performed by the researchers in this domain. Third section presents a detailed discussion about the materials and methodology employed in this paper. The fourth section presents the result and their respective discussion.

II. LITERATURE REVIEW

Many researchers used a variety of techniques and algorithms to classify fruits and vegetables. In [2], the author created a grape picking algorithm for automated fruit picking using robotics and artificial lighting. They achieved 92% accuracy using the minimum bounding rectangle and Hough line detection techniques. In [3], the author proposed a 9-layer deep neural network to classify apples into six different categories, with an accuracy of 99.78%. In [4], the author used feature extraction to classify fruits using the HSV color space to extract the region of interest. In this paper, the author used an SVM classifier to achieve an accuracy of 95.3%.

Many models are available in the literature based on detection, identification, and classification of fruits and vegetables. Other studies in the field of fruit and vegetable classification are based on robotics where a mechanical process is used to picking up fruits from the trees, differentiating between branches that bear the fruit from those branches which do not bear the fruit [5-6]. In [7], the author has classified tomato based on its color content grading from light red, red, pink, light pink and green. Conventional CNN algorithm was implemented along with the feature extraction with number of neurons and hidden layers. In [8] a classification of land cover and types of crops was presented and supervised learning algorithms were implemented. It used deep learning algorithms and used hidden layers in range of 100. For classifying crops, the algorithm resulted in 85% accuracy. In another study for pest detection, a deep learning algorithm was implemented in [9]. It used Principal Component Analysis (PCA) for feature extraction.

In [10] the author was the first to employ the data fusion method and non-intrusive techniques using imaging of objects to grade the tomatoes. In [11], the author classified the fruits and vegetables based on clustering algorithms. In [12], SVMs were used for multiclass classification. In this study 18 different classes were considered consisting of 1653 RGB images to evaluate the performance of the method. Features consisting of combination of color, texture, and shape were used as descriptors to train the model. In this study, the best classification was observed to be 88.2%. In the extension of the study [7], in [12], an additional feature descriptor was considered: color histogram. The classification accuracy of 89.1% was obtained. A hybridized PSO and Artificial Bee Colony (ABC) was used on the same data set of 18 classes and the proposed architecture presented the accuracy of classification at 89.5%.

In another study for fruit based multi class classification, a data set of 15 classes consisting of 2633 images were considered [13]. In this paper, the author used various feature descriptors; texture, color, shape. Several ML based algorithms were used for classification such as SVM, LDA, and KNN. The proposed algorithms presented the best classification accuracy of 97%. In this paper a comparison of different Machine Learning based algorithm and conventional Convolutional Neural Network has been presented. The algorithms are implemented for multi-class classification. Three classes of fruits have been considered: Apple, Banana, and Orange. For classification purpose, a total of 3200 images for each class has been considered. In this paper several Machine Learning based algorithms have been implemented including Support Vector Machine (SVM), Decision Tree (DT), K-Neighbour (KNN), Random Forest (RF), and conventional Convolutional Neural Network (CNN). For evaluation and comparison of these algorithms, performance evaluation parameters including Accuracy, Jaccard Score, Precision Score, Recall, and F1 Score has been evaluated.

III. METHODOLOGY

In this section a detailed description of various stages of methodology are explain in detailed.

Data Generation and Data pre-processing

Three class of images were created: Apple, Banana, and Orange. Each set of class consists of 500 images from the standard data set: Fruit360. Using the method of Image Augmentation, the data set for each class is increased to 3200 respectively making the total size of the data set to be of 9600 images. All these images are of the .jpg format. A sample of dataset is shown in figure 2The images consisting of the data set are not simple images with no background. These images consist of those images as well which have different objects – leaves, tables, bowls, and some half-cut fruits in the background. Also, all the images are of different sizes. For testing and training of the samples, the data set is split in a ratio of 4:1 with 80% of the data set forming training set and remaining 20% forming the testing set. This gave us 7680 images for training set and remaining 1920 images of the data set as testing set. All the images acquired during the data set generation consists of different size. Thus to normalize these images to a common size to run the machine learning multiclass models, image processing is used to prepare the data set for classification models. To normalize the size of the images, all the images have been resized to a constant size of 100x200 pixels.

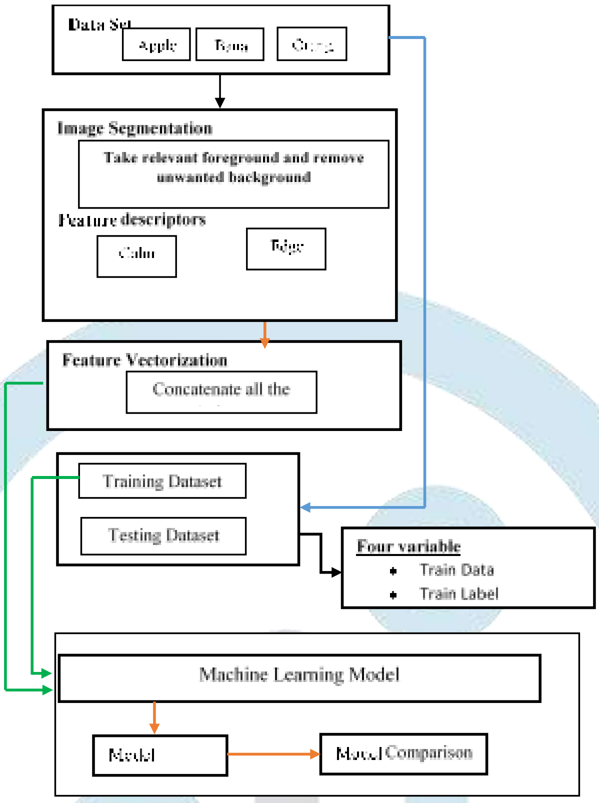

Fig. 1. Flowchart of Methodology

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Object Feature Extraction

The classification of objects is feature based classification. In this paper two features including color and edge are considered for classification of objects. Since these images are in visible spectrum, two color components have been considered for color feature: Red and Green. For edge feature extraction, two detectors are employed in this paper: Canny Edge Detector and Laplacian Edge Detector. The Canny Edge detector uses Gaussian filter to remove any unwanted noise and detects the edges even in the noisy image by using the thresholding method. Laplacian edge detector is very sensitive to the noise. Thus to overcome this drawback, the kernel of small size is convolved Gaussian mask. This convolved kernel is then used to detect the edges of an image using the second order derivative. Since there are 9600 images, and each image is producing four distinct feature, the size complexity of the data set becomes very high. Thus, feature vectorization technique is used to reduce the data content of all the features. This produces a single vectored array of features.

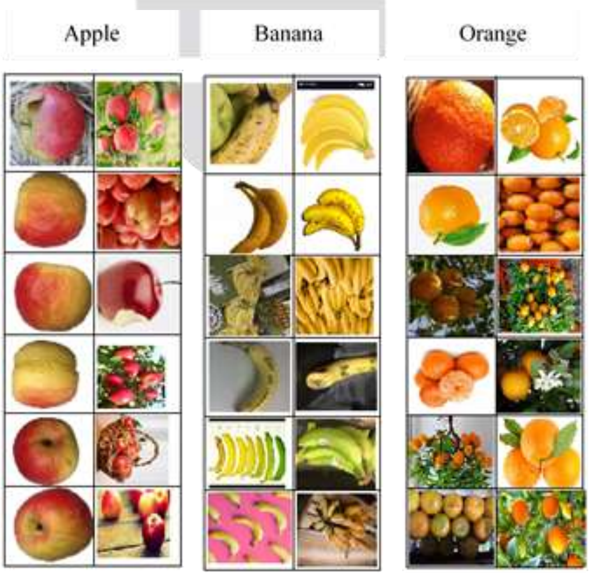

Fig. 2. Subset of the complete Dataset

Machine Learning algorithms

The features extracted so far are used for multi class fruit classification. For classification, machine learning based supervised learning algorithms are used. In this paper, three non-parametric classifiers: Random Forest, Decision Tree, and K-Nearest Neighbour

[14-15] are used and one parametric, Support Vector Machine, [16-18] classifier is used. Apart from these classifier, a Neural Network based Convolutional Neural Network classifier is also used.

Convolutional Neural Network

Mathematically, convolution is the function obtained after integrating two separate functions where one of the functions is time shifted. It represents how the shape of on function is modified by another function [11]. It is given by

$$H(t) = \int_{-\infty}^{\infty} f(\tau)\, g(t-\tau)\, d\tau \tag{1}$$

In image classification, Convolutional Neural Network (CNN) is vastly used where as compared to other Machine Learning models, CNN extracts the features on itself and classifies the objects into different classes. The basic CNN algorithm consists of four standard steps which helps in multi class classification. It uses different types of activation function which provides a Neuro-Output in the intermittent layers of the CNN [19]. The CNN architecture is shown in figure 3.

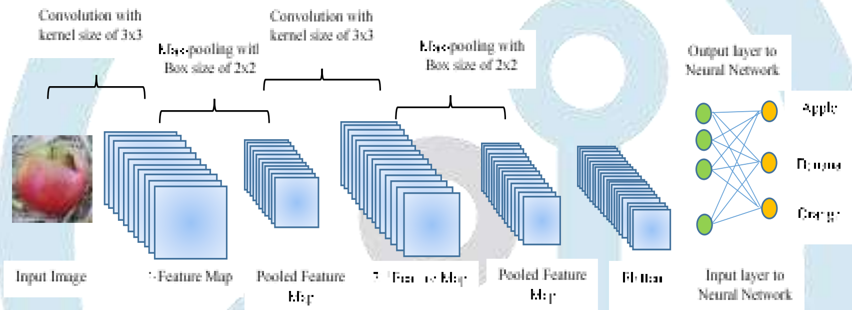

Fig. 3. Convolutional Neural Network

Model Evaluation

To evaluate the performance of the Machine Learning based classification models and Neural Network based Convolutional Neural Network several parameters are used. Following parameters are used:

Table 1: Parameters for evaluating performance of classification models

Parameter Name	Parameter Description	Mathematical Relation
Accuracy (A)	• It is the fraction of predictions that the classification model gets right. • It also represents the proportion of correct classifications.	$A = \frac{TP+TN}{TP+TN+FP+FN}$
Jaccard Score (J)	• The Jaccard function computes the Jaccard score between pairs of labels and its objects. The Jaccard score of the i^{th} sample when the ground truth table is set to y_i. • The idea behind the Jaccard score is that considering two different sets of values: predicted value and the actual values, higher will be the Jaccard score when the similarity between these two sets are higher.	$J(y_i, \hat{y}_i) = \frac{\|y_i \cap \hat{y}_i\|}{\|y_i \cup \hat{y}_i\|}$
Precision (P)	• Precision is the measure of accuracy of the classification model. • Intuitively it is the ability of the classification model not to label a sample as positive when the sample is negative	$P = \frac{TP}{TP+FP}$
Recall (R)	It is the sensitivity of the classification model. It gives the rate of true positive i.e. if the model gives a true positive, then how frequent it gives the true positive	$R = \frac{TP}{TP+FN}$
F-1 Score (F)	The F1 Score or simply the F score is calculated based on precision and recall of each class. • It is the weighted average of precision and recall. Where recall is the sensitivity of the classification model.	$F1\ Score = 2\frac{(P*R)}{(P+R)}$

Simulation

The simulation work has been performed using python programming tool image pre-processing and implementation of machine learning based model for fruit classification. The programming is performed using Anaconda Navigator using Spyder which is an Integrated Development Environment. The system used for programming had an i7 – 9th generation Intel processor with clock speed of 3.0GHz along with 16GB RAM and a 64bit Operating system (Windows 10 Pro).

IV. RESULTS

Classification is done on the basis features extracted from the images. Before features are extracted, the images in the data set has been normalized to a single size as the images in the data set are of different sizes. The normalized images size is 100x200 pixels. After the images has been normalized, the features are extracted. Namely two features are used for classification the color and edge detection. For color, two components have been considered, i.e. Red and Green. For the edge detection, two types of detectors are used, the Canny Edge detector and the Laplacian Edge detector. The result of image pre-processing is shown in figure 4.

In this paper five Machine Learning (ML) based algorithms and traditional Convolutional Neural Network (CNN) is used for multiclass classification. The three classes into which the images are classified are: Apple, Banana, and Orange. For model training size of data set is 7680 images and for model testing, the size of data set is 1920 images. This section provides an insight and performance analysis of the implementation using accuracy, Jaccard Score, Precision score, Recall, and F1 Score as parameters of evaluation.

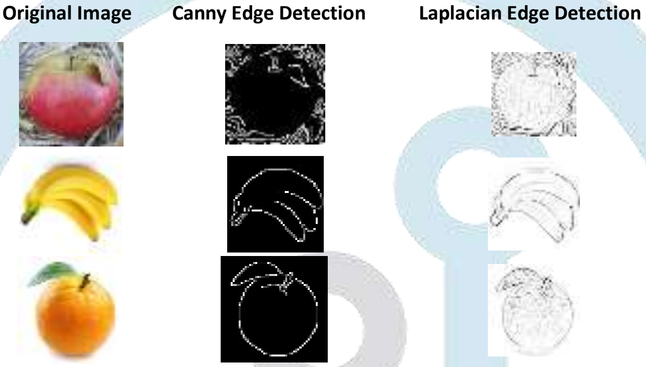

Fig. 4. Image pre-processing

Many research work has been carried out for classification of fruits based upon their color, shape, and size using Machine Learning. Some have used some standard fruit data set that includes Fruit360 which is available on kaggle website where the images are already pre-processed by removing the background of the object of interest whereas others have created their own data set. In all those data set, before classification of fruits. The samples generated by them has to be pre-processed by removing the background information and keeping only the required object. However, in the methodology discussed in this paper, the background information has not been removed in order to obtain the results for solving the real-world problem in real-time. The fruits under consideration will be consisting of background images and have to be classified as such.

Accuracy

After implementation of classification models: Support Vector Machine, Decision Tree, Random Forest, K-NN, and Convolutional Neural Network, the accuracy for every model thus obtained is mentioned in Table 1 and represented graphically in figure 5. Also mentioned are the execution time for each model. From the table it can be observed that the accuracy for Support Vector Machine, is on the lower side. The reason for this can be attributed to the fact that the data set on which these classification algorithms have been implemented vary in a manner that most of the images consists of many foreground and background objects which are not included in the region of interest. This includes the trees, branches, tables and other surrounding objects. However, for CNN it is 97.33% and for K-NN classifier it is 86.19%. For tree-based classification algorithms, i.e. Decision tree and Random Forest Classifier since they construct a tree structure using features as the nodes of the tree, and for all images all the nodes are accessed, accuracy for them is 99.37% and 99.63% respectively.

Table 1. Accuracy of classification model for multiclass classification

Classification model	Accuracy (%)	Execution time (s)
Support Vector Machine	68.54	59.18
Decision Tree	**99.47**	47.71
K-Neighbour	86.19	**40.8**
Random Forest	**99.63**	42.59
Convolutional Neural Network	97.33	1157.16

It is also observed that the time required to execute the classification models, in seconds, is least for K-NN classifier which is 40.8 seconds. In the same range, the highest time required for the classification model is for support vector machine which is 59.18 seconds. However, for Convolutional Neural Network, which provides an accuracy of 97.33 %, the time required for execution of the model is 1157.16 seconds. This high time can be contributed the fact that the CNN is iterated for 20 epochs.

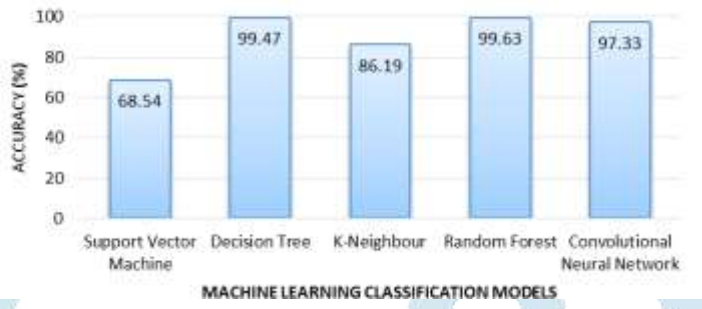

Fig. 5. Graphical Representation of Accuracy for multiclass classification

Accuracy and Validation Accuracy of CNN

To evaluate the performance of CNN model for multiclass classification a graphical representation of accuracy of CNN model along with the validation accuracy is presented in figure 6. Form the figure it can be concluded that up to certain extent when the number of epochs are increased for simulation of CNN based classifier, the Accuracy and validation accuracy of the model increases. At the execution of epoch no. 11, the accuracy and validation accuracy obtained are 92.79% and 92.24 % respectively.

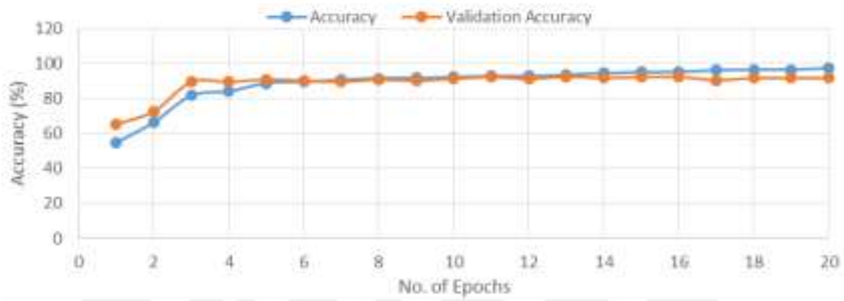

Fig. 6. Evaluation of Accuracy and validation accuracy of CNN model with no. of Epochs

These accuracies are almost equivalent to each other. This is because when the model has memorized most of the data set and therefore not much increase in the accuracy can be expected. This point is called as the overfitting point. After the implementation of 20 epochs of CNN model, the final accuracy and validation accuracy thus obtained were 97.33% and 91.61% respectively.

Jaccard Score

As mentioned earlier, higher the similarity between the predicted class of the object and the actual class of the object, higher will be the Jaccard similarity index. From the table 1 and table 2, accuracy and Jaccard score, it is observed that as the accuracy of the classification model increase, the Jaccard score also increases. Thus, the Jaccard Score for Decision Tree and Random Forest classifier is very high as for these two algorithms are tree based where features are the nodes for each object and for classification each node is accessed for each object for training the model. For different classes different Jaccard score is obtained giving an insight as how the different types of data set for the same model affects the classification accuracy as shown in table 2.

Table 2. Jaccard Score of classification models for multiclass classification

Classification model	Jaccard Score		
	Apple	Banana	Orange
Support Vector Machine	0.7	0.44	0.44
Decision Tree	**0.99**	**0.99**	**0.99**
K-Neighbour	0.84	0.71	0.72
Random Forest	**0.99**	**0.99**	**1**

It can be observed that for K-Neighbor classifier, the Jaccard score of 84%, 71%, and 72% is obtained for Apple, Banana, and Orange sub-Datasets respectively. From the table it can also be observed that the classification accuracy as given by the Jaccard score for Apple sub-dataset is higher as compared to other tow sub-datasets for different classification models except Random Forest classifier and Decision Tree where the Jaccard score is same and almost equal to unity. This fact can also be reconfirmed from the accuracy given in table 1, where these two models produce highest classification accuracy. The results obtained in table 2 are represented graphically in figure 7.

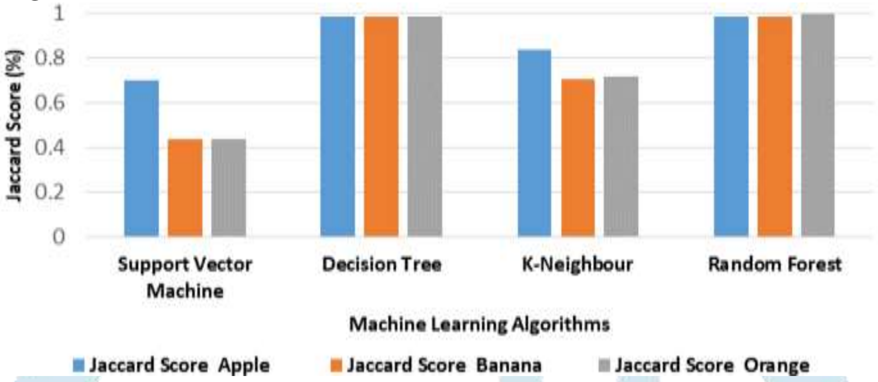

Fig. 7. Graphical Representation of Jaccard Score for multiclass classification

F1 Score

As discussed in equation (6) the F1 Score for the classification algorithm is obtained using the Recall and Precision score of the same. This evaluation parameters indicates how sensitive is the classification model and how precisely it is able to classify an object into their respective classes. In table 3, the obtained values of F1 score for different classes using different classification models is given. From the table 3 it can be concluded that again as was the case in Jaccard Score, F1 score for apple is highest as compared to other two sub-datasets: Banana and Orange. Also, it is observed that using Random Forest and decision tree the F1 score is the best i.e. almost unity for Decision Tree and unity for Random Forest. The same is shown in a graphical representation in figure 8.

Table 1. F1 Score of classification models for multiclass classification

Classification model	F1 Score		
	Apple	Banana	Orange
Support Vector Machine	0.83	0.62	0.61
Decision Tree	0.99	0.99	1
K-Neighbour	0.92	0.83	0.84
Random Forest	1	1	1

Table 4 presents the precision and recall of the classification model for multi class classification of fruits.

Table 4. Precision Score and Recall of classification models for multiclass classification

Classification model	Recall			Precision Score		
	Apple	Banana	Orange	Apple	Banana	Orange
Support Vector Machine	0.85	0.63	0.58	0.8	0.6	0.66
Decision Tree	1	0.98	1	0.99	0.99	0.99
K-Neighbour	0.92	0.83	0.84	0.91	0.83	0.84
Random Forest	1	0.99	1	0.99	0.99	1

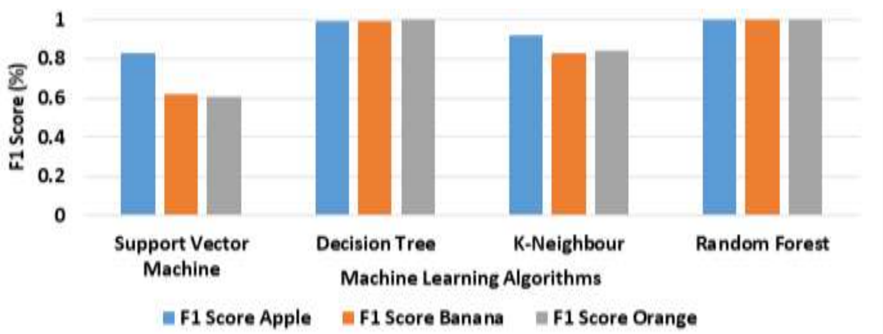

Fig. 8. Graphical Representation of F1 Score for multiclass classification

V. CONCLUSION

In this paper different classification models based on Machine Learning and Convolutional Neural Network are used for multi class fruit classification. The purpose of this study was to compare different classification algorithms for fruit classification which can be used in agriculture based industries for automating the system. This study can help in developing a computer vision based system for segregation of fruits and vegetables in different classes as per the application requirement. The data set consisted of 3200 images for three different sub classes each: Apple, Banana, and Orange. For evaluation of classification model, five different parameters are used including, Accuracy, Jaccard Score, Precision, Recall, and F1 score. Using these evaluation matrices, it was observed that algorithms based on tree structure: Decision Tree and Random forest Classifier presented the accuracy of 99.47% and 99.63% respectively and K-Neighbor classifier presented an accuracy of 86.19%. The classification mode based on deep learning, the traditional Convolutional Neural Network, with 20 epochs and data set split of 80% and 20% for training and testing respectively gave an accuracy of 97.33%. Using other evaluation matrices similar conclusions were reached upon. Jaccard Score and F1 Score also presented that the similarity index of the classification algorithms and sensitivity of these models are higher for Decision Tree and Random forest Classifier. Also considering the time response for the execution of the algorithm, K-NN classifier takes the least time of 40.8 seconds and for CNN takes 1157.16 seconds for the execution of 20 epochs which averages to 57.58 second for each epoch. Thus to decide which classifier to be considered for classification, a trade-off has to be maintained keeping in mind the application and requirement of the person. The potential limitation of machine learning based CNN classifier for classification of fruits into different classes of cultivars arise from the physiological aspects. This includes lighting condition, imaging environment, and familiarity of model usage by the person responsible.

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