Fruit Image Classification using Optimal Features Extracted by Soft-Computing Techniques

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ABSTRACT
Fruit classification is found to be one of the emerging area in computer vision. The accuracy of the classification system depends on the quality of acquired images, number of features, types of features, selection of features from extracted features and type of classifier used. Images taken in poor environment conditions decrease the visibility and hidden information of digital images. Therefore, image enhancement techniques are necessary for improving the significant details of these images. This study provides a review to highlight recent progress of image enhancement techniques for improving the visibility of fruit images.
In this paper, a new fuzzy type-II based image enhancement technique is designed to improve the quality of visibly weather degraded fruit images. The type-II fuzzy logic can automatically extract the local atmospheric light and roughly eliminate the atmospheric veil in local detail enhancement. Thereafter, Teacher-learning based optimization (TLBO) algorithm is used to find an optimal combination of threshold values at different levels for minimizing the cross entropy. TLBO algorithm is inspired by passing on knowledge within a classroom environment where students _rst gain knowledge from a teacher and then through mutual interaction. From experimental results, it is observed that this method is an efficient and feasible method to search an optimal combination of threshold values. Afterwards, fruit images will be classified using Convolution neural network (CNN) and Recurrent neural network (RNN). CNN is utilized to develop discriminative characteristics and RNN is utilized to develop sequential labels. Extensive experiments have been carried out by considering the proposed techniques (i.e., CNN, RNN without type-II fuzzy logic and CNNRNN with type-II fuzzy logic) and existing competitive techniques on fruit images. It is observed that the proposed technique outperforms existing image classification techniques in terms of accuracy and coefficient of correlation. Another contribution of this study is proposal of new image classification technique for weather degraded fruit images. The proposed method is tested on number of fruit images and observed that proposed technique outperforms existing image classification techniques in terms of accuracy. Results of the study are quite promising and justify significance of proposed research.

Keywords
CNN, RNN, LSTM, Deep Learning.

1. INTRODUCTION
Fruits are the important part of our daily diet, that we eat, which offers tremendous benefits to human life. There are so many fruits that are available throughout the year and some fruits are seasonal. Indian economy is still very much depending on agriculture. India is ranked 3rd among the top producers of fruits in the world. So, classification of fruits using soft computing techniques is very much beneficial both for the producers and consumers. At present, computer science is getting more involved in agriculture and production science. Artificial Intelligence and many soft computing techniques are used for classifying fruits, to provide the better quality of the fruits to the consumers.

Classification of Fruits is very important because it is very useful for improving fruit quality, recognizing different kind of fruits is a difficult task in a market, to categorize a fruit to determine its price manually is very difficult, counting manually the reaped fruits and determine its quality is a difficult task. Some major problem related to fruits producing, marketing and safe storing are: rising labor costs; shortage of skilled workers and go-down storing costs etc.

Soft computing vision systems provides considerable information about the nature and attribute of the fruits which reduces cost, guarantees the maintenance of quality of standards and provides useful information. Singh [1] analyzed the image of a real scene by using computers and process it. The techniques used are: Image acquisition; Pre-processing; Feature Extraction; Classification. The object fruit is a combination of its chromatic attributes in the form of color and geometric attributes in the form of shape; size; texture. Classification plays a very important role in the improvement of quality and identification of different fruits images.

Artificial neural networks, fuzzy logic and evolutionary computation models are the chief soft computing models for developing computer aided recognition system. Artificial neural network has the tendency to get training from samples and also perform classification of unseen patterns. Clark [2], gives the simplest definition of an artificial neural network is provided as: “A computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs”. Artificial neural networks are an attempt at modeling the information processing capabilities of nervous systems. An artificial neural network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification through a learning process. Among all approaches, ANN is classified as having fastest speed and best accuracy for classification and recognition type of problems [3]. This classification model includes capturing, processing and analyzing images to facilitate the objective and assessment of visual quality characteristics. The techniques used in image analysis include image acquisition, image pre-processing and image interpretation, leading to quantification and classification of images and objects of interest within images.

Classification techniques that are used for fruit classification are divided into the following phases:

a. Image Acquisition: It is the creation of digital image, typically from a physical scene. The term assumed to imply or include processing, compression, storage, printing, and display of such image. Its name specifies definition. To get image from any source especially hardware based any source is called as image acquisition in the image processing.

b. Pre-processing: Pre-processing is a common name for operations with images at the lowest level of abstraction - both input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing.

c. Feature-Extraction: once pre-processing is completed, then features are collected in the feature extraction stage. Features, as described here, are real numbers obtained by applying some mathematical expression to image data, e.g. spatial domain pixel values or transformed spectral domain. Selection of features is the main task in recognition applications. Optimal feature subset selection increases the search rate and accuracy of the recognition system based on the performance of classifiers.

d. Classification: A classification problem deals with recognizing a given input with one of the distinct classifiers. There are several classifiers used to classify images. Object Classification is an important task within the field of computer vision. Image classification refers to the labeling of images into one of a number of predefined categories. Classification includes image sensors, image pre-processing, object detection, object segmentation, feature extraction and object classification.

e. Evaluation: Evaluation is the last phase of the classifier system. In this phase, proposed classifier is tested for testing patterns.

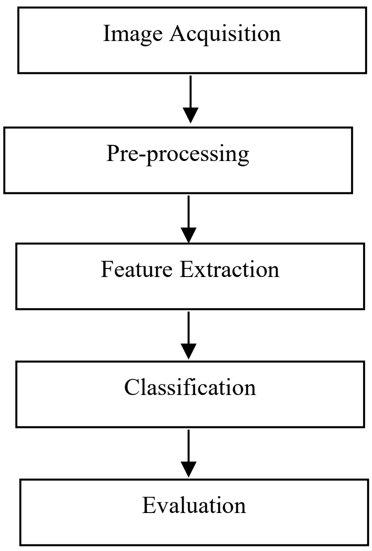


Figure 1: Phases of the proposed classification work

Above figure 1 shows the steps used during image acquisition, enhancement, segmentation and classification. In this research work, images are acquired using the Canon camera with configuration of from the orchards of Agriculture Department, Khalsa College Amritsar (Punjab). To improve the quality of acquired images, type-II fuzzy membership functions are employed to enhance the contrast. Teacher-leaner optimization based minimum cross entropy scheme is used to segment the enhanced fruit images. TLBO is an emerging meta-heuristic algorithm to select the optimal threshold values for image segmentation. Finally, fruit images are classified based on optimal features extracted using soft computing strategies. Hybrid classification model is developed based on optimal features extracted and selected using deep learning approaches. Deep learning has the ability to classify images without any handcrafted features. Soft computing technologies utilizes various image extraction and selection filters to select the best matched features. CNN has the ability to extract the optimal features with the help of distinct Spooling, convolution, and soft-max layers. RNN has the quality to select the optimal matching features. LSTM is specially designed to classify the fruits based on selected and extracted best optimal image festures.

Rest of the manuscript is described as: Fruit images classification related literature is discussed in the section 2. Sections 3 defines the problem formulation. Methodology for fruit image classification is discussed in the section 4.

2. LITERATURE SURVEY

Literature review is a systematic survey focused on a research work, trying to identify, appraise, select and synthesize all high-quality research evidence and arguments relevant to that work. The literature is conducted regarding classification of fruits. Extensive research has been done in the area of image processing and classification. My topic of research is classification of fruits using soft-computing based Techniques. During literature review, I have studied different classification methods and based on my literature survey, I explore the following reviews:

Damodaran [5] presented method based on combining Neural Network (NN) classifiers with Genetic Algorithm (GA). Presents three primitive neural network classifiers to solve tangled pattern recognition problems: multiple multilayer perceptron (MLP) classifier. Experimental results of this study shows that the GA produce better results than other classifiers but increase the complexity and takes more time as compared to other classification method, this remains a research challenge. use Common Classification methods such as Fuzzy classifiers, neural networks, Genetic Algorithms mainly for the data mining related problems and trying to improve that all the methods useful for solving problems related to data mining but many other problems are occurred during this study because they assume that all data is homogeneous in nature but this is not possible because data is spread over multiple websites in the form of different files and they are heterogeneous in nature. *Vijila* [6] and *Guijarro* [7] observed that Multi classifier system (MCS) architecture is better that SVM classifiers for dimension reduction. MCS offers acceptable classification results across the image or sites apart from offering acceptable classification results. The MCS indicates about 5% increase in the accuracy when compared to SVM classifier across the hyper-spectral images and sites. They show only their empirical results, this work needs more study to authenticate such a comparison, which is a topic of research. *Agarwal* [8] used Retinal vessel segmentation to the detect numerous eye diseases. Their work highlights the necessity for optimization algorithms. Liao [9] presents a new unsupervised hybrid classifier that combines several base classifiers through a fuzzy multi-criteria decision making (MCDM) approach that performs favorably as compared with other existing methods. This study combines support of six classifiers under two criteria. It can be easily extended for more classifiers. Guerbai [10] used a (PK-SVM) is proposed technique that incorporates process knowledge into the image processing technique. Zhang [11] proposed a technique for extract welds (linear or curved) from digitized radiographic images. The methodology consists of three major steps: feature extraction, pattern classification, and post processing. They also assumed that all images have homogeneous features and welds in each image are identical. In real sense no images have same feature, this means the problem requires some more work to do in the future. This work does not shows any pre-processing data but fuzzy K-NN classifier needs some pre-processing, i.e. the major drawback of their study, which is a topic of research. Kumar [12] proposed an effective use of the OC-SVM for handwritten signature verification based on writer-independent parameters using only genuine signatures. Sinha [13] presents a hybrid approach as a combination of classification two methods, extreme learning machine (ELM) and sparse representation-based classification (SRC) method. They apply the proposed approach for handwritten digital image classification and face recognition. A feature selection and classification algorithm based on the concept of fuzzy-rough sets is proposed. In their work, they select the few features that reduced computational task and increases the classification accuracy but selecting random or few features do not produce the accurate and reliable results. *Evsukoff* [15] presents new image descriptors based on color, texture, shape, and wavelets for objects and scene image classification. The proposed methods also used for Pattern recognition and handwritten text recognition and face recognition. *Mei* [16] presents a new and robust multispectral image classification algorithm. The classifiers have shown to be robust, flexible and capable of producing reliable images. So therefore, it can be successfully applied to remotely sensed data and other recognition methods. *Alagappan* [18] presents a distributed approach is developed for achieving large-scale classifier training and image classification. They explored the parallelism of their structural learning method proposed in this paper and develop an efficient storage method to save SVM models and avoid the repeated computation of support vectors (SVs) in the testing process for image classification. These proposed methods should be used for improving the classification accuracy of parallel computing approach. Dong [19] Grouped images into (semantically) meaningful categories using low-level visual features is a challenging and important problem in content-based image retrieval. They use Bayesian classifier approach with vector quantization (VQ) to learn the class-conditional probability densities of the features. This work can also be used to categorize the images based on color, texture, histograms etc. Nauck [21] developed a structural learning algorithm to achieve more effective learning of large numbers of inter-related classifiers for supporting large scale image classification and annotation. Their experimental results have demonstrated that the structural learning algorithm can significantly outperform the traditional approaches and other inter-related approaches but their structural algorithms have some shortcomings that they can take only the average weights in the proposed algorithm. Guan [23] presented a Neuro-fuzzy model for pattern classification that can learn fuzzy rules and membership functions from training data by a simple learning algorithm. This study assumed that knowledge in form of fuzzy rules is easily available but this is not possible that always knowledge regarding fuzzy rules are available. So due to this it is not possible to develop the effective classifiers that can produce accurate results. Farid [24], proposed a new, highly stable and very efficient sequential algorithm for SVM training that solved the primal problem for SVM. Giacinto [26] proposed two independent hybrid algorithms. The proposed methods improved the classification accuracy rates of both classifiers in multi-class classification tasks. Lu [27] Proposed a bank of classifiers approach to image region labeling and evaluate Dynamic classifier Selection (DCS) and classifier combination (CC). Wilk [28] used an ensemble of neural networks for pattern recognition, an approach to the development of high-performance image classification systems. Hemanth [29] defined Linear Discriminant analysis (LDA) and biased discriminant analysis (BDA) techniques for dimension reduction. They proposed a novel integrated boosting framework that is used to boost the weaker classifiers. Lashari [30] had shown the possibilities of generalizing the two-class classification into multi-class classification by means of a fuzzy inference system. Experiments shown that the proposed formulation for implementing a fuzzy multi-class classifier performed rather well on some benchmark datasets. This study works well for one-class classifiers but this study needs some work in the future on multi-class classifiers for effective results. Mitrakis [31] proposed a training methodology that substantially improving the efficiency of the conventional neural network for their data. The computational complexity of these networks is also significantly reduced which shows the suitability of these networks for practical applications. However, this method not discusses any time and costs related to the computational of the proposed system. *Connolly* [32] and *jiji* [33] was proposed a self-organizing Neuro-fuzzy multilayered classifier, the GA-SONeFMUC model. Their proposed method was tested on agricultural areas. This is totally new concept for agriculture area classifications. *Guironnet* [34] presented an AND-PSO heterogeneous ensemble of classifiers in response to new problems reference data during video face recognition. Fauvel [35] presented a fuzzy classifier based on a symbolic formulation of fuzzy systems. The experiments shown that the FSM has good accuracy results when compared to similar models. Ghosh [36] proposed a method of camera motion classification based on Transferable Belief Model (TBM), by avoiding low level magnitudes it is not possible to go into depth for research, such a point needs some more research in this field. *Xiao* [37] proposed a technique for neuro-fuzzy (NF) classification and demonstrated successfully its effectiveness for classification of fully and partially labeled patterns. *Giorgio* [39] T uses LaV, the results show that the quantified lateral ventricular (LaV) shape change is relevant to the position of the brain tumor. *Atkinson* [40] presents a two-phase method that combined one class support vector machine classifiers. The experiments on the real-world flight data set produced results different to those from the artificial experiment. So, this work needs some more research in depth to classify the data at different heights is different for each aircraft, so we will not use this experiment for classification of flight data in real world. Lee [41] proposed algorithm for successive learning based on the non-parametric test feature classifier (TFC). This proposed algorithm has been applied to the problem of defect image classification. Cheng [43] discussed about the classifiers that are decision making related to region of suspicion (ROS). Such classifiers of micro-calcifications characterized the clusters based on the selected features.

3. PROBLEM FORMULATION

From the literature survey, it is concluded that fruit classification is one of the emerging area under research. A lot of research has been done in the field of classification in recent years, but still some further improvements are required to increase the accuracy and speed of the classification system. It is observed that focus is to improve the accuracy rate of classification system. The accuracy of the classification system depends on the quality of acquired images, total number of features, types of extracted features, selection of valuable features from extracted features and type of classifiers used.

When an image is acquired, there is a possibility that noise may be occurred in the captured images. So it is mandatory to improve the quality of image by reducing the effect of noise. From literature survey, it is observed that a large number of image enhancement and de-noise techniques are available. Each technique has its own advantages and suitable for particular types of images along with the types of noise in the images. Till date, there is no technique that is suitable to handle different types of noises in different types of images. Thus, in the proposed research work, it is necessary to find and develop a suitable image enhancement technique for de-noising and improving the quality of fruit images.

Image segmentation is the process of partitioning a digital image into multiple segments to trace the objects from the image. Segmentation techniques are used to segment the images based on region-based segmentation, data clustering, and edge-base segmentation. Segmentation techniques used so far are based on Genetic Algorithms, Swarm optimization, fuzzy clustering, K-Means, and ANN etc. The literature survey originate that the large number of segmentation techniques are available for image segmentation. Each technique has its own merits and it is not necessary that it is suitable for all types of images. Up to now, there is no technique found that segments all fruit images properly for morphological based features extraction. So, it is vital to develop a segmentation technique to segment the fruit images to extract morphological based features extraction.

Feature extraction is a most important phase of classifier system to extract suitable features for describing objects in the images. Most researchers have been used spatial domain-based features for classification problems. Fourier and Wavelet domains are two most important domains of digital image processing. Only few researchers used these domains for extracting features. Feature extraction is most important part of CAD systems. There is a great potential to explore these domains to extract features for classification problems.

Feature selection is the process of selecting an optimum subset of features from enormous potential features available in a given problem domain after the feature extraction. But it is very difficult to predict which features or feature combination will achieve better classification rate. Generally, different feature combinations will result in different performance. The choice of features has an important influence on the accuracy and time complexity of classifier. The general guidelines to select significant meta-heuristic optimization algorithms have been flourishing in recent years. These algorithms may play important role to select an optimal set of features for improving the performance of classifiers in terms of accuracy and time complexity. It is a challenging task of finding the subset of feature that achieves better classification accuracy. Population based optimization techniques for feature selection such as ,GA, ACO, SVM have been proposed in recent years. These algorithms plays important role in improving classification accuracy and higher processing speed and with smaller feature set.

To classify objects from images, the several classifiers so far have been proposed in the literatures. For fruit classification problems, it is noted that there are strong visual and objective correlations among the fruit classes. Thus, isolation of inter-related classes is not an easy task. Training the classifiers for such inter-related object classes may result in low accuracy rates for fruit classification. To overcome this problem, a soft computing-based hybrid model can be proposed.

4. METHODOLOGY

The proposed work consists of five steps. Initially the images are acquired. After image acquisition, features are extracted from the images and then the features are selected. Selected features are used to train the classifier. After training phase, proposed system is tested. When an image is acquired, there is a possibility that noise may be occurred in the captured images. So it is mandatory to improve the quality of image by reducing the affect of noise. In the proposed work, wavelet based technique will be used to de-noise the images. After image enhancement and de-noise, the enhanced and de-noised images are segmented on the basis of their shapes and features are extracted. In the proposed research work, spatial, wavelet and Fourier domains based features will also be executed.

Spatial domain features will be executed with the help of following equation:

g(x, y) = T [f(x,y)]

Where f(x,y) is the input image, g(x, y) is the processed image, and T is an operator on f.

Gabor wavelets features are extracted using gabor wavelet transform. Gabor –wavelets capture the local structure of the image corresponding to the spatial frequency, spatial localization and orientation selectively. In spatial domain, a two-dimensional gabor filter is a Gaussian kernel function modulated by a complex sinusoidal wave,defined as:

$$(1+x)^n = \frac{f2}{\pi_{\gamma} n} exp \frac{(x^2 + \Upsilon 2y2)}{2\sigma 2} \exp\,(j2\pi f x + \emptyset)$$

Where x and y are defined as:

x = xcosΘ + sinΘ

y = -xsinΘ + ycosΘ

where f is the frequency of the sinusoid, Θ is the orientation of the normal to the parallel stripes of a gabor function, Ø is the phase offset, σ is the standard deviation of the Gaussian envelope and ɤ is the spatial aspect ratio which specifies the ellipticity of the support of the Gabor function.

GLCM (Grey Level co-occurrence matrix) features: Spatial grey level co-occurrence estimates image properties that are related to second-order statistics, reflecting the relationship among pixels or group of pixels(usually two). The GLCM is a 2D histogram that describes the occurrence of pairs of pixels that are separated by a certain distanced. Let I(x,y) be an image with size N*M and with G grey levels, and (x1, y1) and (x2,y2) be two pixels with gray level intensities I and j, respectively.

The Fourier transform is a representation of an image as a sum of complex exponentials of varying magnitudes, frequencies, and phases. The Fourier transform plays a critical role in a broad range of image processing applications, including enhancement, analysis, restoration, and compression. If f(m, n) is a function of two discrete spatial variables m and n, then the two-dimensional Fourier transform of f(m, n) is defined by the relationship

$$F(W1, W2) \; = \sum_{m=-\infty}^{\infty} \; \sum_{n=-\infty}^{\infty} \mathrm{f(m,n)} e^{-jw} 1^{\mathrm{m}} e^{-jw} \; 2n$$

The variables w1 and w2 are frequency variables; their units are radians per sample. F(w1,w2) is often called the frequency-domain representation of f(m, n). F(w1,w2) is a complex-valued function that is periodic both in w1 and w2, with period 2π. Because of the periodicity, usually only the range $-\pi \leq w1, w2 \leq \pi$ is displayed. Note that F(0,0) is the sum of all the values of f(m,n). For this reason, F(0,0) is often called the constant component or DC component of the Fourier transform. (DC stands for direct current; it is an electrical engineering term that refers to a constant-voltage power source, as opposed to a power source whose voltage varies sinusoidally.)

Statistical Moments can be used to describe shape of boundary segments by using simple statistical moments such as mean, variance and higher-order moments.

We treat the amplitude of a g as a discrete random variable v and form an amplitude histogram p(vi), i= 0,1,2……..,A-1, where A is the number of discrete amplitude increments in which we divide the amplitude scale.

$$\mu n = \sum_{i=0}^{A-1} (\mathrm{vi} - \mathrm{m})\mathrm{P}(\mathrm{Vi})$$

Texture is an important approach to region description is to quantify texture. The three principal approaches used in image processing to describe the texture of a region are statistical, structural and spectral approaches which yield characterizations of textures.

Statistical is one of the simplest techniques for describing texture using statistical moments. Let z be a random variable denoting gray levels and let p(zi) = 0,1,2….,L-1 be the corresponding histogram. Where L is the number of distinct gray levels.

$$\mu n(z) = \sum_{i=0}^{L-1} (\mathrm{zi} - \mathrm{m})\mathrm{nP}(\mathrm{zi})$$

Where m is the mean value of z(the average gray level)

$$\mu n(z) = \sum_{i=0}^{L-1} \mathrm{ziP}(\mathrm{zi})$$

Spectral give the principal direction of the texture pattern. Detection and interpretation of the spectrum features are used to simplifying the spectrum in polar coordinates to yield a function S(r,θ). where S is the spectrum function and r and θ are the variables in this coordinate system.

$$S(r) = \sum_{\theta=0}^{\pi} \mathrm{s}\theta(\mathrm{r})$$

And

$$S(\theta) = \sum_{r=1}^{R=0} \mathrm{sr}(\theta)$$

Where R0 is the radius of a circle centered at the origin.

Wavelet transform features should be used for automatic grading and classification based on the skin of fruits because several disorders lower the quality of fruits due to environmental stress such as high temperature and solar radiations. Wavelet analysis is an advanced feature extraction technique based on windowing technique with variable sized regions.[22]

After this, soft computing based meta-heuristic optimization techniques will be used to select an optimal subset of features. At the end, a hybrid model based on soft computing techniques will be designed to classify fruit classes.

The methodology that can be followed during the achievement of proposed research objectives is as shown below in figure 2:

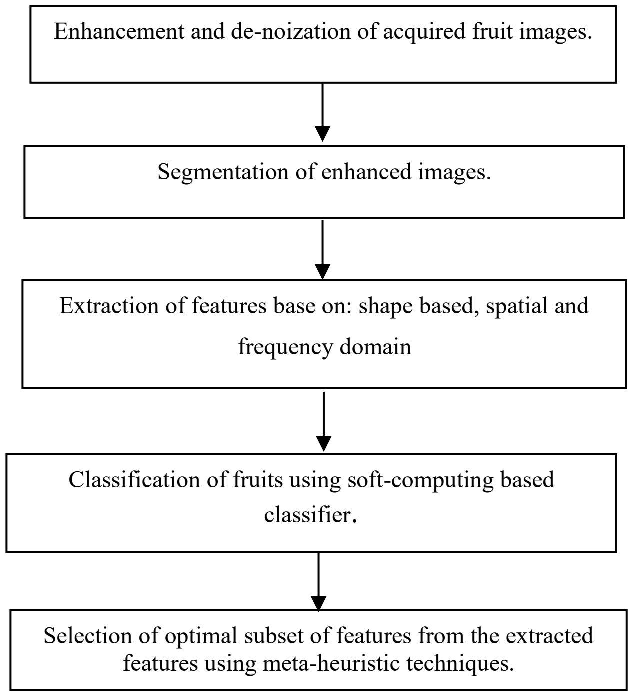


Figure 2: Activity diagram explaining the methodology to be followed

5. FRUIT IMAGE ENHANCEMENT

In this research proposal, Type-II fuzzy approach is involved to enhance the fruit images. Fuzzy has the ability to handle the uncertainties and vagueness efficiently. Fuzzy membership functions are used to divide the image regions into dark and bright. Advantage of fuzzy over CLAHE and HE for brightness improvement and enhancement is that, local atmospheric regions are improved quite efficiently. Fuzzy entropy has the ability to detect the optimal regions. Fuzzy entropy solves the problem of saturated pixels and over/under enhancement issues effectively. Fuzzy c-partition scheme is used to segment the acquired fruit image regions into dark and bright levels. For this, an image I of Size MxN is considered to obtain the minimum and maximum enhancement values. Lmin and Lmax functions are used to set the minimum and maximum fuzzy membership values. Following equation demonstrates the fuzzy membership levels:

$$\mu_I(ij) = \frac{L_{ij} - L_{min}}{L_{min} L_{max}}$$

The most often used method for dealing with uncertainty in threshold values of collected images is fuzzy type-II. Gray-level values, which range from 0 to 255, are used here [34,35]. The Bi-level threshold technique is used to divide image pixels into dark (d) and brilliant (b) categories (b).

$$G\epsilon \left[0, \frac{1}{255} \frac{2}{255} \frac{3}{255} \frac{255}{255}\right]$$

In G, d and b fuzzy membership functions are defined as:

$$\mu_d = \left\{\frac{1}{\alpha} x^2, if x\epsilon\ (0, \alpha) and\ if x\epsilon\ (\alpha, 1)\right\}$$

$$\mu_b = \left\{0\ if x\epsilon\ [\alpha, 0] \frac{1 - B(x)}{1 + \lambda B(x)}\ if x\epsilon\ (\alpha, 1)\right\}$$

Where α ϵ (0,1) is the crossover point and x ϵ W is the independent variable. We partitioned the W into dark and bright regions.

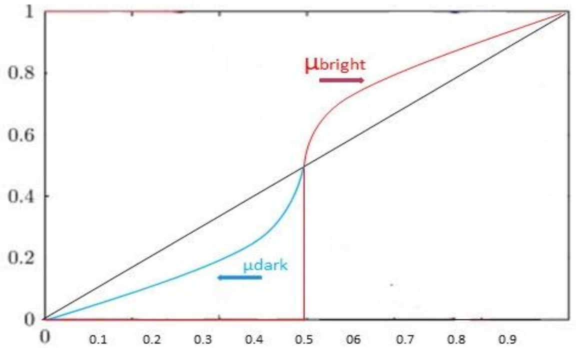


Figure 3: The membership functions µdark and µbright

After divide the fruit image into dark and bright regions, Fuzzy sure entropy parameter ϵ is a positive image threshold value. For fruit image segmentation, ϵ is related with the enhancement results effectively. Enhanced fruit image is controlled by setting the ϵ. To select the positive ϵ, first order fuzzy moment m and M(Lc) are defined as follows:

$$m = \sum_{i=0}^{L=1} t(i)\tilde{h}_I(i)$$

(18)

And,

$$M = (L_C)_{max} = \max(M_\alpha\,(L_C)|\alpha\epsilon\,(0-1))$$

Where L is the grey level, $\tilde{h}_I(i)$ is the probability of the histogram normalization.

$$M = (dar\ k)_{max} = \max(M_\alpha\,(dar\ k)|\alpha\epsilon\,(0-1))$$

(19)

. Corresponding to the grey level i of the fruit image (I) as [26]:

$$t(i) = \frac{i}{L-1}$$

(20)

M (LC)max defines the maximum value of the partition Mα (LC) with respect to the range (0,1) [37].

M(dark)max and M (bright)max are defined as maximum and minimum values in the proposed work as:

M (dark)max = max (Mα (dark) | αϵ (0,1)

(21)

M (bright)max = max (Mα (bright) | αϵ (0,1)

(22)

Then, we can assign ϵ value as shown below:

$$\epsilon = \begin{Bmatrix} \dfrac{p\,(bright)max}{2} \\ \dfrac{p(dark)max}{2} \end{Bmatrix} if\ m \le 0.5\ otherwise$$

(23)

During image enhancement process, exhaustive research strategy is involved to obtain the effective type-II fuzzy values by setting L from 0 to 255 normal gray level values. Then compute the histogram values to set membership levels for separating the image regions into bright and dark levels. Compute the dark and bright values using fuzzy events. For this involution membership strategy is utilized. If the satisfactory results are obtained then visual analysis are done the images as per the following figure 4.

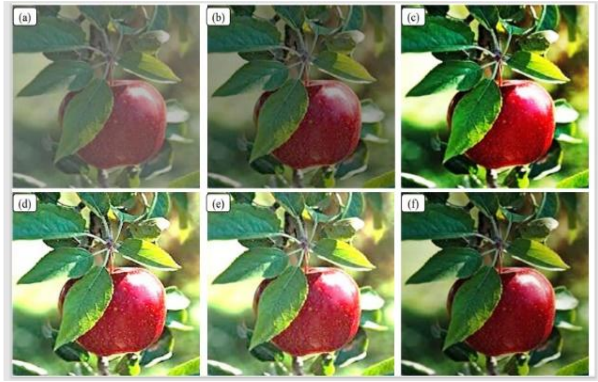


Figure 4: Fruit image visual analysis [28, 30]

In figure 4, fruit images 1(a, b, c, d, e, f) are enhanced using The Adaptive Trilateral Contrast Enhancement (ATCE), Brightness Preserving Dynamic Histogram Equalization (BPDHE), Gamma Correction (GC), Contrast Limited Adaptive Histogram Equalization (CLAHE), and by Fuzzy Type-II. ATCE shows the improved radiometric information but color distortions issue is still present. BPDHE has the ability to preserve the edges and has less spectral distortion issues as compared to ATCE. GC shows lesser number of halo facts and CLAHE has both good spectral information edge preservation ability. Fuzzy Type-II handles all the mentioned issues very effective and has better enhanced results as compared to ATCE, BPDHE, GC, and CLAHE.

Fruit image Segmentation

Fruit image segmentation is a method of partitioning an image into various segments to trace the objects from the image. Segmentation techniques are used to segment the images based on region-based segment, image data clustering, and edge-base image segmentation. Segmentation techniques used so far are based on Genetic Algorithms, Swarm optimization, Fuzzy clustering, K-Means, and ANN etc.

Figure 5: Fruit Image Segmentation (a)input image, (b) segmented fruit image

In this Figure 5, image segmentation process is defined. (a) is the input fruit image and (b) is the segmented fruit image by T LBO-based MCET technique. Apple fruit image boundary is detected and used for further segmentation approach. The literature survey originate that the large number of segmentation techniques are available for image segmentation. Each technique has its own merits and it is not necessary that it is suitable for all types of images. Up to now, there is no technique found that segments all fruit images properly for morphological based features extraction. So it is vital to develop a segmentation technique to segment the fruit images to extract morphological based features extraction. Thresholding is the most popular image and object segmentation technique because it is mathematically simple to calculate and rarely fails to define connected boundaries and disjoint regions. Primary goal is to divide the input image into target regions and background regions by threshold values. Intensity value of each pixel of the image is compared to the threshold value. If the intensity value is greater than threshold value, then the pixel is considered as target intensity pixel and set to white: otherwise, the pixel is considered as background and set as black.

The Type- II Fuzzy logic partition cross entropy (EC) process has been primarily utilized to choose image threshold values during image segmentation based on two parameterized fuzzy logic MF0 s (S and Z) to form fuzzy− partition of the input image. Two membership functions: (Z) and (S) are used to partition an input image into foreground and background regions respectively. Entropy (E) of regions (foreground and background) are defined with the help of Shannon entropy (SE). The optimal threshold value is selected based on searching the combination of optimal parametric values of fuzzy MF0 s. Liu et al. proposed a Fuzzy classification approach for image thresholding [8]. Cheng et .al [9] used Fuzzy c-partition entropy approach to select threshold. In this approach, parameterized fuzzy MF0 s are used to classify pixels of image into target and background. This approach is based on the selection of an optimal set of parameters of fuzzy MF for maximizing the entropy of Type-II Fuzzy partition. After this, the selected optimal parameters are used to find optimal threshold. Benabdelkader & Boulemden [10] proposed a recursive approach to search a suitable combination of parameters of fuzzy MF. In this approach, trapezium fuzzy MF with two parameters is used. Tang et al. also proposed a recursive programming approach to find a suitable combination of fuzzy MF parameters. This recursive approach is applied on two fuzzy MF0 s (s-function and z-function) with three parameters [11]. zhao et al. applied ant colony optimization to search a optimal combination of parameters of fuzzy MF for maximizing the entropy of Type-II Fuzzy partition[12]. Li et al. proposed minimum cross entropy approach for image segmentation [13]. Nie et al. proposed a thresholding method that is based on two-dimensional cross entropy. In this method, gray level co-occurrence matrix is used to obtain two-dimensional cross entropy[14]. M. Horng proposed honey bee mating optimization algorithm for calculating the MCET objective function [15]. Tang et al. used genetic algorithm to reduce computation burden for computing the MCET objective function[16]. Horng and Liou proposed FF algorithm to search multilevel thresholds by using EC principal. Recently, fuzzy entropy based techniques have been proposed by numerous researchers to find optimal threshold. These techniques are frequently used for thresholding because it is the general belief that fuzziness and uncertainty exist in images. Although the cross entropy has been applied by many researchers to search multilevel thresholds for image segmentation, it is worth noting that selection of an optimal combination of thresholds for minimizing the cross entropy of fuzzy 2-partition in reasonable amount of time is a challenging task [15]. Thus, selection of an optimal combination of thresholds for minimizing the cross entropy can be formulated as a combinatorial optimization method[17].

Over the last decade, various meta-heuristic algorithms have been used by researchers to solve combinatorial optimization problems. Such algorithms are Genetic Algorithm (GA) [18, 19, 20] Ant Colony Optimization (ACO) algorithm, Biogeography based Optimization (BBO) approach [21], bacterial foraging optimization algorithm gravitational search algorithm, cuckoo optimization algorithm [22], hybrid approaches [A,B] etc. Teaching-Learning-Based Optimization (TLBO) algorithm is a newly introduced member in the optimal algorithm family[23, 24]. T LBO is inspired by the philosophy of teacher-student learning. The search mechanism of T LBO algorithm is a population-based. Initially, a set of some feasible solution candidates of the given method is randomly generated called the population. After this, feasible solutions are modified to achieve optimal solution by the simulation of a classical school learning process. This process consists of two phases: teaching phase and student phase [25]. Teacher phase simulates the learning of the 11 students through the teacher. During this phase, the best feasible solution acts as teacher. Other feasible solutions are improved by moving their positions towards the position of the teacher by taking into account the current mean value of the feasible solutions. Student phase simulates the learning of the students through their mutual interaction. During this phase, two feasible solutions are randomly selected. If the first one is better than second one, then the first one is moved towards the second one. Otherwise, the first one is moved away from the second one. Main advantage of T LBO algrithm over other optimization algorithms is that it used only common controlling parameters while it is free from algorithm-specific parameters [26].

Common controlling parameters are common in running any population based optimization algorithms like population size and number of generations while algorithmspecific parameters are specific to that algorithm and different algorithms have different algorithm-specific parameters to control. For example, GA algorithm-specific parameters are mutation rate and crossover rate. Similarly, BBO algorithm-specific parameters are maximum immigration rate and mutation rate. The optimal selection of algorithm-specific parameters is also a problem. The improper selection of algorithmspecific parameters decreases the performance of optimization algorithms. Due to the improper selection of algorithm-specific parameters, either the computational cost of the algorithm will increase or yield the local optimal solution [27]. Recently, T LBO algorithm has been widely applied to obtain global optimal solutions for a variety of optimization problems [28, 29, 30, 31] with less computational cost and high consistency rates. From this motivation, the feasibility of T LBO algorithm is investigated to search an optimal combination of thresholds for minimizing the cross entropy. Main goal of image segmentation is to segment the image into regions that are desirable for a particular work. In this research work image thresholding is employed to segment the fruit images. Teacher learning based optimization minimum cross entropy is implemented to find the optimal features. Cross entropy based TLBO-scale digital image segmentation is used to segment the fruit images by the concept of cross entropy and framing of threshold values.

Teacher-Learning-based Optimization Algorithm

The TLBO algorithm is a new type of metaheuristic algorithm that is built on teaching and learning strategies. Rao et al. [12] were the first to apply it to constraint-based mechanical design optimization issues. It was inspired by how kids learn from a teacher and then interact with one another in the classroom [13]. The TLBO algorithm is a population-based optimization technique in which a class or group of students is considered a population. As a result, a classmate may be considered a viable solution to the issue. The fitness value of a valid solution to the optimization issue is viewed as the student's performance.

There are two stages to the TLBO algorithm: the instructor phase and the student phase. The operation of these stages is detailed in the following sections [14-17].

5.1 Teacher Phase

The teacher phase means learning of the students from the teacher. The most experienced, educated, and highly learned person in society is called a teacher, according to teaching-learning philosophy. The teacher aims to improve learners' knowledge and assist them in achieving good grades. However, learners gain information and receive scores depending on the teacher's instruction and the ability of the students in the classroom [18].

5.2 Student Phase

During a certain time, students exchange information with one another. A student engages with other students in the class at random to enhance his or her knowledge. If a classmate (ʋ) has more knowledge than the student (μ), the student (μ) learns something new from the classmate (ʋ). If a student (ʋ) is better than a student (μ), the student (μ) is promoted to the position of the student (ʋ). If this is not the case, the student (μ) will be reassigned to a different location (ʋ).

Proposed fruit image segment TLBO Algorithm

The TLBO algorithm can be rewritten in the following phases [19-22] based on the prior discussion:

Step1: [Initialization]

Population size (learner's number): Np

Iterations: In

Parameters (subjects/ courses offered)

Variable limits

Step2: [Population Initialization]

Generate random population randomly and the variable design length.

Pop=X Np, K-1]

The population is represented by a matrix of size Np× k-1

$\{X_{i1}\} \in T_1, \{X_{i2}\} \in T_2, \ldots\ldots\ldots \{X_{ik-1}\} \in T_{k-1}$, i = 1, 2, 3, ……..,Np

Individuals in the population are chosen at random. A randomly formed population does not have to satisfy the constraint:

$0 \leq T_1 \leq T_2 \leq \ldots\ldots\ldots \leq T_{k-1} \leq L_{max}$.

Step3: [Fitness Evaluation]

Feasible solutions evaluation to obtain the objective function.

$F_i^I = O(X_i^I), I = 1,2, \ldots\ldots\ldots\ldots\ldots, I_{max}$ and i = 1, 2, 3,………., Np

Arrange the population's viable solution candidates in ascending order based on their individual goal function numeric values. X_i^I and the value of the related fitness function F_i^I

$$\text{i. e. } X^I = \begin{bmatrix} X_1^I \\ X_2^I \\ . \\ . \\ X_{N_p}^I \end{bmatrix} \quad \text{and} \quad F^I = \begin{bmatrix} F_1^I \\ F_2^I \\ . \\ . \\ F_{N_p}^I \end{bmatrix}$$

$$\{X_{i1}^I\} \in T_1, \{X_{i2}^I\} \in T_2, \{X_{i3}^I\} \in T_3, \ldots\ldots\ldots\ldots, \{X_{ik-1}^I\} \in T_{k-1}$$

Step4: [Teacher Phase]

Modify the methodology by simulating the concept of student learning through the teacher.

For this, select the best solution ($X^I_{O(X_i^I)=min}$) who acts as a teacher for that iteration

$X_{Teacher}^I = X_1^I = X^I_{O(X_i^I)=min}$

Calculate the population means column-by-column, which offers the mean for the specific course (design variable or parameter) as:

$M^I = [m_1^I, m_2^I, m_3^I, \ldots\ldots\ldots, m_{k-1}^I]$

$$m_1^I = \frac{X_{11}^I + X_{21}^I + \ldots + X_{N_p1}^I}{N_p}$$

$$m_2^I = \frac{X_{12}^I + X_{22}^I + \ldots + X_{N_p2}^I}{N_p}$$

$$m_3^I = \frac{X_{13}^I + X_{23}^I + \ldots + X_{N_p3}^I}{N_p}$$

……………………………………………

$$m_{k-1}^I = \frac{X_{1k-1}^I + X_{2k-1}^I + \ldots + X_{N_pk-1}^I}{N_p}$$

The teacher will attempt to alter the mean from M^I to $X_{Teacher}^I$ which will serve as the iteration's new mean.

Step5: [Student Phase]

Modify the solution by imitating the concept of student learning through mutual interaction.

Select two feasible solution candidates X_u^I and X_v^I from X_{new}^I

$$If \quad F_u^I < F_v^I$$

$$X_{new\_SP,u}^I = X_u^I + r(X_u^I - X_v^I)$$

$$Else$$

$$X_{new\_SP,u}^I = X_u^I + r(X_v^I - X_u^I)$$

$$Endif$$

Where F_u^I, F_v^I are fitness values of X_u^I, X_v^I respectively.

After this, evaluate the fitness value ($F_{new\_SP,u}^I$) of $X_{new\_SP,u}^I$

$$If \quad F_{new\_SP,u}^I < F_{new,u}^I \,\&\&\, 0 \leq X_{new\_SP,u1}^I \leq X_{new\_SP,u2}^I \leq \ldots\ldots\ldots\ldots \leq X_{new\_SP,uk-1}^I \leq$$

$$X_{new,u}^I = X_{new\_SP,u}^I$$

$$Else$$

$$X_{new,u}^I = X_{new,u}^I$$

$$Endif$$

Thus, a new population is generated as follows:

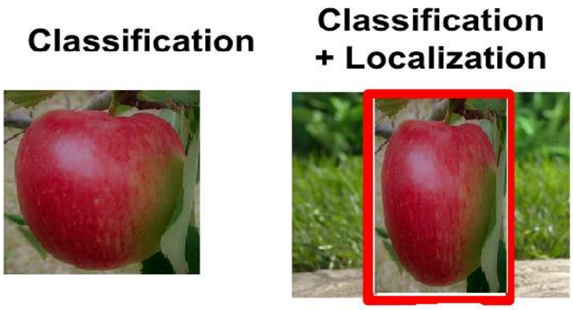
$X^{I+1} = X_{new}^I$

Step6: [Repeat] Go to Step 3 until the stopping criteria (maximum iteration: In) are not met.

Step7: Stop

Fruit image feature extraction:

Feature extraction and selection is the major course of action in image processing. Agriculture is the backbone of the Indian economy. Manually grading and sorting is very difficult and time consuming process. Many developing countries using machine vision system for automatic Classification of fruits and vegetables. Classification on fruits based on features as: shape, color, texture and intensity, very important for grading of fruits. The methodology of fruit classification involves several tasks such as: Fruit grading and sorting is an important process for the agriculture sector. To determine the quality and price , it is necessary to classify the fruits so that it meets all the quality standards either for eating or exporting here we are classifying the fruits based on the parameters: shape, size , colour, intensity and texture. From the literature survey it is observed that different researchers using different techniques for grading and sorting of fruits and vegetables. Feature extraction is most important phase of classifier system to extract suitable features for describing objects in the images. Most researchers have been used spatial domain based features for classification problems. Fourier and Wavelet domains are two most important domains of digital image processing. Only few researchers used these domains for extracting features. Feature extraction is important part of CAD systems. There is a great potential to explore these domains to extract features for classification problems.



Feature Selection

The choice of features has an important influence on the accuracy and time complexity of classifier. The general guidelines to select significant meta-heuristic optimization algorithms have been flourishing in recent years. These algorithms may play important role to select an optimal set of features for improving the classification rate of classifiers. It is a challenging task of finding the subset of feature that achieves better classification accuracy. Population based optimization techniques for feature selection such as GA, ACO, SVM have been proposed in recent years. These algorithms plays important role in improving classification accuracy and higher processing speed and with smaller feature set. To classify objects from images, the several classifiers so far have been proposed in the literatures. For fruit classification problems, it is observed that there is strong visual and objective association among the fruit classes. Thus, isolation of inter-related classes is not an easy task. To train the classification procedure for these correlated 16 object classes may be result in lower accuracy analysis and classification rates for fruit sorting and classification approach. To overcome this problem, a soft computing based hybrid model can be proposed. The features that are most relevant and useful for classification process are selected. These selection set of features are used to train the classifier model to classify the images based on best matching features. These selected features can be used to identify and detach unwanted, and un-necessary set of features from acquired data that do not contribute to the accuracy of a classification model. Feature selection plays a major role in classification criteria because the features that are not relevant may lead to poor classification and affects the accuracy rate of the classification methods. As shown in the Figure.1.10, features extracted from fruit images for classification. Features are selected and then evaluated with the help of feature selection algorithms to find the best group of extracted features as shown in figure. Optimal image features extracted using feature classification procedures are then further used for image classification approaches.

Fruit classification Method

MATLAB 2013 software is used to recognize the different fruit image captured from the orchards of Agriculture Department, Khalsa College, Amritsar(Punjab). This classification method is train with the help of optimal features extracted from acquired fruit images. During classification process, matched features are collected and train the recognition system and then test the best matched feature images number of time for development of efficient fruit classification technique. Feature extraction and selection is one of the main task during the classification process. Success rate of classification procedure depends on the selected optimal features. In this research work, optimal features extracted using image feature extraction method is used to train the classification process and then test phase is used to classify the fruits based on these extracted features. For training and classification, Integrator generator classifier is used. CNN based generator is used to obtain the distinct optimal image features and integrator generator classifier is used to label hierarchical labels to classify the fruits.

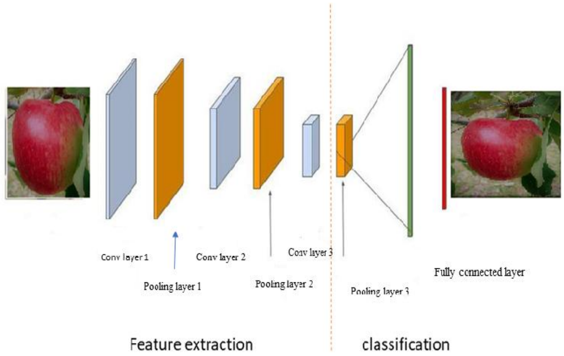


Figure: Fruit image Feature Extraction Model

Fruit images classification technique

The primary goal of this efficient image classification technique is to originate the hierarchical labels of acquired fruit images simultaneously. To this point, we can apply these two types of classifiers: a CNN-based generator and a integrated generator. Integrator (RNN −CNN) classifier is a hierarchical learning process and has the ability to understand better than other image classification systems. CNN is employed to obtain distinct image features from the acquired fruit images, and RNN used to enhance the coarse category and fine category classification labels based on sequential labels. In this research work, CNN and RNN is employed to obtain distinct image features and sequential labels respectively.

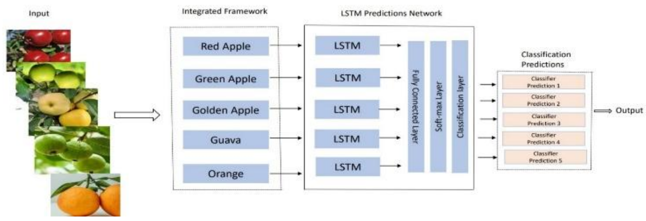


Figure: Fruit Classification Model using Soft Computing Techniques

6. CONCLUSION

In this proposed work, Deep learning applications are used to classify fruit images. CNN is employed to extract optimal features. RNN is employed to label the features. LSTM is employed to deal with the exploding and vanishing gradients that occurred during RNN labelling. LSTM classify the fruits by optimal features extracted and labelled by CNN and RNN. Extensive experiments have been done by using the proposed technique and existing competitive techniques on fruit images. To increase dataset during classification procedure from 40% to 50%, 50% to 60%, and 60% to 70% for classification does not affect the classification rate. The proposed scheme has better classification performance as compared to the existing schemes during feature selection, extraction, and classification. It is also proved that coefficient of correlation and RMSE measures has low values during large training dataset too. It has been concluded that the proposed technique outperforms existing image classification techniques in terms of quantitative and accuracy analysis.

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