CHAPTER 3

METHODOLOGY

Nowadays, export industries, retailers and individual persons or public have high expectations on the quality of food products. The 21st century is envisaging intense interest in the field of export industry and as a consequence, majority of the companies are paying more attention on improving and meeting the customer food product quality requirements. This is considered as a challenging job with fruits and vegetables, as their life period after post harvest is very small, when compared with other commodities. This research is focused on quality assurance of the Mango fruit and one of the most important post harvest operation to improve quality of mango fruit delivered to the market is to determine the defects that degrade their quality.

There are several factors that have to be met by the mango fruit before it is transported and marketed. Out of these factors, external skin appearance is considered as the most important factor while deciding the quality of mango. Inspection of external skin appearance is to make sure that the mangoes are free from external damage and the usage of computer vision systems in this stage, as confirmed by literature study (Chapter 2 - Review of Literature), is very popular.

In order to meet the objectives formulated in Chapter 1 (Introduction), this research work aims to answer the research question 'How to improve the process of skin defect detection in mango fruit?'. Answer to this question can be achieved in terms of two main features. The first is to improve defect detection accuracy (thus reduce mis-detection) and the second is to improve speed of detection. The proposed Automated External Skin Defect Detection System for Mango (AESDDM) is designed to find optimized solutions that can achieve these two features. This proposed defect detection methodology is based on the effective, synergistic integration of several schemes that aims to efficiently discover defective portions in the external part of the mango fruit.

This chapter outlines that the various techniques used during the design and implementation of AESDDM. This chapter begins with a discussion on the various steps involved in automatic defect detection system, followed by the research design along with the techniques used in each of the steps during defect detection.

3.1. AUTOMATED DEFECT DETECTION SYSTEM (ADDS)

The main aim of any ADDS is to have non-destructive algorithms that identify precise locations on mangoes that have the defect. These systems should be consistent in establishing the quality of mangoes and should be designed to increase the accuracy and speed of surface defect detection (Guruprasad and Behera, 2009). Successful implementation of such a system will help to reduce manual inspection costs, improve mango product quality and increase export efficiency (Henry *et al.*, 2011). An Automated Defect Detection System (ADDS) has several applications as listed below.

- Quality Control
- It is used by export companies for checking the quality of fruit.
- Used extensively in agriculture field to improve agricultural produce.

The ADDS consists of various steps during quality assessment and they are listed below.

(i) Image acquisition
(ii) Preprocessing
(iii) Segmentation
(iv) Feature extraction
(v) Comparison and decision

All these sequential steps of the automated system used for defect detection purpose in mangoes mainly focus on the use of a computer vision and image processing along with pattern recognition and machine learning algorithms system to detect differences between defective / defect free mango images (Kim *et al.*, 2005). The success of these systems relies on the correct and accurate approach used in each of these steps. These steps are illustrated in Figure 3.1.

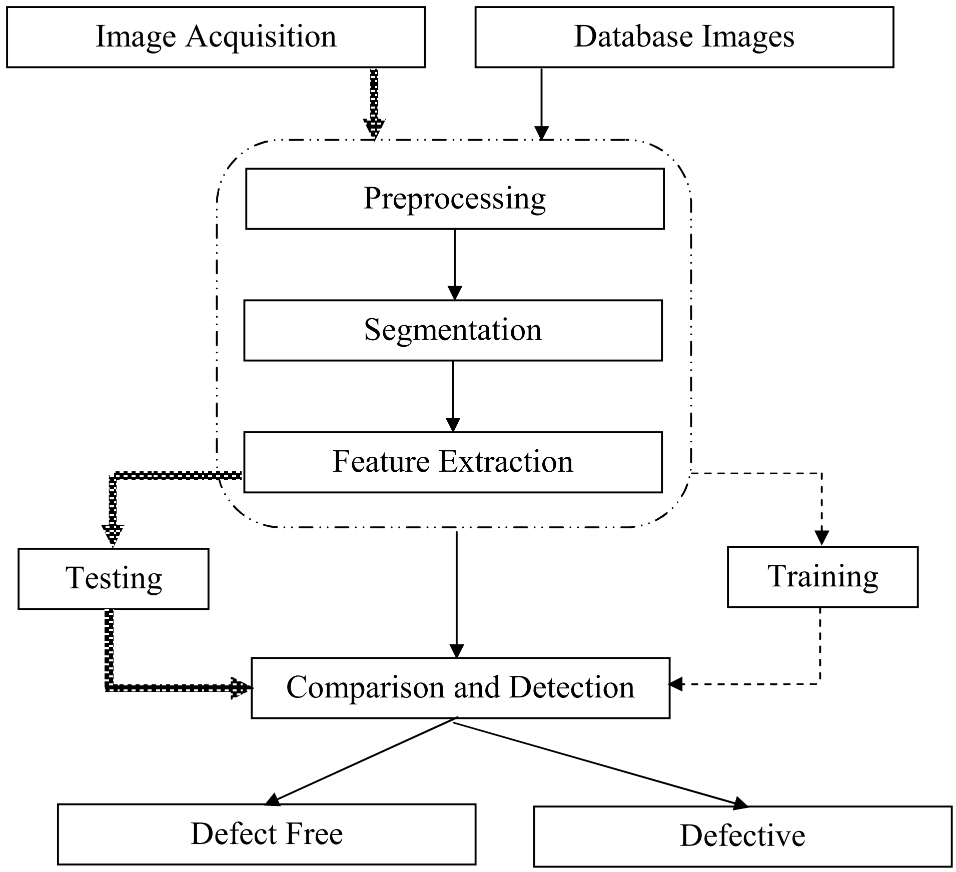


Figure 3.1 : General Framework of ADDS

Image acquisition is the process of capturing the images. A database of defective and defect-free mango images is constructed with the help of acquisition devices. Examples of such devices include digital camera, webcam or mobile phones. These devices help to acquire 2-dimensional digital images of the mango fruits. The common requirement of acquired images is vibration-free and even illuminations for good quality images.

The second step, preprocessing, is used to reduce or remove the various errors acquired during the first step. Examples of such errors include quantization errors (Mak and Pang, 2008), noise (Qiu and Sun, 2006) and lighting variation errors (Ngan *et al.*, 2005). This step uses techniques to improve the visual quality of the image using techniques that adjust contrast, correct lighting variations and remove noise. Correct utilization of techniques in this step is vital, as the result of this step has a direct impact on the performance of the subsequent processing steps. This stage can use any of the various noise filtering and transformation algorithms for this purpose.

After enhancing the image, the next step performs segmentation. Segmentation is the process of grouping similar surface areas of the mango image. These techniques can be manual, semi-automatic or automatic. Manual segmentation is performed by an expert or skilled operator, who draws manually to identify the various regions of the mango (Hatsuda *et al.*, 2009). On the other hand, semi-automatic techniques (Zhang *et al.*, 2010b) combine manual expertise and automated systems. Here, the operator makes use of several computer aided tool and software for separating similar regions. Both these techniques while being versatile, demand high skills of the operator, which may not be available always.

Moreover, experts with such skills are often costly. Automatic techniques (Nandi *et al.*, 2009) avoid human intervention and use various characteristics (features) of the image to identify similar regions. Currently, the automatic segmentation is widely used in all pattern recognition tools as it is very inexpensive both in terms of time and manpower aspects. Several techniques like dynamic contour, region growing and feature-based segmentation have been proposed.

The next step of ADDS performs the feature extraction. Here, a set of known features are extracted from the segmented image to characterize a specific application domain. It is the task of extracting quantitative measurements of the fruit mango image that can help during the detection of defects. The feature extraction techniques focus on generating a set of vectors that efficiently represent an input image (Brown *et al.*, 2012). Several types of features like color features, texture features, shape features and geometric features can be extracted from the input image and the type of features extracted depends on the application being used. The purpose is to obtain good classification results based on such features. In general, features can be evaluated on two aspects: good classification ability and low computational complexity.

For supervised learning, there exists an intermediate stage called a training stage (or learning stage), between feature extraction and detection. Certain amount of defect-free and defective images are collected and used as reference images for training. Depending on different feature extraction methods, the training will be fine tuned to collect the optimum parameters and threshold values in detection. Machine learning classifiers are abundantly used for this purpose during the identification and classification of defects (Devi and Vijayarekha, 2014).

Comparison and detection step, otherwise known as testing, helps to identify defective mangoes and further to identify the type of defect degrading the fruit. Several techniques like thresholding, machine learning classifiers, statistical modeling are used in this step (Susnjak *et al.*, 2013). Usage of ADDS during mango fruit quality assessment and inspection provides various advantages like simple to implement and operate, reduced false acceptance/rejection, speed of detecting defective fruits and cost effectiveness. Thus, overall, these system increases the efficiency of production and quality of mango fruit, thus improve export process and economy of the country.

3.2. RESEARCH METHODOLOGY

The proposed AESDDM that detects the external skin defect mangoes consists of four phases. They are listed below.

(i) Preprocessing

(ii) Segmentation

(iii) Feature extraction

(iv) Defect Detection and Classification.

In this research work, each of the above mentioned steps is treated as a separate phase, which has to be applied in a sequential manner during defect detection. The methodology is planned in a manner that each step attempts to improve its respective task, so as to improve the operation of defect detection. During the flow of defect detection, the output of one phase is used as input by the next phase. The proposed research methodology is presented in Figure 3.2 and described in the following subsections.

3.2.1. Data Acquisition

The mango image database was constructed by the researcher using mangoes collected from the orchards at Coimbatore. The images were acquired using professional digital camera in JPEG format. All the images were captured in RGB format. The database constructed had a total of 1800 mango images. Some sample images are shown in Figure 3.3. Each mango is captured in six different angles to cover the entire surface. The images collected belonged to four different varieties of mangoes, namely, Alphonso, Banganapalli, Neelam and Sendura. These four varieties were selected because of its easy availability in the orchards.

The images collected belonged to both healthy and defective mangoes. Four different defects, namely, bruises, russet, blemish and shrink, were considered. These four defects were considered because they are the frequent cause of degradation of mango fruit skin. To avoid computational delays associated with further image processing analysis, all the captured images were resized to 256 x 256 pixels.

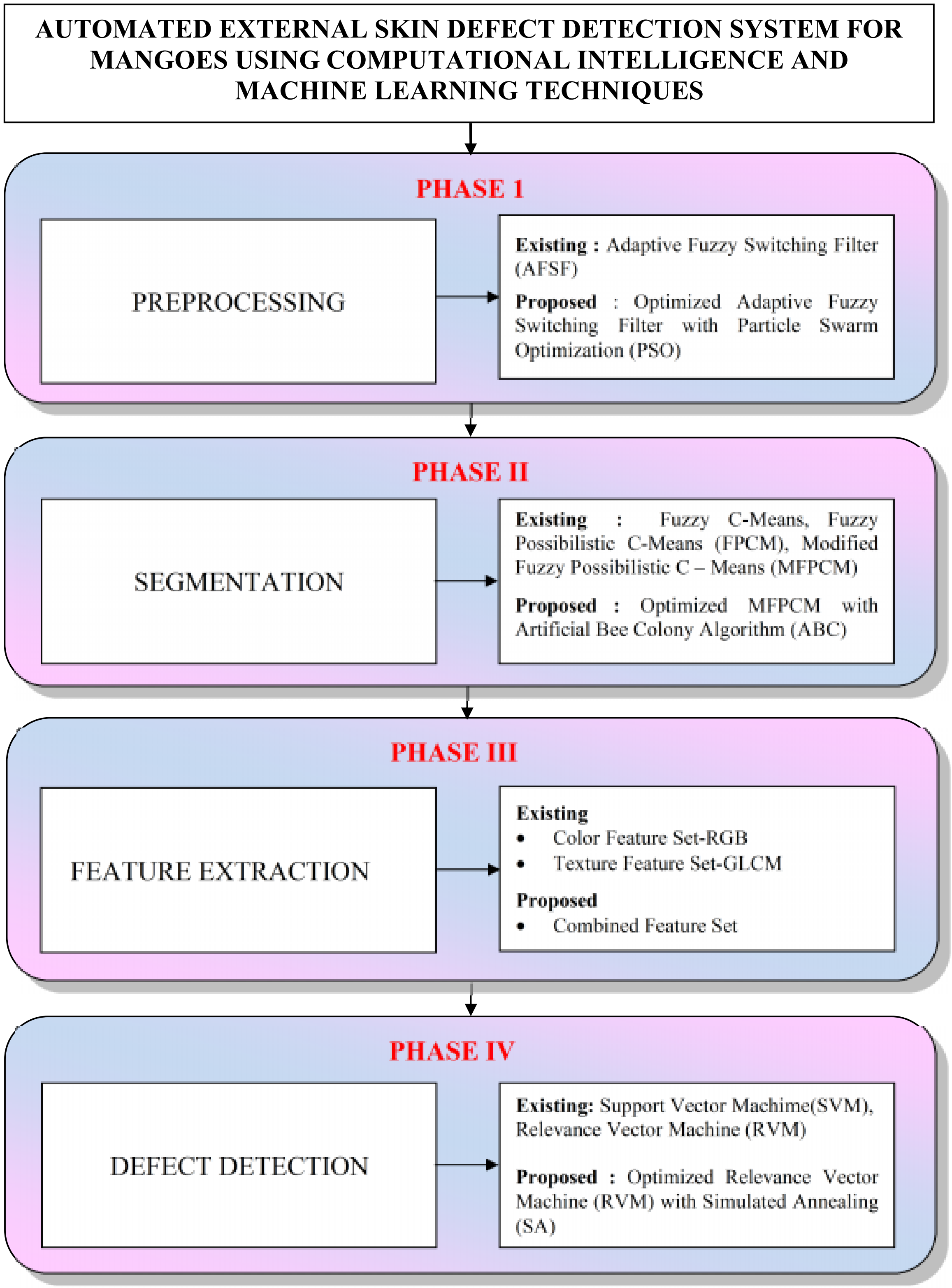


Figure 3.2 : Research Methodology

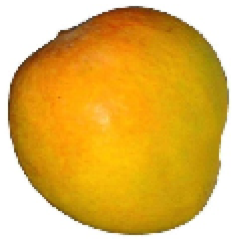
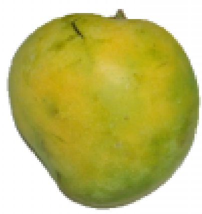
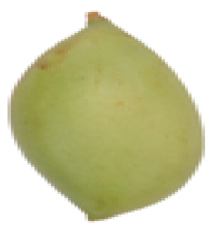
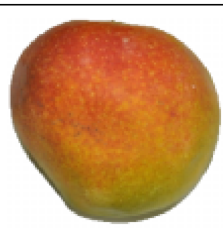
Healthy Mangoes		Mangoes with Skin Defects	
Alphonso			
			
Banganapalli			
			
Neelam			
			
Sendura			
			

Figure 3.3 : Sample Images from Mango Database

3.2.2. Phase I: Preprocessing

Preprocessing is the process of enhancing the quality of an input mango fruit image and is an important step in AESDDM because imprecise image preprocessing has a negative impact on the end result of defect detection.

Mango images captured using digital images are degraded by the presence of impulse noise. Conventionally, ADDS uses Median filter to remove impulse noise from mango fruits. The median filter instructs input pixel values from the current filter window and assigns the middle value to the output pixel value. The median value is not affected by the original value of the noise cells and the median filter is especially good at removing both the isolated and random noise found in the images (Ponraj *et al.*, 2011). The performance of a median filter depends on the size of the window used and is normally fixed during noise removal. A large window suppresses impulse noise effectively, but smoothen the whole, while smaller window size does not remove noise effectively. Moreover, the median filter also destroys fine details and produces steaks and blotches in restored images.

Attempts to solve these issues has been probed by the use of the Switching Median Filter (SMF), the center weighted median (CWM), the multistage median filter and rank-ordered mean filter (ROM) (Sau *et al.*, 1987). Careful analysis of these algorithms revealed that these while effective when compared to the conventional median filter still failed to remove impulse noise effectively while preserving details of the image, especially where there is a high probability of impulse noise.

Xu and Yue (2009) proposed a Fuzzy Adaptive Switching Filter (AFSF) to solve the above issues. This algorithm solved the problem of fixed sized window of SMF and removed impulse noise in digital images, while achieving optimal detail preservation. The algorithm used a maximum-minimum exclusive median method to handle the corrupted pixel. The method uses a fuzzy decision maker to identify noise and noise-free pixels. The adaptive behavior of AFSF made it capable of expanding the size of Filter's window with respect to noise intensity. Thus, a severe impulse noise could also be filtered efficiently.

One main drawback of this algorithm is the selection of the two threshold values (T1 and T2) used while applying fuzzy noise decision maker.

The AFSF used constant values of 10 and 30 assigned to thresholds T1 and T2 respectively. However, these values did not produce good result with mango images and extensive repeated execution of the algorithm was required to find optimal values. This is a time consuming job, which has to be repeated for each variety of mango. To solve this problem, the study proposes the use of Particle Swarm optimization (PSO) to estimate the threshold membership values automatically. Details regarding the existing and proposed algorithm are presented in Chapter 4 (Preprocessing Algorithm) and the performance evaluation of the proposed method on denoising different varieties of mango images is presented in Chapter 7, Results and Discussion.

3.2.3. Phase II: Segmentation

Segmentation is the process of partitioning a digital image into multiple segments based on pixels. The main goal is to group pixels into clusters in a manner that pixels inside a cluster have maximal similarity, while the similarity between pixels in different clusters is minimal. There are different types of clustering algorithms such as k-means, density based, hierarchical, partitioning based and Fuzzy C-Means (FCM) clustering. Among these, this research focuses on FCM to perform a clustering-based segmentation for separating the similar regions of mango image. It is one of the most widely used clustering algorithms for image segmentation (Lu *et al.*, 2013). Its success is chiefly attributed to the introduction of fuzziness about the pixels' membership to clusters in a way that postpones decision making about hard pixels' membership to latter stages. Therefore this allows retaining more information from the original image compared to hard clustering methods.

FCM clustering is based on minimizing an objective function and is simple to implement and use for segmentation. However, the FCM algorithm is sensitive to initial states and gets stuck in local optima solutions. To solve the problem of local optima solutions several authors (Bezdek, 1981; Barni *et al.*, 1996; Pal *et al.*, 1997; Berry, 2003; Lung, 2005) have used a Fuzzy Possibilistic C-Means (FPCM) clustering algorithm which is a hybrid algorithm that combined the characteristics of both fuzzy and Possibilistic C-Means (PCM) algorithm (Fayyad *et al.*, 1996). This algorithm while successfully solving the problem of local optima solutions, still has to be improved when used with color image segmentation. To solve this problem, Saad and Alimi (2009), proposed a modified version of FPCM by modifying its objective function, in order to make the algorithm more suitable for image segmentation. This algorithm was termed as MFPCM.

However, both FPCM and MFPCM still were sensitive to the initial cluster centroid values. Through this improper selection, it may lead to fall local minimum value. Due to local minimum pixels FPCM is unable to segment the defected regions accurately. In order to address these issues, many fuzzy clustering algorithms based on bio-inspired methods have been introduced. The natural and intelligent behavior of biological systems, the characteristics of living organisms, their processes and behaviors evolved over thousands of years, such as self-organization, mechanisms of survival and adaptation have inspired most of the existing stochastic search heuristics. The main idea is to generate a population of candidate solutions to an optimization problem, which is iteratively optimized according to a bio-inspired dynamics in order to find better-quality solutions. Candidate solutions are selected using the fitness function, which measures their quality with respect to the optimization problem. Several algorithms including the usage of Genetic Algorithms (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Differential Evolution (DE) and Artificial Bees Colony (ABC) algorithm have been proposed in this field (Ouadfel and Meshoul, 2012).

Motivated by the ability of bio-inspired optimization techniques compared to analytical methods to cope with local optima by maintaining and evolving several candidate solutions simultaneously, several researchers have applied them to perform fuzzy clustering of data. Within this issue, several population based algorithms have been proposed to be used with FCM algorithms. Examples include GA (Bezdek and Hathaway, 1994), ACO (Liu, 2010), PSO (Szabo *et al.*, 2011; Sivaraman *et al.*, 2011; Li *et al.*, 2012), DE (Das *et al.*, 2008; Maulik and Saha, 2010), ABC (Taherdangkoo *et al.*, 2010; Zhang *et al.*, 2011) among others. Most of these algorithms have been applied to improve the performance of the conventional FCM algorithm.

This research work, in order to improve the performance of the MFPCM algorithm, Artificial Bee-Colony (ABC) (Dongli, 2012) optimization technique is used. The ABC algorithm is first used to obtain the initial centroids which are later used by MFPCM algorithm to group similar pixels in the mango fruit image. The detailed description of the proposed algorithm is presented in Chapter 4, Segmentation Algorithm and the results obtained during performance evaluation are presented in Chapter 7, Results and Discussion.

3.2.4. Phase III: Feature Extraction

Feature Extraction is a procedure that extracts salient characteristics from the input image to form a pattern vector that can be used effectively for analysis. This research work, extracts two groups of features from a mango image. They are (i) Color features and (ii) Texture features.

Color features are extracted using color histograms. The histogram creates 9 bins, where each bin defines a small range of pixel values. The value stored in each bin is the number of pixels in the image that are within the range. These ranges represent different levels of intensity for each RGB component. The values in each bin are normalized to 0-1. The constructed histogram is then used to construct the color feature vector.

Texture feature vector is constructed using GLCM (Gray Level Co-Occurrence Matrix) features. A total of eight features are used to construct the texture feature vector. They are, mean, standard deviation, energy, entropy, homogeneity, correlation, contrast and coarseness. In order to improve the performance defect detection, the research work proposes the use of combined color and texture features. Detailed description on these feature extraction techniques are presented in Chapter 6 (Feature Extraction and Defect

Detection). The effect of these features on defect detection is presented in Chapter 7 (Results and Discussion).

3.2.5. Phase IV: Defect Detection

The last phase of the study uses the above created feature vectors to design and build classifiers that can group mango images as either defective or defect-free. In general, to model human classification of human experts during defect detection, several classifiers have been proposed. Examples include BackPropagation Neural Network (BPNN), K-Nearest Neighbour (KNN) and Support Vector Machine (SVM). Among the various available classifiers, SVM is most popular used because of its efficiency in classification. Recently, the usage of another classifier, called Relevance Vector Machine (RVM) classifier is also used in place of SVM.

The SVM (El-Naqa, 2002) is a state-of the-art maximum margin algorithm based on statistical learning theory. SVMs have an intuitive geometrical interpretation, they classify by maximizing the margin separating both classes while minimizing the classification error. The RVM (Tashk, 2007), on the other hand, is a probabilistic Bayesian classifier. It optimizes the expansion coefficients of a SV-style decision function using a hyperprior which favours sparse solutions.

It has been proven by several researchers that the performance of RVM is better than SVM during classification (Bowd *et al.*, 2005; Xiang-min *et al.*, 2007; Rafi and Shaikh, 2013). Owing to these successful reported results, this research enhances RVM for defect detection. The RVM classifier requires parameters to be randomly generated, where incorrect initialization of parameters might lead to non-optimal values, which in turn might decrease the classification performance. To solve this issue, Simulated Annealing (SA) optimization is used to fine tune the parameters values. These optimized values are then used to train the RVM for defect detection in mango fruits. The working of this algorithm, termed as SA-RVM in this research work, is described in Chapter 6 (Feature Extraction and Defect Detection). The advantages obtained by the proposed classifier over SVM and RVM are presented in Chapter 7 (Results and Discussion).

3.3. RESEARCH CONTRIBUTIONS

The main aim of the research work is to design and develop an automatic defect detection system for mango fruits. External skin defects, namely, bruises, russet, blemish and shrink on four types of mangoes, namely, Alphonso, Banganapalli, Neelam and Sendura, were analyzed. The methodology combines and enhances various image processing and classification algorithms and the contributions made in each step are presented in this section. The research work combines each of the enhanced algorithm from each phase and combines them to form a ADDS for mango fruit.

Mango fruit images are often corrupted by the presence of impulse noise. The enhancement phase (Phase I), proposes techniques to remove / suppress this noise from mango image. For this purpose, a denoising algorithm that enhances switching median filter is proposed. The enhancement is brought forward by the inclusion of Adaptive fuzziness and Particle Swarm Optimization.

In order to improve the classification process, the segmentation algorithm is used to group similar pixels into clusters. For this purpose, a clustering-based segmentation algorithm is proposed. This algorithm enhances Fuzzy C-Means algorithm for this purpose. The enhancement operations include the usage of a more advanced Modified Fuzzy Possibilistic C-Means algorithm which is optimized through the use of Artificial Bee-Colony algorithm for automatic initial centroid selection.

Feature extraction is performed to extract two categories of features, namely, color feature and texture feature. The research work, in order to improve the accuracy of the classifier, proposes the use of combined color and texture features.

In the fourth phase of the study, the use of machine classifiers to detect the different type of skin or surface defects in mango fruits is proposed. For this purpose, a Relevance Vector Machine is enhanced to use Simulated Annealing algorithm to estimate optimal parameters automatically.

3.4. CHAPTER SUMMARY

Computer vision has the potential to become an essential component of automated food processing operations to increase the computer capabilities and the defect detection accuracy result. The analysis can be used to obtain valuable insight and can be used to detect the defects in the mangoes. This research work focuses on the development of mango fruit defect detection algorithms that can help machine vision for quality inspection. This chapter provided an insight to the various algorithms that are to be used to implement the proposed AESDDM. The next chapter (Chapter 4 – Preprocessing Algorithm), presents a detailed description of the denoising algorithm used to enhance the visual quality of mango image.