Fruit Quality Analysis using modern Computer Vision Methodologies

Diksha Mehta[+]
School of Computer Science, University of Petroleum and Energy Studies (UPES)
Dehradun, Uttarakhand, India
dikshamehta4214t@gmail.com

Shriya Sehgal[+]
School of Computer Science, University of Petroleum and Energy Studies (UPES)
Dehradun, Uttarakhand, India
sshriya713@gmail.com

Tanupriya Choudhury[+]*
School of Computer Science, University of Petroleum and Energy Studies (UPES)
Dehradun, Uttarakhand, India
tanupriya1986@gmail.com

Tanmay Sarkar[+]
Department of Food Technology and Biochemical Engineering, Jadavpur University
Malda Polytechnic, West Bengal State Council of Technical Education
Kolkata, West Bengal, India
tanmays468@gmail.com

*Corresponding author
[+] marked author contributed equally

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Abstract: **The field of agriculture is one of the most profitable fields for a country. The produce of this industry i.e., fruits and vegetables, is tremendous and thus the quality insurance of these products are of utmost importance. Evaluation of fruits can be done manually but due to inconsistent results and huge time consumption, it is necessary to have the automated systems to perform the quality tests. In this study, computer vision has been used to build an architecture that is competent to detect whether the fruit is rotten or fresh. VGG16 CNN (Convolutional Neural Network) model is employed to extract the features from the images of Apples, Bananas, Guava and Oranges. With the help of extracted features, the classification is performed through Decision Tree, Support Vector Machines (SVM), and Logistic regression models. Support Vector Machine performed the best classification with an accuracy of 99%**

Keywords: **Machine learning, CNN, Deep Learning, Image Processing, Decision Tree, Support Vector Machines and Logistic regression**

I. Introduction

Computers are emerging as the most utilitarian products in human society and therefore the application of computers in form of techniques like computer vision and machine learning has spread in various domains in order to reduce manual work. Extensive research has been done in the field of Computer Vision to develop effective and efficient techniques to resolve a number of the day-to-day issue [1][2]. In the field of Agriculture and Cultivation, it is necessary to detect and assess the quality of food with efficiency and accuracy. Fruits that are out for commercial distribution are huge in numbers, making the manual assessment take plenty of time and effort and can also be inaccurate in certain situations. In this regard, computer vision technology can be implemented to classify the fruits based on their edibility [3]. These methodologies can be accurate and much faster in practical use cases. There are countless use cases of computer vision in this industry such as disease detection, crop monitoring, grading, and assessment of fruit/vegetable quality [4][5]. Quality Assessment of many agricultural products is done with the help of machines to reduce the erroneous manual work.

Quality assurance of the fruits/vegetables through computer vision can be done by following certain steps i.e., Image Acquisition, Pre-processing, Segmentation, Feature Extraction, and Classification [6] as in Figure1.

A. *Image Acquisition:* Images of the fruits can be gleaned using various tools such as a camera, MRI, Computer Tomography, and ultrasound. The images captured should be in a coloured format, so that, the features based on colour can be studied with accuracy.
B. *Pre-processing:* This step includes processing of fruit image by reducing the noise and colour space transformation (CST). Hue, saturation and intensity are the parameters taken into consideration while deciding the colour space for the fruit images.
C. *Segmentation*: Segmentation of the pre-processed fruits images is in order to segregate the rotten areas of the fruit based on colour and texture. This segmentation helps in decision making on the quality of fruit. The techniques used for segmentation are threshold and clustering based.
D. *Feature Extraction:* The Maturity of the fruits are checked by certain features i.e., colour, texture, and morphological features. The feature extraction and descriptions can be done using deep learning models, Histogram of oriented gradients (HOG), Fourier descriptors, etc.

E. *Classification:* After extracting the features, those features are used to classify the fruits into the classes i.e., rotten/fresh or edible/non-edible based on the quality assurance measures.

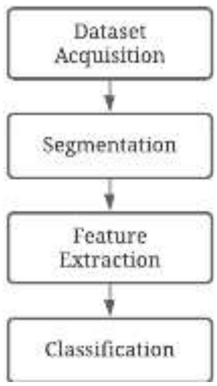

Figure 1: Fruit Quality Detection Process

The article is further structured as follows. Section 2 contains the Literature survey of the techniques and methods that have been used till now for the quality detection of fruits. Section 3 presents a detailed view of our solution to this problem. The results obtained are analyzed in section 4. Then the conclusion and future work is presented in section 5 and section 6 respectively.

II. LITERATURE SURVEY

With the ever emergence of Computer Vision and Image processing techniques, researchers have been applying these to images of fruits to detect their quality and classify them on the basis of edibility.

In [7] Mozafati Date grading system has been proposed, which has been developed based on Mamdani fuzzy inference system (MFIS). The parameters accessed for the quality detection are quantity of juice, size and freshness, and were assigned quality features of Low, Mid and High. For each parameter, the membership function has been calculated and based on those results has been inferred. With the MFIS approach, 85% of the results were similar to that of the results gathered by human experts. In [8] SVM classifier is used to detect the change in colour of mangoes to brown. In the proposed approach, colour measurements are taken in L, a and b system, and the degree of browning is depicted as a function of fractal dimension i.e. FD. Box counting, correlation, and dilation methods have been used to calculate the FD. Based on different values of parameters (regularization parameter (Υ), RBF kernel function parameter (σ^2)) of LS-SVM classifier, the accuracies achieved are 100%, 85.19% and 88.89% for ($\Upsilon = 6.13$, $\sigma^2 = 9.36$), ($\Upsilon = 1.13$, $\sigma^2 = 5.52$) and ($\Upsilon = 6.68$, $\sigma^2 = 2.44$) respectively. In [9], quality assessment of guava and lemon fruit has been done using the Fast Discrete Curvelet Transform (FDCT). The measures/features that were considered are energy, mean, standard deviation and entropy, in order to know local and global details of the texture of the fruit. The selected features from t-test analysis were input to PNN (Probabilistic Neural Network) and SVM to classify images into the healthy or defective class. 96% of the accuracy has been achieved through this process. In [10], an automated system is proposed to classify Guava fruit into 4 categories i.e., green, ripe, overripe and spoiled. The classification is done by segmenting the image into RGB following which chromaticity coordinates(x,y) were calculated and compared with RGB threshold setpoints. Subsequently, PCA (principal component analysis) is used to differentiate between the states of fruit ripeness based on the RGB values and coordinates calculated. ANN is also used to classify the fruits into the desired classes for enhanced results. In [11], Mango is classified as defected or non-defected classes by extracting features like shape, colour and size. Based on these features, the calculation of the area of mangoes (a) is done in a binary image, which is further used to calculate the ratio (b). The image is classified as defected if b>=0, otherwise it is classified as not defected. In [12], the evaluation and quality detection of persimmon fruit has been conducted based on its shape. The proposed methodology involved the usage of Elliptical Fourier Descriptors (EFD) and the SHAPE program to segment the fruit in a longitudinal and transverse manner. Further, the Principal Component Analysis (PCA) is applied to the vectors from EFD to get important features. In [13], 200 Peaches are evaluated on the basis of eleven features; volume, density, shape, mass, impedance, solid concentration, firmness, acidity, colour, phase angle and sugar-acid ratio, over 48 hours. Using the collected indicators, correlation analysis is performed. Using the backpropagation neural network model, quality prediction of dielectric properties is done thereafter with 86.9% accuracy and using PCA, K-means quality comprehensive evaluation model is created. In [14], mono and bi-coloured apples have been evaluated using fuzzy c-means for segmentation. Various statistical, geometrical, Gabor Wavelet and Discrete Cosine Transform Features have been taken, while for classification, KNN, Sparse Representation Classifier (SRC), and SVM have been used. The maximum accuracy achieved was 95.21% with SVM have been used. The maximum accuracy achieved was 95.21% with SVM have been used. The maximum accuracy achieved was 95.21% with SVM.

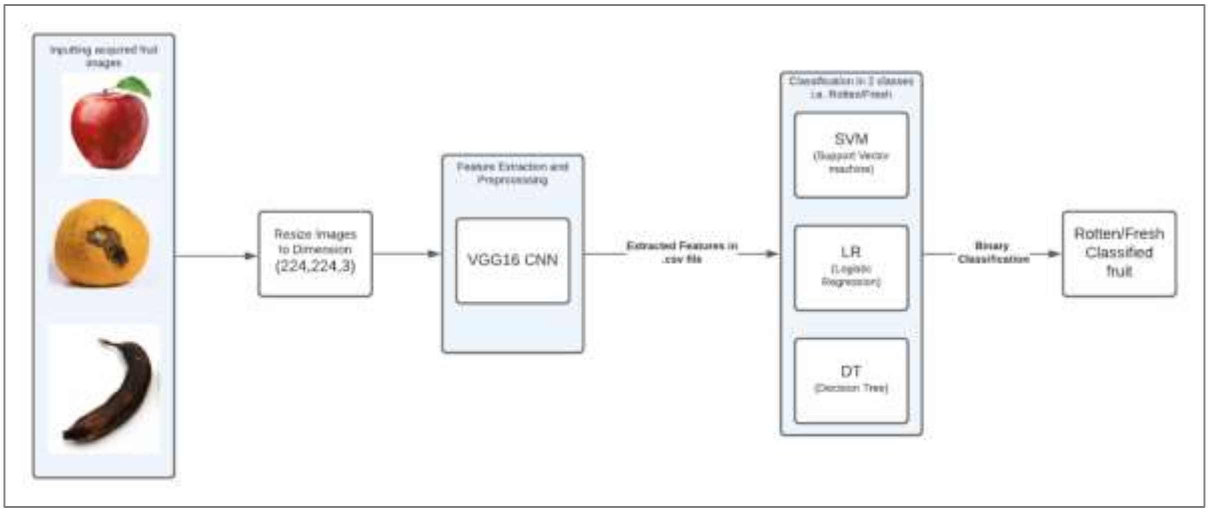

Figure 2: Architecture Diagram of Proposed Methodology

III. Methodology

The proposed approach is making use of computer vision technology to classify the fruit images collected using the VGG16 CNN model [15] for preprocessing and feature extraction [16]. SVM, Logistic Regression and Decision Tree are used as classifiers to classify the fruit images into rotten/fresh categories based on the features extracted from the CNN model. The architecture of the proposed approach is shown in Figure 2

A. Algorithms Involved:-

The proposed approach makes use of the following deep learning and machine learning models:

B. Convolutional Neural Network (CNN)

CNN's are the type of neural network models which are specifically used for extracting useful information out of images. These models constitute three main types of layers i.e., convolution, pooling and classification layer [17]. The Convolution layer extracts the features from the input image by convoluting the image step by step using the convolution operation. The Pooling layer is used as a dimensionality reduction layer for the feature vectors achieved from the VGG16 Model. This is done in order to increase the accuracy as only those features are chosen which are the most important ones and will help in gaining the accuracy. The Classification layer is used to classify the image on the basis of its feature vector into desired classes. There are some state-of-the-art CNN model architectures that have been tried and tested for years now, such as, VGG16 [15], Xception [18], InceptionNet [19], and Resnet [20] etc.

VGG16 was developed by researchers from the Oxford Visual Geometry Group [15]. It is one of the largest pre-trained CNN models available which is trained on ImageNet Data, the largest image database available. ImageNet Data is organized according to the WordNet hierarchy, which currently consists of nouns only, where each node of the hierarchy is depicted by hundreds and thousands of images [21]. VGG16 contains 16 weight layers including thirteen convolutional layers. This model is capable of removing the unrelated data to provide fine results using the size and stride of filters.

C. Logistic Regression: -

Logistic regression is a classic supervised learning classification algorithm used to predict the probability of a target variable. Logistic regression transforms its output using the logistic sigmoid function to return a probability value as in Eq1.

$$\sigma(x) = \frac{1}{1+e^{-z}} \qquad \text{Eq1}$$

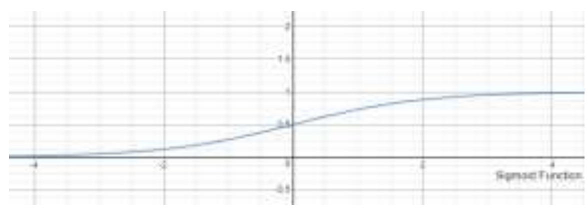

Figure 3: Sigmoid Function

D. Support Vector Machine (SVM): -

Support vector machine is a Machine Learning model which works on the principle of finding a hyperplane in an N-Dimensional Space (where N refers to the number of features), classifying the data points distinctly and maximizing the margin between the data points of different classes. The loss function, or the hinge loss, of an SVM Classifier, is given as:

$$c\big(x, y, f(x)\big) = \begin{cases} 0, & if\ y * f(x) \geq 1 \\ 1 - y * f(x), & else \end{cases} \qquad \text{Eq2}$$

If the predicted and actual value has the same sign, the cost is 0. However, if they have different signs, the cost is calculated by Eq2.

E. Decision Tree: -

A Decision Tree is a type of Supervised Machine Learning method that splits the data recursively according to certain parameters until the leaf nodes are reached. These parameters at each level are decided according to their Gini value, which calculates the impurity of the split or Entropy value, which in turn calculates the amount of randomness. This model can be used for both, classification and regression problems.

$$Gini\ Index = 1 - \sum_{i=1}^{n}(P_i)^2 \quad \text{Eq3}$$

Here, Pi is the probability of an element being classified for a class.

$$Entropy = -\sum_{j=1}^{n} P_j * Log_2(P_j) \quad \text{Eq4}$$

Here p is the probability that it is a function of the entropy

F. Procedure Followed: -

1. Set necessary paths to the dataset.
2. Load VGG16 network, and set head Fully Connected layers off (model base).
3. Construct a custom fully connected layer set (head of the model).
4. Freeze base layers to instantiate transfer learning.
5. For every subsequent compilation, reset training and testing generators -
   A. Compile the model with an SGD (Stochastic gradient descent) with an extremely small learning rate.
   B. Reset the data generators for re-compilation.
   C. Unfreeze the final set of layers in the network, preferably the last block, and compile with a similar learning rate and momentum.
6. Load the classifier (logistic regression, decision tree, SVM) with the features extracted using the CNN along with the label encoder for the Training and validation set.
7. Compile and fit the data on the classifier function.
8. Use the trained model for predictions.

G. Dataset Used: -

The dataset used to train and test the images is a publicly available dataset containing around 13K images of apples, bananas, and oranges in png format [22]. The whole dataset is divided into two parts i.e. Test data and Train Data within which around 10K images were training images and the rest 3K were part of testing images. Within these categories each there are 6 folders with respective images i.e. freshapples, freshbanana, freshoranges, rottenapples, rottenbanana, rottenoranges. Along with that, around 230 images of the guava fruit was collected by ourselves over a period of 22 days to collect the images of fresh fruit till it gets rotten for testing purposes.

IV. Results and Reports: -

This section contains the results obtained from the training and testing of the proposed framework. The results have been shown in form of Precision, Recall, F1 Score and Accuracy calculated through Eq5, Eq6, Eq7, Eq8. Table 1 shows the results obtained from the Logistic Regression, Support Vector Machine and Decision Tree classifiers applied on the fruit feature vectors extracted from the VGG16 model [13].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{Eq5}$$

$$Precision = \frac{TP}{TP+FP} \quad \text{Eq6}$$

$$Recall = \frac{TP+TN}{TP+FN} \quad \text{Eq7}$$

$$F1\ Score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad \text{Eq5}$$

Here,
TP(True Positive) is an outcome where the model predicts the datapoint correctly against the positive class
TN(True Negative) is an outcome where the model predicts the datapoint correctly against the negative class
FP(False Positive) is an outcome where the model predicts the datapoint incorrectly against the positive class
FN(False Negative) An outcome where the model predicts the datapoint incorrectly against the negative class

Table 1: Performance of proposed methodology with Logistic Regression, Support Vector Machine and Decision Tree as classifiers applied on the features extracted from VGG16 trained on the Fruits Dataset

Metric	Classes	Logistic Regression	SVM	Decision Tree
Precision	Rotten	1	1	0.93
	Fresh	1	1	0.88
Recall	Rotten	1	1	0.91
	Fresh	1	1	0.91
F1 Score	Rotten	1	1	0.92
	Fresh	1	1	0.90
Accuracy	N.A	0.98	0.99	0.91

Figure 4, contains the test images output of the proposed system. The figure contains both rotten and fresh fruit images along with labels. Figure 4(a) and Figure 4(b) are self-clicked images of guava fruit, these images were used for testing purposes.

Figure 4(a)

Figure 4(b)

Figure4(c)

Figure4(d)

Figure4(e)

Figure4(f)

Figure4(g)

Figure4(h)

Figure 4: Labelled Dataset Images into classes Fresh and **Rotten**

Figure 5, shows the confusion matrices of the outputs obtained which are depicting the exact numbers of misclassified and correctly classified fruit images. It can be concluded from the confusion matrix of SVM that it is misclassifying only 4 fruit images as rotten when the true label is fresh. While it is classifying 3 fruit images as fresh which are rotten in reality. Apart from these all other predictions are correct from the SVM classifier.

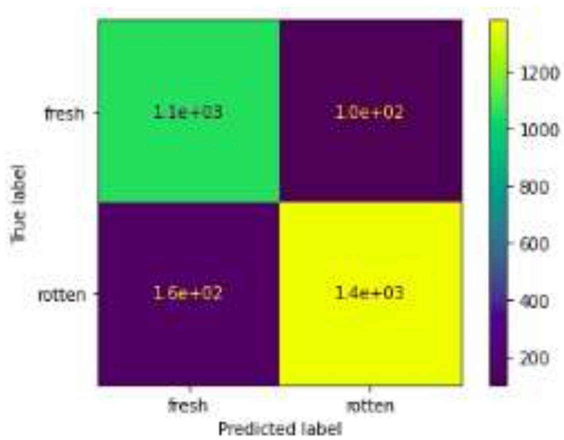

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Fig 5(a): Decision Tree

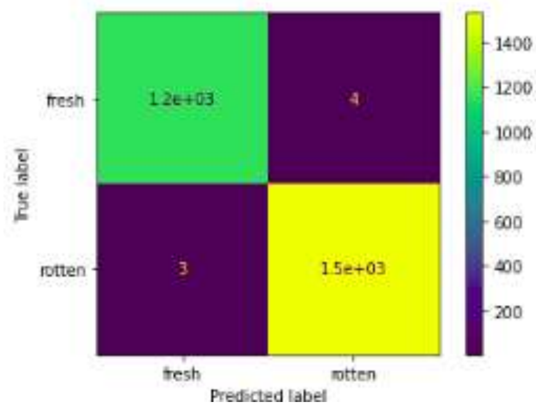

Fig 5(b): SVM

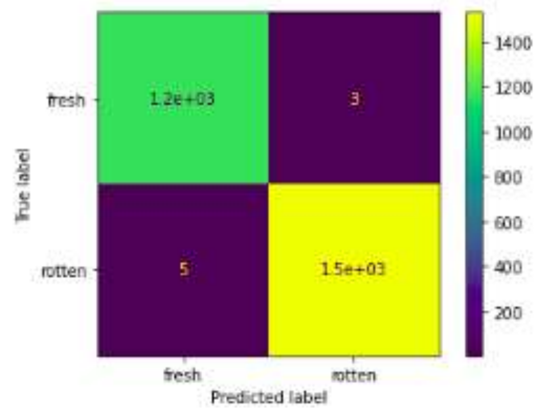

Fig 5(c): Logistic Regression

Figure 5: Confusion Matrix of implemented Classification Models

Figure 6, shows the AUC – ROC curve of the SVM, Decision tree and Logistic Regression which depicts an evaluation of performance for the problems caused by classification at various threshold settings. ROC is a probability curve that sums up the entire trade-off between the genuine and false-positive rate for a predictive model utilizing different probability thresholds. AUC measures the degree of separability. It tells how capable the model is for recognizing distinct classes. Higher the AUC, the better the model is at predicting 0 classes as 0 and 1 classes as 1.

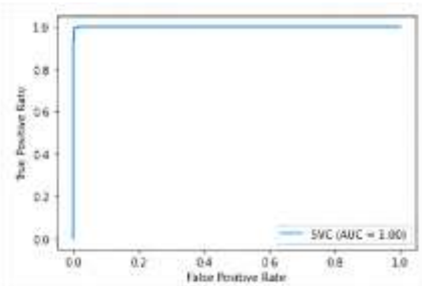

Fig 6(a): SVM

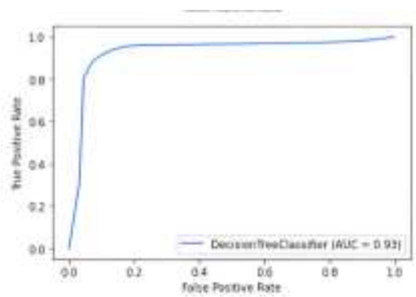

Fig 6(b): Decision Tree

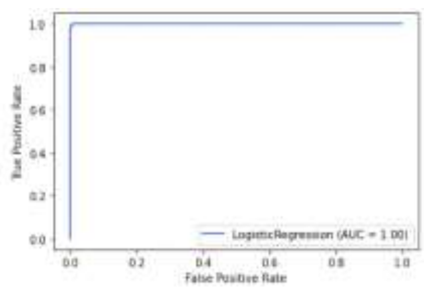

Fig6(c): Logistic Regression

Figure 6: ROC-AUC Curve

According to the achieved results, it is evident that machine learning models differ considerably even after providing them with the same feature vectors based on the edges and curves of the fruit from the pre-trained VGG16 CNN model. While the Logistic Regression and Support Vector Machine gave an excellent result, the Decision Tree could only classify and differentiate the rotten fruits from the fresh ones with an accuracy of 91%. This is owing to the complexity of this model as well as the higher probability of overfitting found in the Decision Tree. However, the results of all the models improved significantly after applying Transfer Learning, i.e., using the CNN model as the feature extractor.

V. Conclusion

In this study, a system has been proposed to detect the quality of the fruits using machine learning and deep learning algorithms with the aim of improving the overall process by reducing time consumption and human errors. Fruits considered in this study were apples, bananas, oranges and guavas. Pretrained VGG 16 CNN model was used to preprocess the images and extract the useful features out of them. These extracted features were input to three classification algorithms; Decision Tree, SVM and Logistic Regression. Based on classification accuracy, the classifiers were compared to conclude that SVM classified the fruit images into rotten/fresh categories with the highest accuracy of 99% followed by Logistic Regression at 98% and subsequently Decision Tree at 90%.

VI. Implications For Future Research

In future, it is planned to extend this research by involving more fruits in this study and try to classify them simultaneously [23]. In order to be more informative, it will be tried to extend the output where the model is able to give the precise amount of area that is rotten along with the type of rotting for future precautions.

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