ABSTRACT

Fruit classification is a difficult and important task in supermarkets, as the cashier or the receptionist has to identify and then to category it and price it accordingly. But now the researchers are trying to the same by the computer system using computer vision. But there is a problem that the packaged food are being identified and categorized by the computer system using bar code but the problem is that the bar code can't be done for each and every fruit as it will be a lengthy process and the system may corrupt by scanning the same category of the fruit different times. So the researchers have identified four different problems which they will simplify later and will make the computer to identify it automatically.

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DECLARATION

I declare that this is written submission represents my ideas in my own word and where other ideas or words have been included, I have adequately cited and referenced the original source.
I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data source in my submission.
I understand that any violation of the above will be cause for disciplinary action of the college and also evoke penal action from the source which thus not been properly cited or from whom proper permission has not been taken when needed.

(Signature)

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Date :

Contents

1 SUMMARY

Fruit classification is a difficult and important task in supermarkets, as the cashier or the receptionist has to identify and then to category it and price it accordingly.

But now the researchers are trying to the same by the computer system using computer vision.

But there is a problem that the packaged food are being identified and categorized by the computer system using bar code but the problem is that the bar code can't be done for each and every fruit as it will be a lengthy process and the system may corrupt by scanning the same category of the fruit different times.

So the researchers have identified four different problems which they will simplify later and will make the computer to identify it automatically.

1.1 Computer Vision Process

- **1st Problem :** First of all the computer needs 3 different sensors to identify the different category of the fruit, that is a gas sensor to identify the fruit is fresh or rotten, and the next is an invisible light sensor to obtain the shape and size of the fruit, and a weight sensor to identify the weight of the fruit.

- **2nd Problem :** Second problem is that the classifier is not suitable to categories the different variety of the fruits, it can only recognize the varieties of the same category.

- **3rd Problem :** Third problem is that the classifier can't differentiate between different fruits as because many fruits can have same shape and size as well as weight also.

- **4th Problem :** The last problem was that due to the above problems the customer will blame the supermarket that there is a misclassification among the fruits.

2 INTRODUCTION

Fruit classification is a difficult challenge due to the numerous types of fruits. In order to recognize fruits more accurately, we proposed a hybrid classification method based on fitness-scaled chaotic artificial bee colony (FSCABC) algorithm and feed forward neural network (FNN).

First, fruits images were acquired by a digital camera, and then the background of each image were removed by split-and-merge algorithm.

- First we used a square window to capture the fruits, and download the square images to 256 _ 256.
- Second, the color histogram, texture and shape features of each fruit image were extracted to compose a feature space.
- Third, principal component analysis was used to reduce the dimensions of the feature space.
- Finally, the reduced features were sent to the FNN, the weights/biases of which were trained by the FSCABC algorithm.

We also used a stratified K-fold cross validation technique to enhance the generation ability of FNN.

The experimental results of the 1653 color fruit images from the 18 categories demonstrated that the FSCABC _ FNN achieved a classification accuracy of 89.1%.

The classification accuracy was higher than Genetic Algorithm–FNN (GA _ FNN) with 84.8%, Particle Swarm Optimization–FNN (PSO _ FNN) with 87.9%, ABC _ FNN with 85.4%, and kernel support vector machine with 88.2%.

Therefore, the FSCABC _ FNN was seen to be effective in classifying fruits.

3 FEASIBILITY STUDY

Result visualization is the key feature of the project. In visualization, user is prompted with the predicted fruit label and the probability of prediction accuracy of that fruit which is based on the input provided to the system.

It is done in web interface by rendering the amount of accuracy percentage calculated by the classifier algorithm that is being implemented.

3.1 Analysis

Feasibility Analysis

After gathering of the required resource, whether the completion of the project with the gathered resource is feasible or not is checked using the following feasibility analysis.

Technical Feasibility

The project is technically feasible as it can be built using the existing available technologies.

The tools, modules and libraries needed to build the system are open source, freely available and are easy to use.

Operational Feasibility

The project is operationally feasible as the user having basic knowledge about computer and Internet can use while concept of Machine learning is a plus point.

Furthermore the system built in the project can be easily tested by users' if the computer have Internet access and browser is installed in computer.

Schedule Feasibility

The schedule feasibility analysis is carried out using the CPM method.

With CPM, critical tasks were identified and interrelationship between tasks were identified which helped in planning that defines critical and non-critical tasks with the goal of preventing time-frame problems and process bottlenecks.

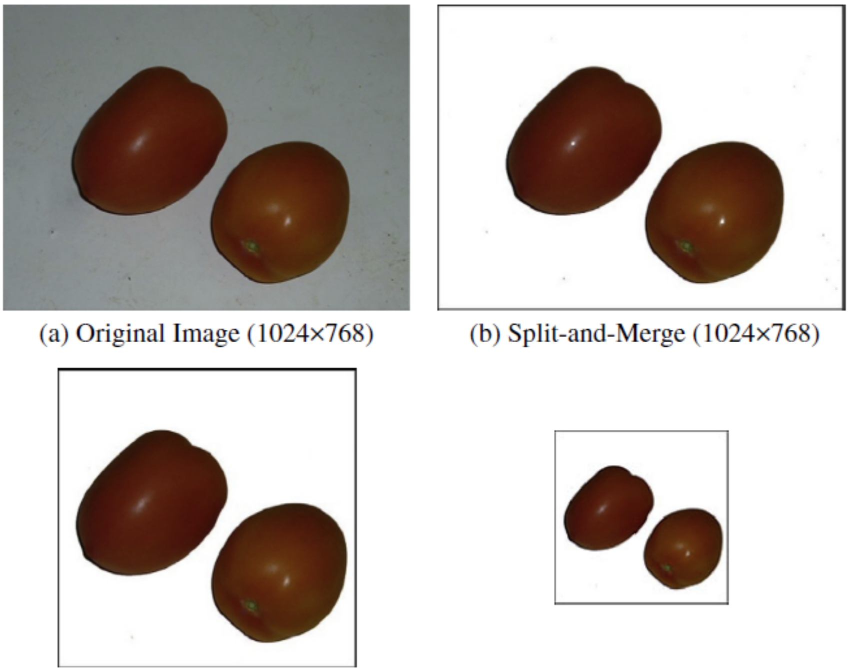
4 PRE - PROCESSING

- **1st process**First of all the computer needs 3 different sensors to identify the different category of the fruit, i.e a gas sensor to identify the fruit is fresh or rotten, and the next is an invisible light sensor to obtain the shape and size of the fruit, and a weight sensor to identify the weight of the fruit.

- **2nd process**Second process is that the classifier is not suitable to categories the different variety of the fruits, it can only recognize the varieties of the same category only.

- **3rd process**Third process is that the classifier can't differentiate between different fruits as because many fruits can have same shape and size as well as weight also.

- **4th process**The last problem was that due to the above process the customer will blame the supermarket that there is a misclassification among the fruits.



(a) Original Image (1024×768) (b) Split-and-Merge (1024×768)

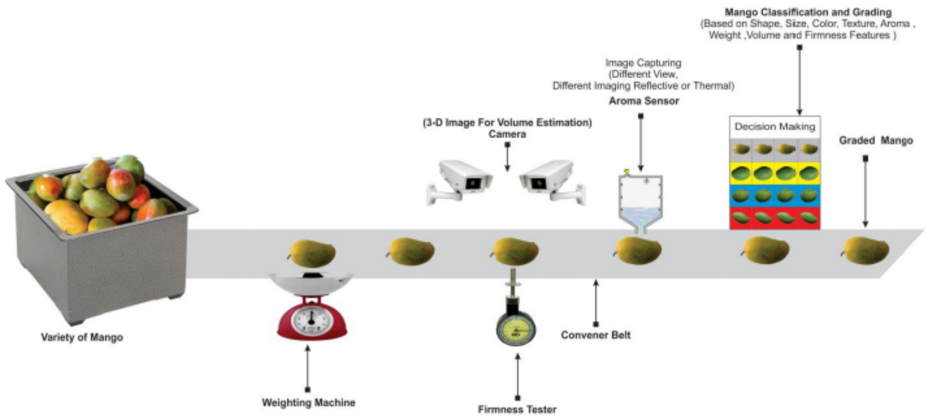
(c) Square Window (768×768) (d) Downsampling (256×256)

<u>Four steps in pre - processing.</u>

The above picture states that first the **background of the original fruit (1024 x 768)** has been removed,
and then it has been **split and merged using split and merge algorithm** and then it has been captured into a **square window (768 x 768)** size,
so that it can further be divided and identified clearly and last but not the least the square window has again been **reduced to (256 x 256)**,
so that the size of the image can be reduced and again it can be rejoined to form the original image and,
can easily be identified by the computer to classify its category to which it belongs to.

5 DATA - PROCESSING

Data processing of the fruit is the way in which the fruit is being processed to recognize it.



Data Processing of Classification Model.

- In this process first we have to use image segmentation technique to remove the background of the image as we have to concentrate only on the fruit.

- After removing the background of the fruit then the fruit is being sliced into four square size homogeneous pieces (the splitting process), i.e. of equal shape and size.

- Now the homogeneous pieces are being slice into many pieces and are being merged (the merging process), to recheck its original shape and size.

- Second, we used a square window to capture the fruit, making the fruit lying in the center of the window.

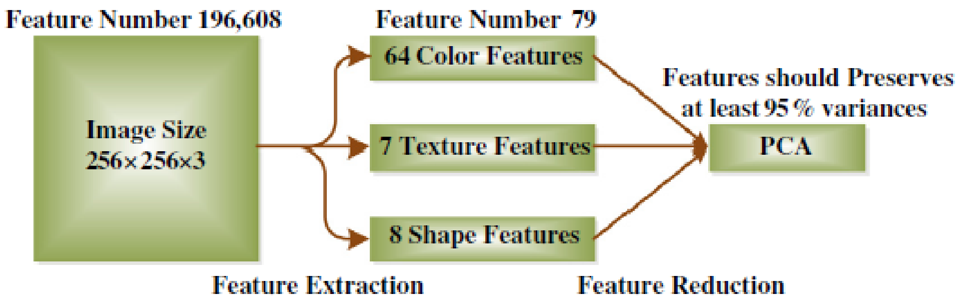
- Finally, we down sampled the square images to 256 _ 256. There are totally 256 _ 256 _ 256 = 224 = 16,777,216 different colors.

- Then, we use 4 bins to represent each color channel. Bin 0, 1, 2, 3 denotes intensities 0–63, 64–127, 128–191, and 192–255, respectively.

- Although the down sampling degraded the image quality, it made the algorithm performed faster.

6 SHAPE - FEATURE

In this study, we proposed eight mathematical morphology based measures listed below. The measures can be extracted using following three steps. Below listed shape measures and their corresponding meanings.



Shape feature procedure.

Step 1: Extract "area", "perimeter", and the "Euler number" features directly from the object.

Step 2: Create a convex hull using Graham Scan method which is the smallest convex polygon that covers the object, then extract the "convex area" and "solidity" features.

Step 3: Create an ellipse that has the same second-moments as the object, then extract the "minor length", "major length", and "eccentricity" features.

Step 4: It should be noted that the input vectors should be normalized to have zero mean and unity variance before performing PCA.

Step 5: The normalization is a standard procedure. Details about PCA appears in Ref. The readers can use the "PCA" command by the Mat lab platform to perform a standard PCA operation.

7 EXTRACTION TECHNIQUE

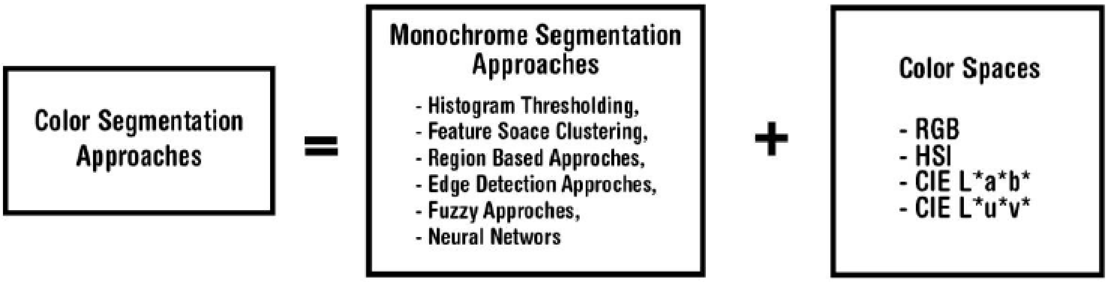
Feature extraction is a low-level image processing application. For a picture, the feature is the "interest" part. In the pattern recognition literature, the name feature is frequently used to designate a descriptor.

Repeat-ability is the desirable property of a feature detector. After image segmentation, the next step is to extract image features useful in describing fruits.

Various features can be extracted from the image: color, shape, size, texture. There are some local feature detector and visual descriptor, which are used for object recognition and classification.

Some of them are Speeded Up Robust Features (SURF), Histogram of Oriented Gradient (HOG) and Local Binary Pattern (LBP). All these features, feature detectors and visual descriptors are explained in next section.

7.1 Feature Extraction



Feature Extraction Technique.

Next step in fruit classification and grading process after segmentation is feature extraction.

Main and important visual external features for fruit are its color, size, shape and texture.

Feature descriptor is a representation of an image or part of it, which extract useful information and discards unnecessary information.

It is mainly used for image recognition and object detection. In this section, we have briefly discussed all.

Some of the feature descriptors used to detect and recognize object are SURF, LBP and HOG.

We have discussed these feature descriptors also here in brief.

7.2 Color Extraction

As color is most visually striking feature of any image it pays an important role in classification and grading system and also to identify defective fruits from normal fruits.

Most of the existing system defines maturity of fruits by comparing its color with the existing predefined reference colors.

Color models are divided into several models like HIS, HSV, JPG, L*a*b*, GALDA, RGB, sRGB, etc.

Color models like RGB, HIS and L*a*b* are used with different methods like dominant histogram, mean of color channels, etc.

Color features extraction methods broadly fall in two categories:

1. Global methods (global color histogram, histogram intersection, image bitmap).

2. Local methods (local color histogram, color correlogram, color difference histogram).

For color feature extraction, some of the Python functions are available at skimage.color.

Some functions are rgba2rgb(), skimage.util.invert(), label2rgb(), skimage.exposure.histogram(), rescale_intensity() and equalize_hist().

7.3 Texture Extraction

Set of two-dimensional array calculated to quantify visual texture of an image is called image texture.

It provides details about the spatial organization of color or intensities in an image (region of an image).

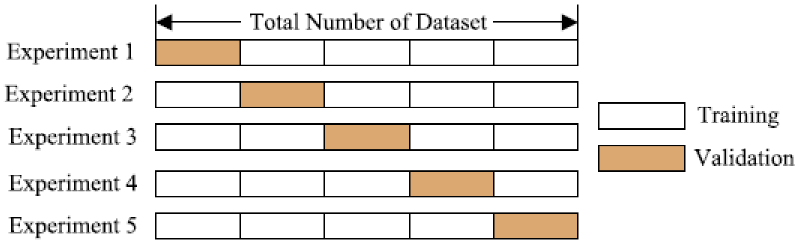
Traditional fruit recognition algorithms either ignore the texture feature of fruits, or use texture features that couldn't represent better texture of fruit images.

Fruits recognition based on color and texture features are available in literature.

To analyze an image texture in computer graphics, there are two approaches: Structured Approach and Statistical Approach.

8 K-Fold Cross Validation

After feature reduction by PCA, we divide the data into training and test set.



Cross Validation.

The training set is used for train the weights/biases of the classifier, meanwhile the test set is used as test the performance of classifier.

In order to enhance the generation capability of the classifier, we used the cross validation technique on the training set.

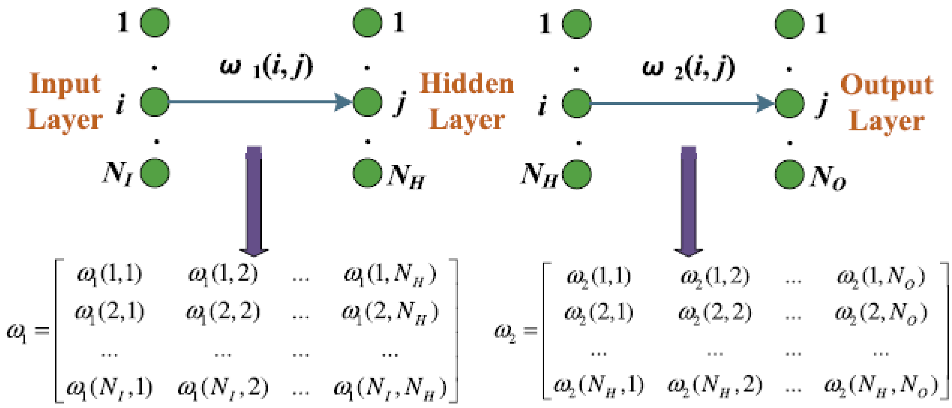
The K-fold cross validation is applied due to its simple and easy properties, while using all data for training and validation.

The mechanism is to create a K-fold partition of the whole data set, repeat K times to use K $_-$ 1 folds for training and a left fold for validation, and finally average the error rates of K experiments.

Alternatively, if K is set too small, the computation time will decrease, the variance of the estimator will be small, but the bias of the estimator will be large.

9 Power Rank Fitness Scaling

Fitness scaling converts the raw fitness scores that are returned by the fitness function to values in a range that is suitable for the selection function.



Fitness Scaling.

The selection function uses the scaled fitness values to select the bees of the next generation. The selection function assigns a higher probability of selection to bees with higher scaled values.

There exist bundles of fitness scaling methods. The most common scaling techniques are linear scaling, rank scaling, power scaling, top scaling, etc.

Among those fitness scaling methods, power scaling finds a solution nearly the most quickly due to improvement of diversity, but it suffers from instability. Meanwhile, rank scaling shows stability on different types of tests.

10 FNN Weights Optimization

FNN is chosen as the classifier because it is widely used in pattern classification, and it does not need any information about the probability distribution and the a priori probabilities of different classes.

The training vectors were presented to the FNN, which is then trained in batch mode.

The general one-hidden-layer model of FNN devises a structure illustrated.

It is clearly perceived that there are three layers contained in FNN: input layer, hidden layer, and output layer.

Nodes of each adjacent layer are connected completely and directly to form the links.

Each link has a weighted value that presents the relational degree between two nodes.

In the next paragraphs, we shall discuss how to choose the optimal weights of FNN, and convert it to an optimization problem.

11 Encoding Strategy

Let NI represents the number of input neurons, NH the number of hidden neurons, and NO the number of output neurons.

Suppose x1 and x2 represents the connection weight matrix between the input layer and hidden layer, between the hidden layer and the output layer, respectively.

It shows the formation of the weight matrix x1 and x2.

The encoding style can be presented as the combination of the vectorization of the (x1, x2).

The span of cn falls within (0, 1). We define another chaotic number series in that falls within the range (1, 1).

Random parameters in standard ABC are generated by pseudo-random number generators, which cannot ensure the ergodicity.

Therefore, chaotic number series are employed to replace the random parameters, with the aim to improve the performance of standard ABC.

12 Chaotic Operator

The chaotic theory pointed out that minute changes in initial conditions steered subsequent simulations towards radically different final results, rendering long-term prediction impossible in general.

Sensitive dependence on initial conditions is not only observed in complex systems, but even in the simplest logistic equation.

In the well-known logistic equation. Where cn represents chaotic number series.

A very small difference in the initial value of c would give rise to a large difference in its long-time behavior as shown in (a and b).

The track of chaotic variable cn can travel ergodically over the whole space of interest.

(c–e) indicates that the series cn will lose chaotic property it its initial value is one of 0.25, 0.5, and 0.75.

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Random parameters in standard ABC are generated by pseudo-random number generators, which cannot ensure the ergodicity.

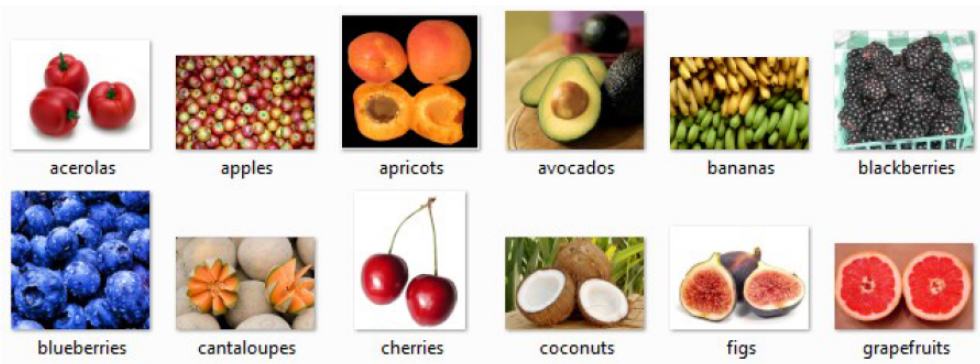
Therefore, chaotic number series are employed to replace the random parameters, with the aim to improve the performance of standard ABC.

13 DATASET DESCRIPTION

Keggel Fruit-360 Dataset

The data set has the following features.

- Total number of images: 1653
- Training set size: 1322 images (one fruit/image).
- Test set size: 331 images (one fruit/image).
- Multi fruit set size: 79 images.
- Number of classes: 18(fruits).
- Image size: 256x256 pixels.

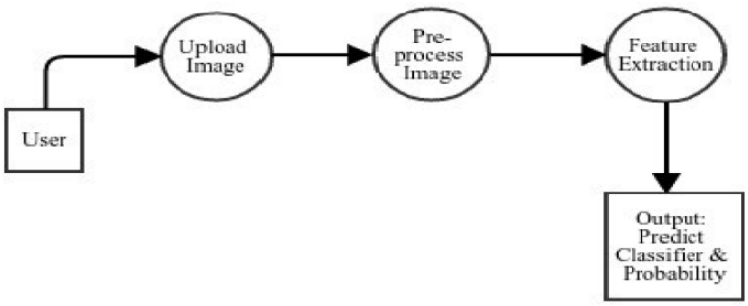


Fruit dataset.

14 Training Method Comparison

Now that there are 14 reduced features remaining, the structure of the FNN is set to 14-11-18.

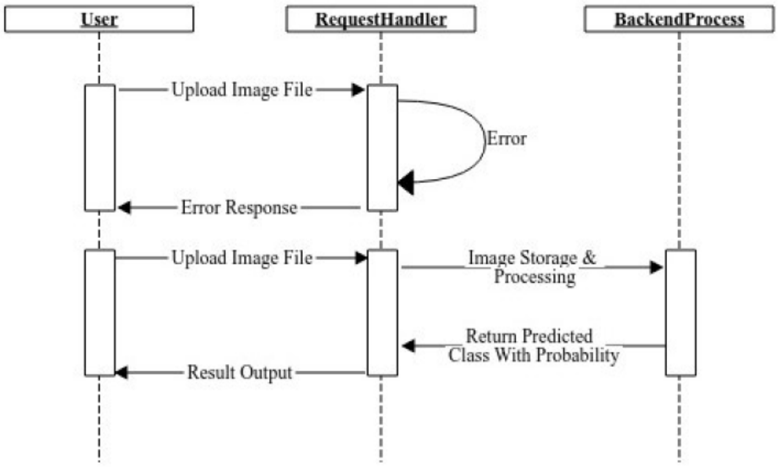
The input neurons NI correspond to the number of features as 14. The number of hidden neurons NH are set to 11 via the information entropy method.



Event Diagram.

The number of output neurons NO correspond to the number of categories of fruits as 18.

We compared our FSCABC method with latest training algorithm, including BP, momentum BP (MBP), GA, SA, PSO, and ABC.

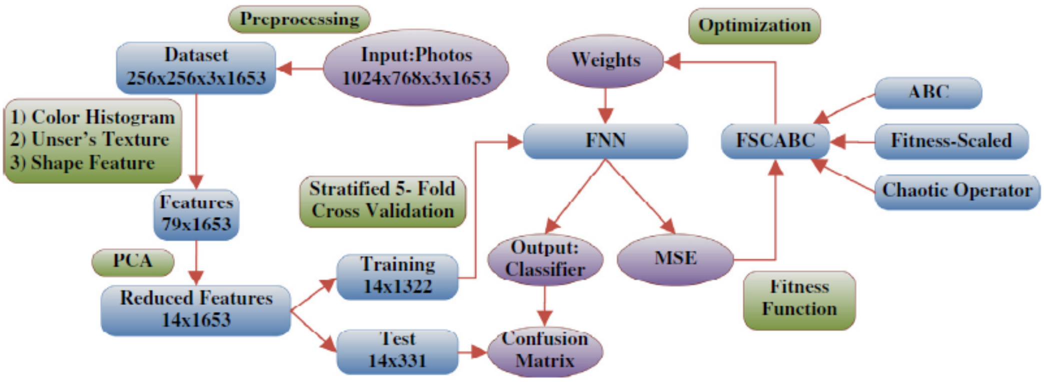


Sequence Diagram.

The parameters of these algorithms are obtained using trail-and error method and listed in table.

The maximum iterative epochs are set as 500. Each algorithm ran 20 times on the training set.

15 DATA FLOW DIAGRAM



DFD.

The above figure states that the flow of the process of the fruit until the class is being recognised by the computer.

So as stated before first the image is being captured by the computer and the background of the image is being removed so that the computer won't be confused while classifying the fruit according to its category.

After the image is being captured then the fruit is being passed through three different sensors i.e light sensor weight sensor and invisible light sensor to check the weight, freshness of the fruit.

Now from the entire dataset 10 _ 10 fruits of each dataset has been combined together and formed an test set so the a small size of dataset can be formed and can be tested whether the computer can recognise the fruits according to their respective category

Now various algorithms have been applied so the correct result can be at last like split and merge algorithm, FNN feed forward neural network, FSCABC fitness-scaled chaotic artificial bee colony.

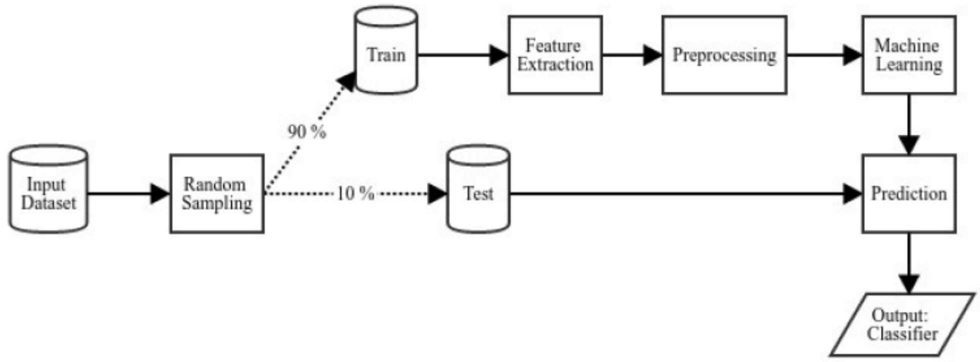
As shown in figure each image in the training samples are passed to extract the features of the image. These feature includes, Hue Histogram Feature, Haar-Like Feature and Edge Histogram Feature.

The extracted features are first preprocessed or standardized using Standard Scalar. The preprocessed data are then fitted into AdaBoost classifier 24 algorithm which is the final trained data.

This trained data is saved in the local storage as an object file. Later to test the input image, feature extraction for the image provided is carried out.

The trained data from local storage is loaded and prediction is carried out for the features of new image.

16 FLOW ALGORITHM



Data Flow.

The flowchart of the proposed fruit recognition system is shown below. The pseudo codes of the recognition system are written as follows:

Step 1: The input is a database of 1653 color images consisting of 18 categories of fruits, and each image size is 1024 _ 768 _ 3 (length = 1024, width = 768, and color channel = 3).

Step 2: Pre processing: Remove background. Crop and resize each image to 256 _ 256 size. Retain 3 color channels.

Step 3: Feature extraction: 79 features are extracted from each 256 _ 256 _ 3 image. These 79 features contain 64 color features, 7 texture features, and 8 shape features.

Step 4: Feature reduction: The whole 79 features are reduced via PCA, and the preserved feature standard is to cover at least 95% of the whole variance.

Step 5: The 1653 samples are split into training set (1322) and test set (331) in the proportion of 4:1 randomly. Meanwhile, the training set is divided by stratified 5-fold cross validation.

Step 6: The training set is submitted to train the FNN. The weights/biases of the FNN are adjusted to make the average MSE minimal. FSCABC is the training algorithm.

17 CONCLUSION

This project aims to classify the fruit images based on its Haar-Like, Hue and Edge histogram features.

The project is designed in such way that it reads image, extracts features, preprocesses it, implements machine learning algorithm and generate output based on the input provided.

The project has been able to classify the fruit images based on the fruits features.

The cross validation score obtained is 54.9% with learning rate of 0.7 and the prediction accuracy of the system is above 55%.

We have tried many algorithms and many logic's to make the project successful, but the success level was 89.1%. So the future research work will concentrate on following points:

Other reason of non-destructive automation can be its ability to produce accurate, rapid, objective and efficient results over manual work.

Though some challenges are still need to overcome, but machine vision will prove to be the future for non-destructive fruit classification and grading.

1. Extending our research to fruits in severe conditions, such as sliced, dried, canned, tinned, and partially covered fruits;

2. Including additional features to increase the classification accuracy;

3. Employing cloud computing and other parallel technique to accelerate the algorithm;

4. Applying our algorithm in other similar fields as chestnut quality assessment etc.

18 RECOMMENDATION

It is seen that the AdaBoost ensemble algorithm doesn't perform well for the fruit classification problem.

If other ensemble machine learning algorithm such as Random Forest is chosen for these kinds of classification problem, satisfactory result can be obtained.

Similarly, as for now only 5 fruits are taken as the training sample and only 3 features are extracted from each image.

If more fruits data images are taken as training sample, then the prediction accuracy as well as the cross validation score might increase.

Extracting multiple features from the image has massive impact in the prediction and cross validation score in addition with choosing of different powerful machine learning algorithm might increase the prediction accuracy.

However, implementation of neural network can produce more better and accurate results and will be faster as well.

19 FUTURE ENHANCEMENT

For future enhancements to this project, the trained data and aforementioned algorithm can be tuned further in order to obtain the best results.

Extraction of more features other than that are mentioned in the report above will assist in increasing the prediction accuracy.

Implementation of better ensemble algorithm other than the FNN algorithm can provide better results.

We can also prepare algorithms and machines for fruits and vegetable grading.

It can also be used for plants/ leaves/ flowers identification and classification.

A system can be develop which will identify plant/leaf/flower and provide information regarding it.

We can also work on some more features for grading and classification, which can identify types of disease and/or texture structure of fruits.

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