Wood Defects Detection by Using Texture Analysis

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January, 2017

Declaration

I certify that this research work titled "*Wood Defects Detection by using Texture Analysis"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged / referred.

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2014-NUST-MS-Mts-082

Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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(Supervisor)

Copyright Statement

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Abstract

Machine vision based inspection system are in great focus nowadays for quality control applications. The proposed work presents a novel approach for classification of wood knot defects for an automated inspection. The proposed technique utilizes gray level co-occurrence matrix and laws texture energy measures as texture feature extractors and feedforward back propagation neural network as classifier. The proposed work involves the comparison of gray level co-occurrence matrix based features with laws texture energy measures based features. Firstly it takes contrast, correlation, energy and homogeneity as input parameters to a feedforward back propagation neural network to predict wood defects and then it take energy calculated from laws texture energy measures based energy maps as input feature to a feedforward back propagation neural network.

The mean squared error (MSE) for training data is found to be 0.0718 and 90.5 % overall average classification accuracy is achieved when laws texture energy measures based features are used as input to the neural network as compared to gray level co-occurrence matrix based input features where MSE for training data is found to be 0.10728 and 84.3 % overall average classification accuracy is achieved. The proposed technique shows promising results to classify wood defects using a feed forward back propagation neural network.

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CHAPTER – 1

INTRODUCTION

This chapter presents an introduction to wood defects and wood defects detection using various methods with focusing on research methodology, motivation lying behind the thesis and importance of wood industry.

1.1 Overview

Wood industry plays a vital role in the overall economy of the country. The importance of wood in many aspects of our lives is out weighed by no other single material. Wooden furniture makes up for 77 percent of the revenue generated by the furniture business the world over, which is estimated to be around US$23.2 billion. Pakistan contributes a meagre US$12 million to this, despite boasting of a long history of innovation in the domain. The local market is hugely dependent on wooden furniture, which grosses 95 percent of the total revenue. The most prominent centers for furniture work in Pakistan are Chiniot, Gujrat, Peshawar, Lahore and Karachi. Karachi is the leading exporter among cities followed by Lahore and Peshawar. The future prospects for the business paint a gloomy picture, with exporters encountering various problems while local business takes a beating from heavy imports of furniture. A look at the world leaders in furniture shows that Europe dominates the industry, with Italy being the largest exporter of furniture closely followed by Germany and Canada [1]. As far as wooden furniture is concerned, United States bags the number one spot with Germany and France filling the other two in the top three. Wood plays a vital role in the manufacturing of a host of utilities, furniture, musical instruments, sporting equipment, and household utensils to name a few [2]. It is hard to imagine what our quality of life would be without this resource. It comes second to none in terms of beauty and allure. It's a documented fact that the presence of wooden articles helps lower heart rate, soothes people and helps in sociable behavior [3]. A number of factors determine the quality of wooden products, professionalism in the handling of raw materials, production techniques and manufacturing process being the prominent ones. To help prevent a decline in quality, proper skill training, industry wide production standards and strict agency inspections need to be promoted [4].

There are different classes of wood defect including knots, shake, stains, worm holes, resin Pocket, splits and cracks. In order to curtail damage to the overall structure, timely identification of source of the defect and its nature is paramount. Only through this can a workable solution be found. Quality of wood cannot be stressed enough, a structure with knots or cracks is susceptible to being unstable. With inconsistent strength, the chances of breakage due to critical weight rise [5].

1.2 Motivation

Wood defects, of any type, can hamper the strength of the wood decreasing the quality of the wooden article in the process. Additionally, defect can also have adverse effects on the paint coat done on the article, hence affecting the outward appearance negatively. Important wood plate characteristics such as elasticity and stiffness are also impacted.

Over the years, a number of techniques have been put forth by several researchers to identify defects in wood. Generally, wood defects are identified by manual inspection. This process in addition to being slow does not also ensure error free results. This renders the quality control process less credible. On the other hand, machine vision based inspection system have gained a lot of attention due to their ability to curtail time and by providing timely detection and enhancing quality check measures.

1.3 Research Methodology

To detect different kind of knot defects present in wood a new machine vision based technique is proposed. The proposed technique is based on features extraction and feature classification methods. The technique utilizes gray level co-occurrence matric (GLCM) and laws texture energy measures (LTEM) for texture feature extraction. Laws texture energy measures has never been applied for texture features extraction of wood. Feed forward neural network trained by back propagation is used as classifier.

1.4 Thesis Organization

The thesis is organized in following sections. Chapter 2 presents the previous work related to wood defects detection techniques and feature extraction and classification methods. Chapter 3 explains the theory behind the chosen methods while chapter 4 and chapter 5 explain the experimental setup and data acquisition, and the results and detailed discussion respectively. Chapter 6 discusses the challenges related to implementation of the proposed technique and Chapter 7 discusses conclusion and the future work.

1.5 Summary

This chapter describes

- Manufacturing sector has a major share in country's economy and it needs to improve its productivity. Many problems were faced by local manufacturers due to different defects in wood that leads to production loss of quality wooden products. Therefore, there is a need of predictive detection of defects.
- Different types of methods are used to detect different defects in wood; direct methods and indirect methods. Direct methods involves visual inspection which is a very slow process, therefore, indirect methods involving different machine vision based techniques are usually preferred in the regard. Various indirect methods have been proposed by researchers.
- Texture analysis is an important concept in detection of wood defects. Laws texture energy measure were employed as texture feature extraction technique and feed forward back propagation neural network is used for classification.

CHAPTER – 2

LITERATURE REVIEW

This chapter provides a discussion on various methods that have been used to detect different wood defects. A review of different texture feature extraction techniques for detection of wood defects is also provided in the chapter. Various techniques used for the classification are also explained. Lastly, a discussion on laws texture energy measures as feature extraction method is also included in the chapter.

2.1 TECHNIQUES IN WOOD DEFECTS DETECTION

Different techniques have been proposed by different researchers to detect different defects in wood including knots, shake, stains, worm holes, resin Pocket, splits and cracks. These techniques can generally be divided into two categories, direct methods and indirect methods. Direct methods involves visual inspection which is a very slow process, moreover this method is labour intensive and does not ensure accurate detection.

In direct methods, vision based systems are in use to detect wood defects. There are many advantages of these systems.

1. There is no physical contact of the system with the work-piece.
2. The system cannot be affected by fatigue as visual inspection is minimal.
3. The system provides 2D information about the process.
4. Results are more feasibly interpreted and data trends are followed which leads to more accurate and timely prediction of defects.
5. The system is more flexible and cost effective
6. Effective allocation of resources in other areas leading to more productivity.
7. Service is improved by using machine vision based systems leading to more effective long term planning.

Zhang et al. [7] proposed wood surface detection by using a computer vision based technique. His experimental setup consists of a mechanical system which was divided into four sections. The first section is for image acquisition of wood surface. Images were processed and analyzed by using control system. Processed parts of wood plates were exposed by transmission system. Results were executed by pneumetic system. The complete experimental setup is shown in Figure 2.1.

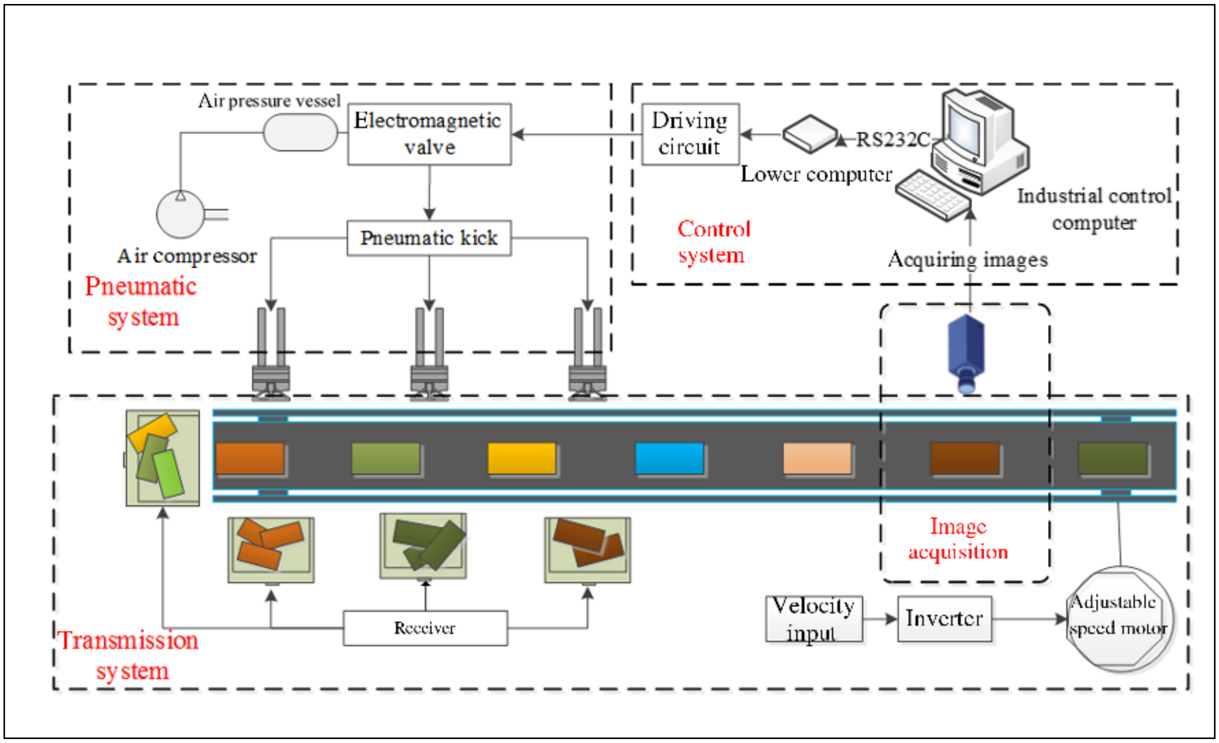

Figure 2.1: Experimental Setup for wood surface defects detection [7]

He developed a method in which three-leveled, dual-tree complex wavelet transformation was applied on the image in order to extract corresponding feature parameters and detect different defects like live knot, worm hole and dead knot. Feature selection was done by using particle swarm algorithm and in the end a feature classifier was developed by using compressed sensing. Accuracy achieved for classification was achieved 94.7 %. A review of another technique for wood defects detection is given in [8]. Longuetaud et al. [8] developed a new algorithm for the automatic and non-destructive extraction of knots in trees. CT images of wood were used for experimentation. Knots are detected in 3D moreover the algorithm also gave measurements for knot diameter as it involves the use of 3D distance transform and 3D connex components. Detection rate of 85 % was achieved by using the algorithm.

Ruz et al. [9] classify wood defects by using automated visual inspection system (AVI). The work involves the segmentation of images by using fuzzy min-max neural network. The segmentation of images for detecting defects in wood involves different stages as shown in figure 2.2.

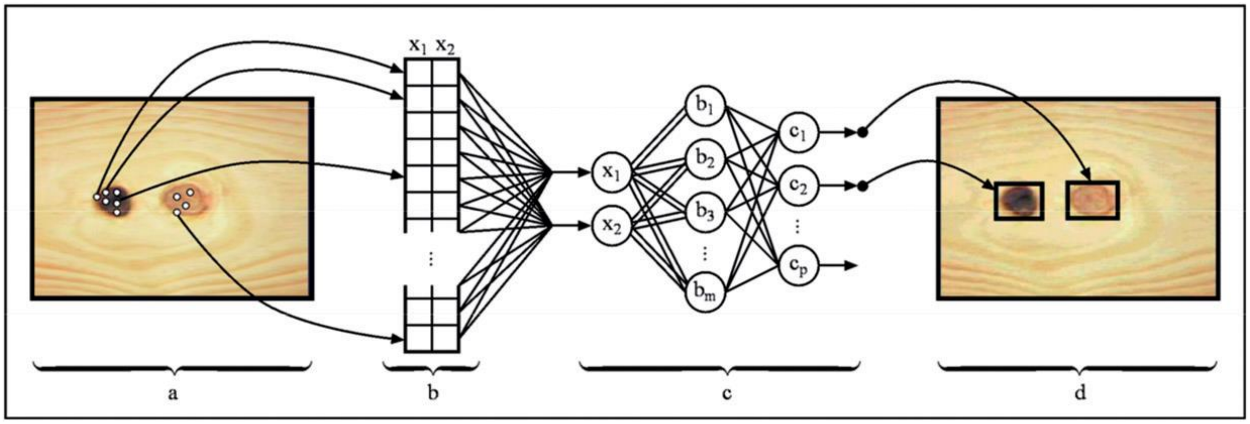

Figure 2.2: Stages for Method of Image Segmentation [9]

The stage (a) in figure 2.2 involves the method of seed selection for increasing the speed for the process of image segmentation, stage (b) is for selecting the input patterns which were then fed to fuzzy min-max neural network in stage (c) for image segmentation and in the end fuzzy min-max approach is used to draw a rectangle on each defect using the min and max points. Gray Level Co-occurrence Matrix (GLCM) was used for feature extraction and features like contrast, correlation, energy and homogeneity were calculated from gray scale images. Classification module includes the comparison of multilayer perceptron (MLP) neural network with multiclass support vector machine. Classification of defects was done by using Pairwise Support Vector Machine (SVM) which yield 91% classification accuracy. A new technique based on image processing was proposed by Yuce et al. [10]. He used integration of principal component analysis (PCA) and artificial neural network (ANN) to detect wood veneer defects. Feature selection was done by using image processing based methods. Preprocessing technique based on principal component analysis was used to select inputs for the artificial neural networks and back-propagation was used as learning method. Results were analyzed and the identification of best ANN configuration was done by Taguchi method. YongHua and JinCong [11] used image processing technique based on texture features to identify the defects in wood. He gathered 300 samples based on different wood defect images including live knot, dead knot and poles and then scanned these samples through scanner and present them in digitized form in the computer. The sample of his database is shown in figure 2.3.

(a) Samples of Dead knot (b) Samples of Poles (c) Samples of Live knot

Figure 2.3: Samples of wood defects [11]

Matlab was used to calculate features like contrast, linearity, coarseness, directionality and roughness based on tamura texture and contrast, entropy, variance and correlation based on glcm. Feature based on tamura texture and glcm were then used as input to Back Propagation neural network for classification of defects. The input features based on glcm show more promising results than the features based on tamura texture. The classification accuracy for input features of tamura texture and glcm was calculated by using equation 2.1

$$\text{Accuracy}\ (\%) = \frac{\text{Correctly classified samples}}{\text{The total number of test samples}} \times\ 100 \qquad (2.1)$$

The classification rate was 90.67 % when feature based on tamura texture were used as input to back propagation neural network, whereas the highest classification accuracy was found to be 91.33% when features based on gray level co-occurrence matrix was fed as an input to back propagation neural network.

Silven et al. [12] proposed a new approach for the inspection of wood. The method uses non-supervised clustering and relies on self-organizing map to detect and recognize the defects. This method uses a clustering method and samples were not labelled individualy. The block diagram for self-organizing map based classification is shown in figure 2.4.

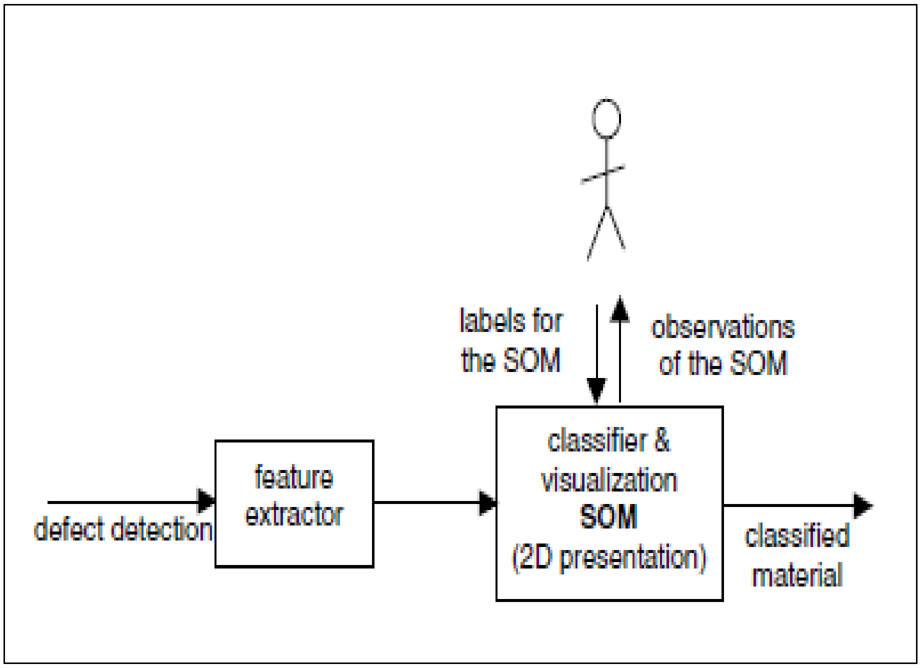

Figure 2.4: Classifier based on Self-organizing map [12]

Wang et al. [13] proposed wood defects detection based on wavelet neural network. An ultrasonic device was engaged for recognition and the analysis of internal wood defects by using wavelet transform and artificial neural network. He used 150 samples that were divided into different categories including defect free samples, single, double and triple hole samples moreover splits and knots based samples were also included. More than 90% accuracy was achieved for recognizing the different defects in wood. Moreover more than 80% accuracy is achieved when the position and size of hole defects in wood were tested.

Funck et al. [14] gave review of different algorithms for image segmentation that were applied to wood for detecting different defects. He used optical scanner to capture images of different defect types which includes knots, blue stain, clear wood and pitch pocket. Nine different algorithms based on thresholding, edge detection and region based algorithm were applied. Results that were obtained from different algorithms for detecting feature of wood surface were presented and performance of the algorithms was examined. Region based algorithm show better performance as compared to the other algorithms. A review of another technique based on image processing for wood defects detection is given in [15].

Todoroki et al. [15] used image processing for the detection of knots. He used a set of digital images of veneer sheet. Algorithm based on two phases was proposed by him for detection.

The first phase involves global thresholding that was utilized for image segmentation by using morphological operations to isolate knots. The second phase uses red component and grey scale segmented images and adaptive thresholding was applied on them for more enhanced segmented knots. The second phase involves different steps that were performed on both gray scale images and red component images separately. Steps applied on gray scale image for second phase are shown in figure 2.5 (a)-(i).

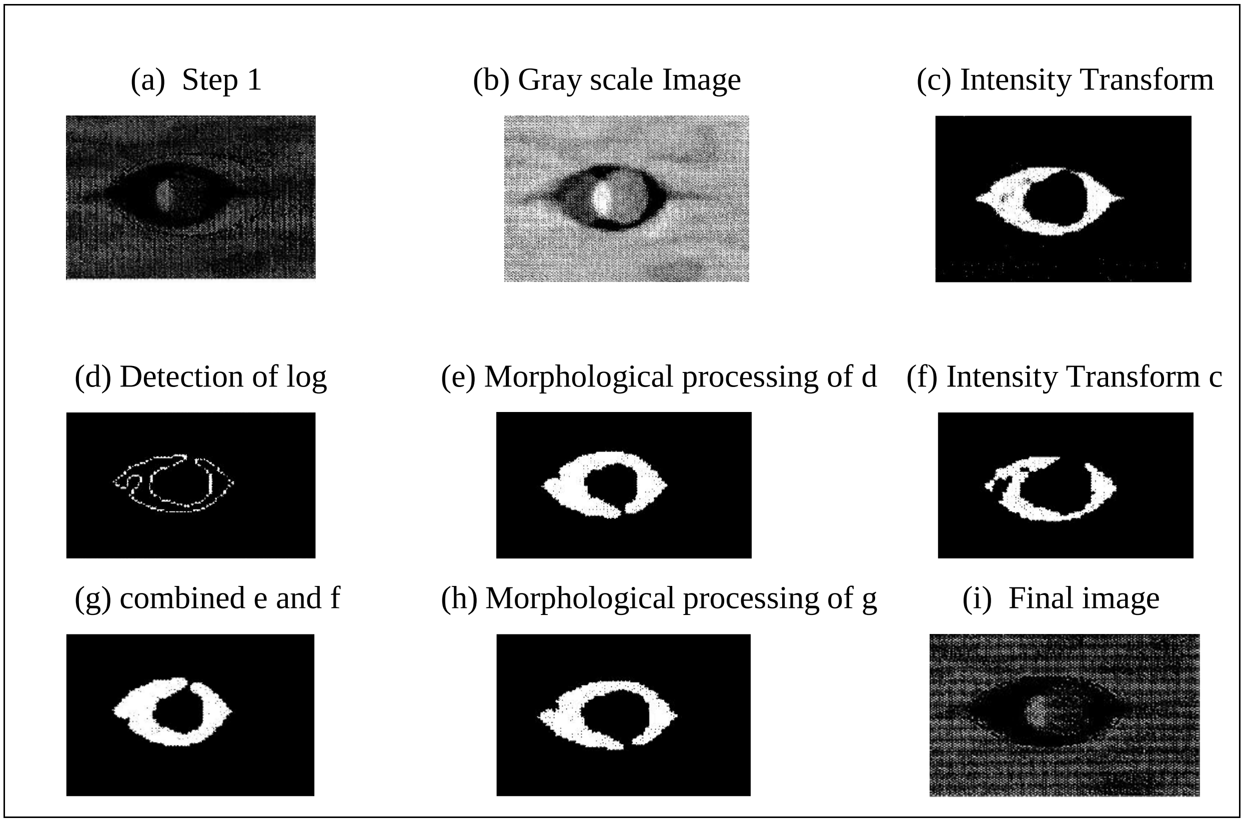

Figure 2.5: Steps applied on image for detection of knot [15]

Confusion matrix was used to test the performance by using different performance measures that includes precision, recall and accuracy. Red component images shows more accurate results than grey scale images. Conners et al. [16] developed automated inspection system for locating and identifying defects on wood surface. He used two stage sequential classifier in the first stage tonal measures including mean, skewness, variance and kurtosis based on co-occurrence matrix were used to separate samples containing defects from clear wood samples. The second stage uses texture measures including energy, entropy, and homogeneity in combination with tonal measures for pairwise classification. A review of a technique based on computed tomography images for wood defects detection is given in [17].

Sarigul et al. [17] used computed tomography images to identify defects like split, knot, bark, and decay in hardwood logs. Artificial neural network was used as classifier which classify CT images by giving pixel by pixel identification of defects. Labels were assigned to pixels in CT image by artificial neural network. Morphological operations were applied on these labeled images as a post processing technique. The overview of the proposed technique is shown in figure 2.6.

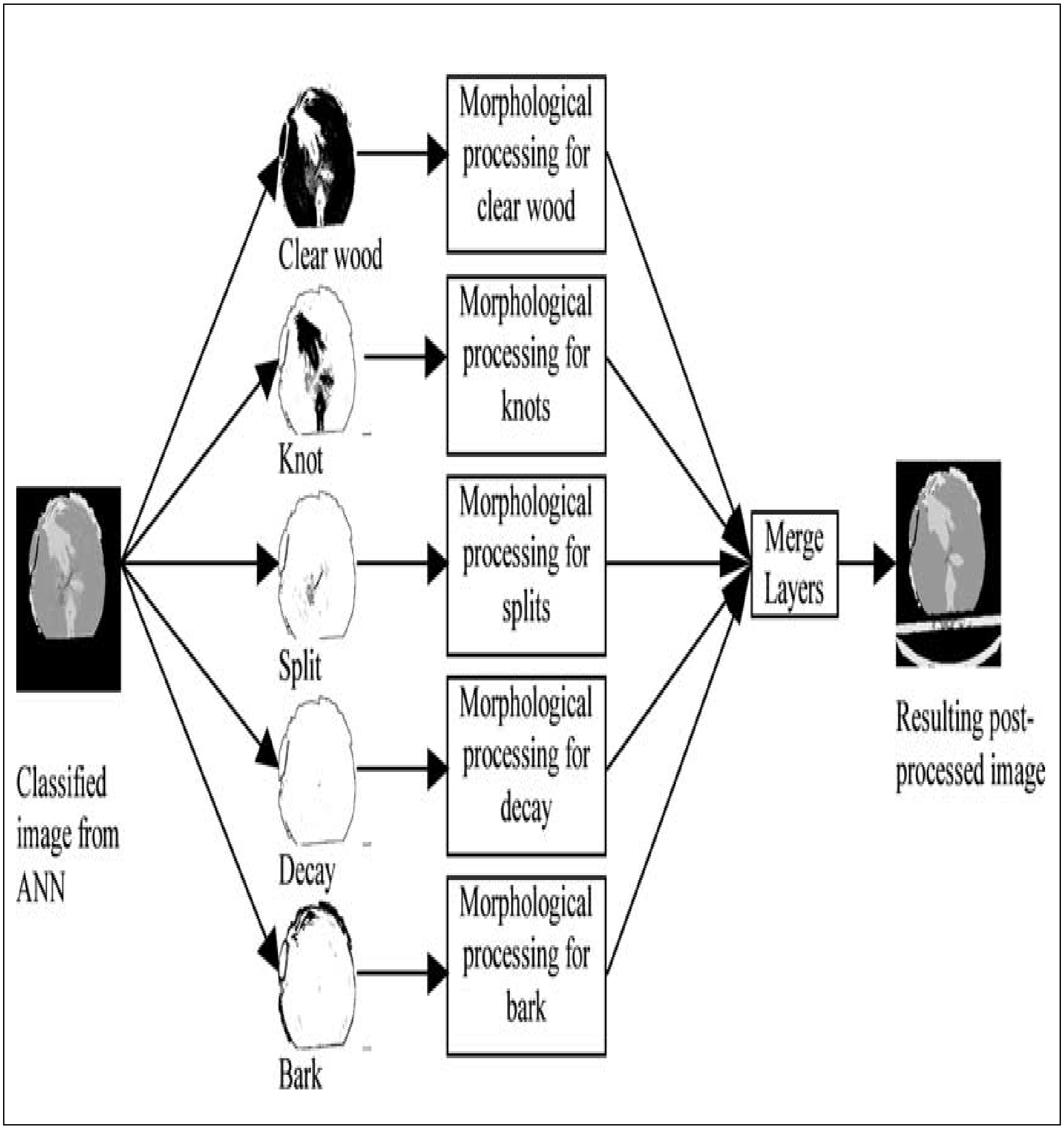

Figure 2.6: Morphological operation overview [17]

Kim and Koivo [18] proposed image processing based approach for the classification of defects that were present on the surface of dusty wood boards. Firstly thresholding was applied on the image data and then other techniques were applied on that thresholded images which were shrinking and expanding in order to get more enhanced defect regions after that image data is divided into two regions that were dark and bright. Example of the preprocessing technique is shown in figure 2.7.

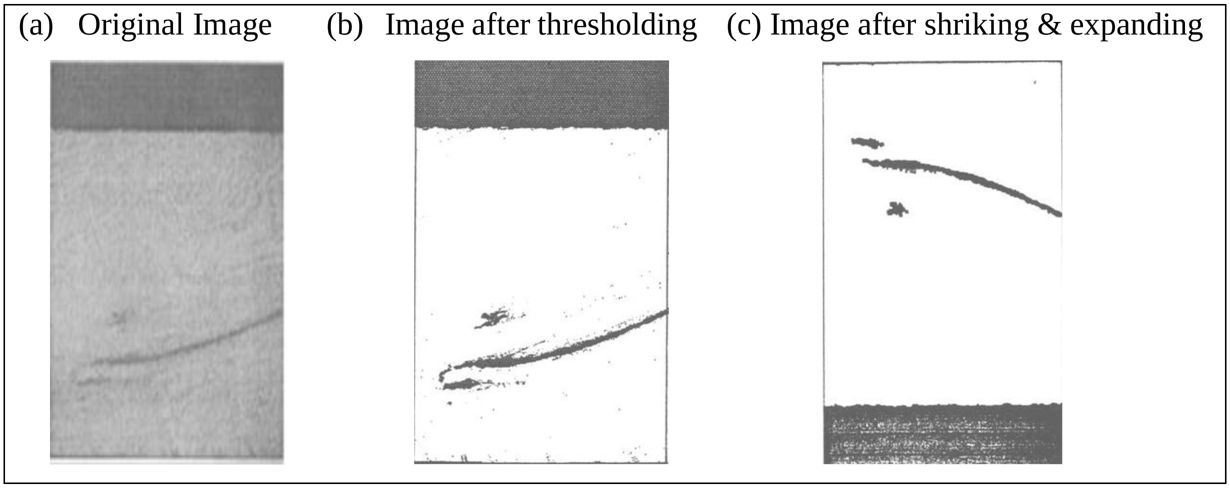

Figure 2.7: Preprocessing method example [18]

The priori knowledge about the defect location was used to identify the dark region whereas texture features that are mean and variance were used to classify bright regions by using Bayesian classifier. Baradit et al. [19] developed a microwave system for knot detection in wood. Microwave emitter and receiver was used in his experimental design which is used for scanning the knots in wood samples. Graphic visualization was performed by calibrating signals in the end results were viewed in 2-D and 3-D.

Ruz and Estévez [20] proposed a technique based on neural networks to detect wood defects called fuzzy min-max neural network for image segmentation. The proposed work included image segmentation process based on the fuzzy min-max neural networks. The method uses seed pixels in wood defect images to create bounded rectangles around the defects. The segmentation of wood board images were used which contained 10 defect types to evaluate the performance of Fuzzy Min Max neural network for Image Segmentation method. Detection rate of 95 % for defects was achieved by using this method whereas the false positive rate was as low as 6 %. Another review of technique for wood defect detection using image processing is given in [21]

Cavalin et al. [21] proposed a robust algorithm in order to detect wood defect. He used a database which contains 500 sample images containing different defect categories. Sample images from the database used are shown in figure 2.8. Monochromatic sensors were used instead of color sensors to achieve cost effectiveness and to built a feature set that includes gray scale images.

Figure 2.8: Database of wood containing knot defects [21]

Feature extraction was done by using gray level co-occurrence matrix (GLCM) and entropy, correlation, energy and contrast were extracted from gray scale images. Genetic algorithm were used for feature selection. Support Vector Machines (SVM) and neural networks trained by multi layer perceptron were used as a learning models and in the end the performance of both algorithms by using gray scale based features and color based features was compared.

Niskanen et al. [22] proposed a Self-Organizing Map (SOM) based approach that depends on non-supervised training as a solution to the limitations in detection of defects of lumber boards. He used a two phase methodology for defect detection that involves detection of defective region in the first phase and examination of defects in the second phase. Boundaries were manually drawn to differentiate between defective and sound wood. Selection of boundaries was based on optimistic and pessimistic conditions as shown in figure 2.9. Pessimistic selection procedure gives more information about defect and its background thus gives more improved classification results when SOM based classifier was used.

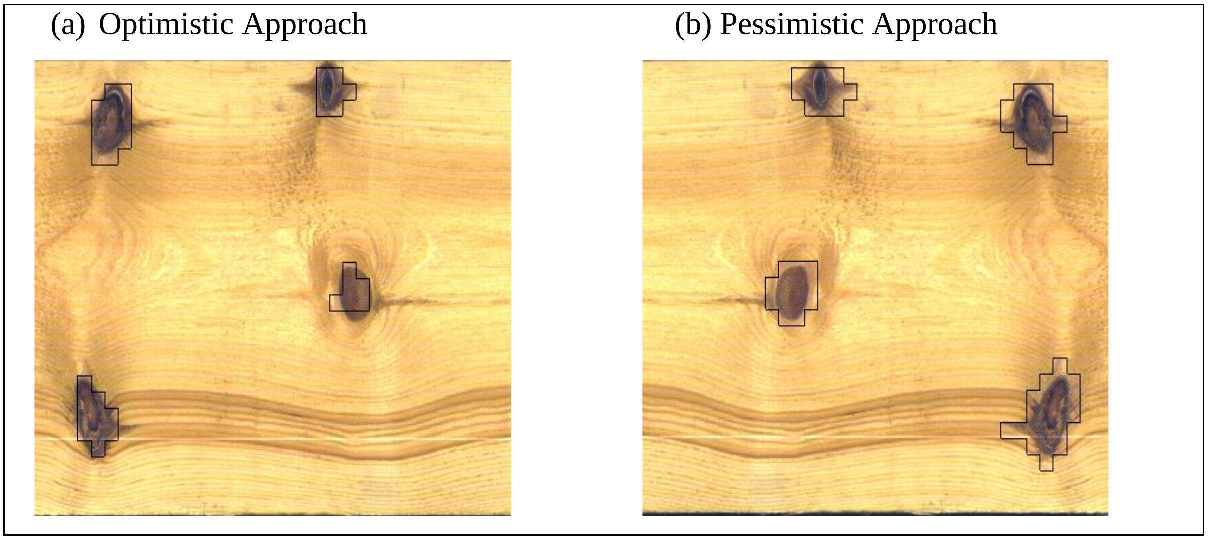

Figure 2.9: Boundary selection Procedures [22]

A new technique based on color wood images was proposed in [23]. Zhang et al. [23] used Local Binary Pattern (LBP) and Dual-Tree Complex Wavelet Transform (DTCWT) for the extraction of features to locate the wood defects and named them United Statistical Features by Local Binary Pattern & Dual-Tree Complex Wavelet Transform (USF-LDT). Support vector machine based classifier was used for classification.

Shahnorbanun et al. [24] proposed classification of wood defects by using a spiking learning vector quantization network. Supervised learning vector quantization algorithm was used to trained (s-lvq) network. Spiking neurons were used instead of common neurons as a processing elements in this network. Seventeen features were used to train supervised learning vector quantization algorithm, the features used as an input were extracted from wood images. The proposed algorithm (s-lvq) gives an accuracy of 89.6 % with less number of iteration when compared with learning vector quantization algorithm which gives an accuracy of 97.8% with greater number of iterations.

Another technique put forth by França and Gonzaga [25] that utilizes two neural networks that work on one input feature enhanced the classification of wood plates. So much so that the proposed system was considered to be more adept at categorizing wood plates once the outcome of the neural network was put together with a fuzzy logic for the purpose of feature extraction and eventual classification of wood plates. The inspection system proposed consist of five parts as shown in figure 2.10.

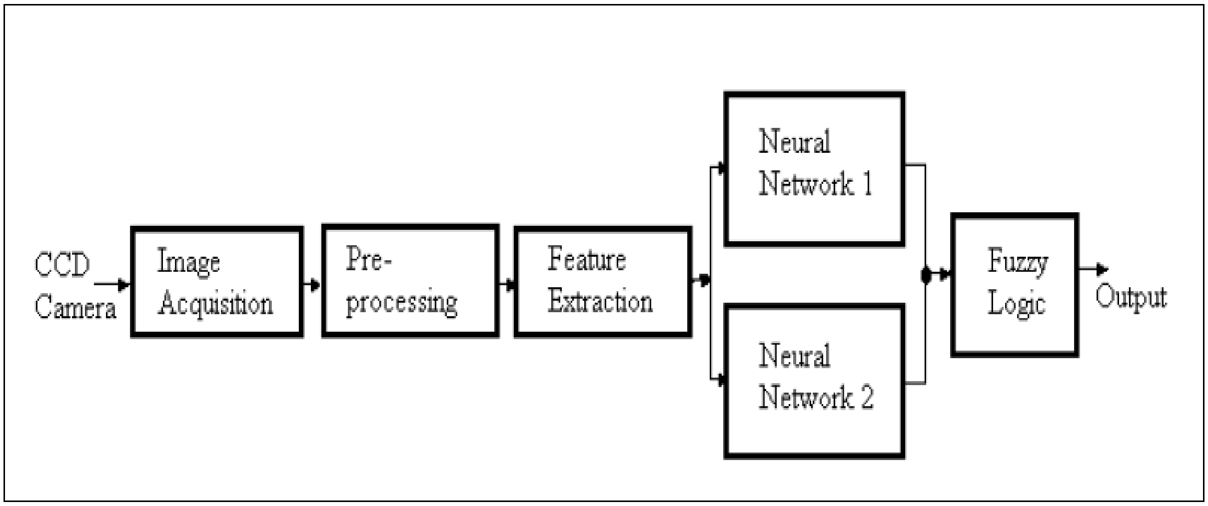

Figure 2.10: Inspection system for wood plates [25]

CCD camera was used for image acquisition and then iterative selection was used as pre-processing technique to get more enhanced images. Features like mean, entropy and variance were calculated. The features are fed as input to the neural network named multi-layer perceptron neural networks trained by algorithm which is back propagation in the end fuzzy logic is used to analyze the output of the neural network and give final classification. The classification range varies from 63.81 % to 66.33 % for first neural network and 63.81 % to 67.33 % for second neural network with both neural networks adopting one feature as input.

Mahram et al. [26] used machine vision based technique to detect and classify defects in wood. The proposed method involves feature extraction by using gray level co-occurrence matrix, statistical moment functions and local binary systems together and feature reduction was done by using principal component analysis and linear discriminant analysis. Classification was done by using support vector machine classifier and k-nearest neighbor based classifier. Wood database containing different wood defects was used in his experimentation.

T. Zafar et al. [27] proposed a PSO trained neural network for heath monitoring of tool for a wood milling process using acoustic emission. An unsupervised technique based on neural networks for detection of different defects in wood was proposed in [28].

Kauppinen et al. [28] used a non-segmenting approach for defects detection in which classification of defects is done by using self-organizing maps (SOM).The technique relies on visual inspection, proposed methodology is shown in figure 2.11.

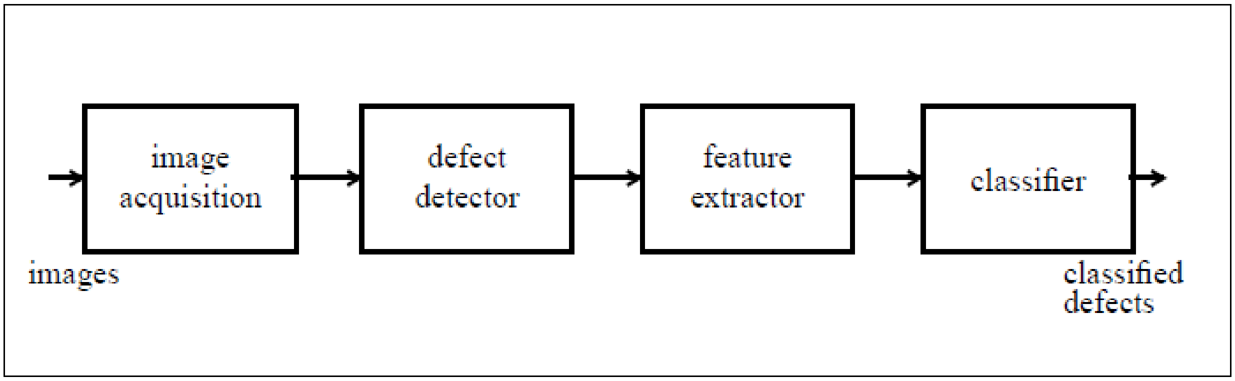

Figure 2.11: Block diagram for defects classification [28]

Combination of non-segmenting with segmenting method was used in proposed inspection. Defect areas were detected by using non-segmenting method that relies on RGB camera & segmentable defects were located by using segmenting method. Segmenting method was also compared with non-segmenting method. Image is restricted to meaningful portion in case of segmenting method by using different techniques which includes thresholding and split merge. Example of wood defect detection by using a thresholding based segmenting method is shown in Fig 2.12.

Figure 2.12: Segmenting method for defect detection [28]

Non-segmenting method [28] does not restrict the image to concerned portions thus more information is provided by the non-segmenting method. Example of non-segmenting method for detection of defects in wood is shown in figure 2.13.

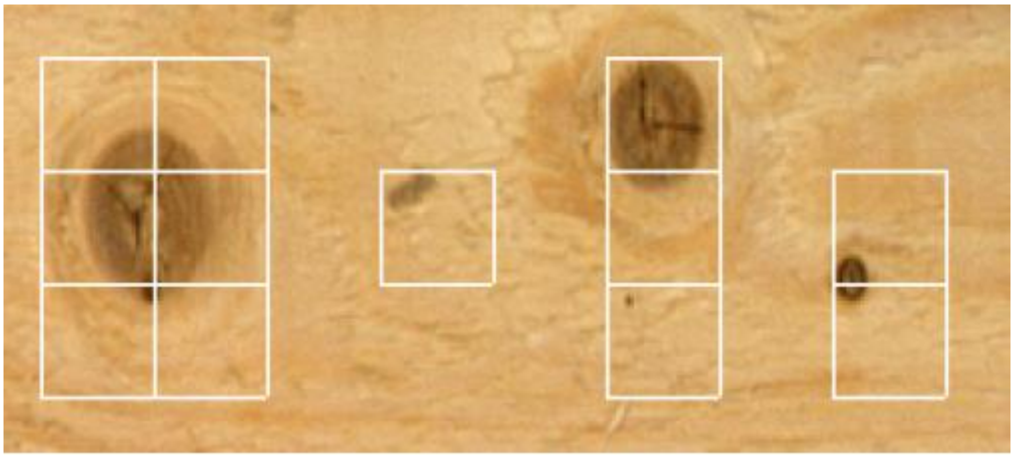

Figure 2.13: Non-segmenting method for defect detection [28]

The proposed method [28] used feature extraction based on color histogram and an unsupervised classifier based on self-organizing maps was used for classification. Self-organizing maps does not need individual sample labels for classification. Wang et al. [29] proposed recognition of Wood Texture by using Gray Level Co-occurrence matrix features and then applied Back Propagation (BP) Neural network for classification. He used 100 sample images for each kind of wood that are ash, red pine, oak, larch and birch for experimentation. Seven glcm based features extracted from sample images of different wood types were used as input features for back propagation based classifier. 90.25 % recognition rate was achieved by using neural network trained by back propagation algorithm.

Mohan et al. [30] proposed classification of wood defects by using hybrid optimization. He used a dataset of 400 images containing different knot defects for experimentation. The Proposed work involves feature extraction by using Hilbert transform and feature reduction by Gabor filter and in the end different types of neural networks and naïve bayes were used as classifier for defects classification. The types of neural networks used for classification include multi-layer perceptron neural network and neural network trained by particle swarm optimization (PSONN). Classification accuracy of 79 % was achieved by using naïve bayes classifier, 86 % for multi-layer perceptron (MLP) neural network and 91 % classification accuracy was achieved from neural network trained by particle swarm optimization algorithm. Another image processing based wood defects detection was proposed in [31].

Mu and Qi [31] developed a technique in which recognition of patterns of different defects of wood is proposed. Testing system which was non-destructive used to collect X-ray images of three wood defects which were rot, knot and grub-hole. Image processing operation were applied on the images before feature extraction as shown in figure 2.14.

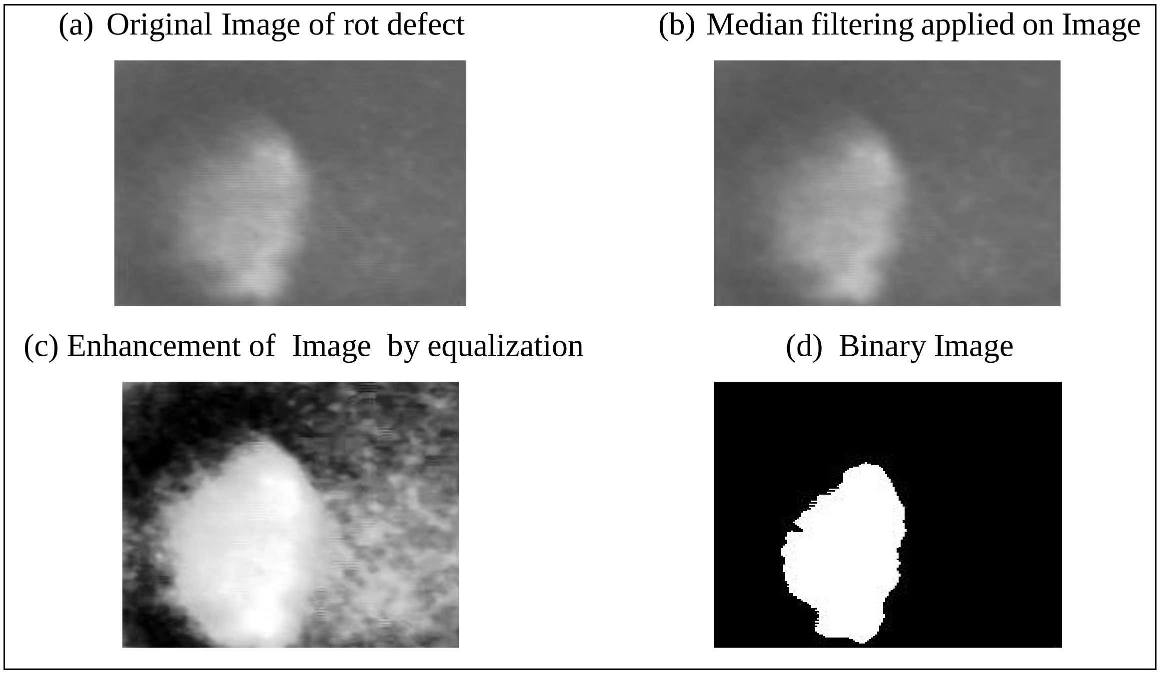

Figure 2.14: Image processing methods applied on X-ray image [31]

Processed images obtained were used to extract features using hu invariant moments because of the fact that hu invariant moment based features have low computational complexity. The features extracted were fed to neural network as input. Training of neural network was done by using back propagation method. 86 % recognition rate was achieved for different wood defects by this method.

Radovan et al. [32] improved the classification of wood defects by developing a machine vision system in which automated inspection of wood boards is performed for the detection and classification of both biological and mechanical defects. The inspection methodology is shown in figure 2.15.

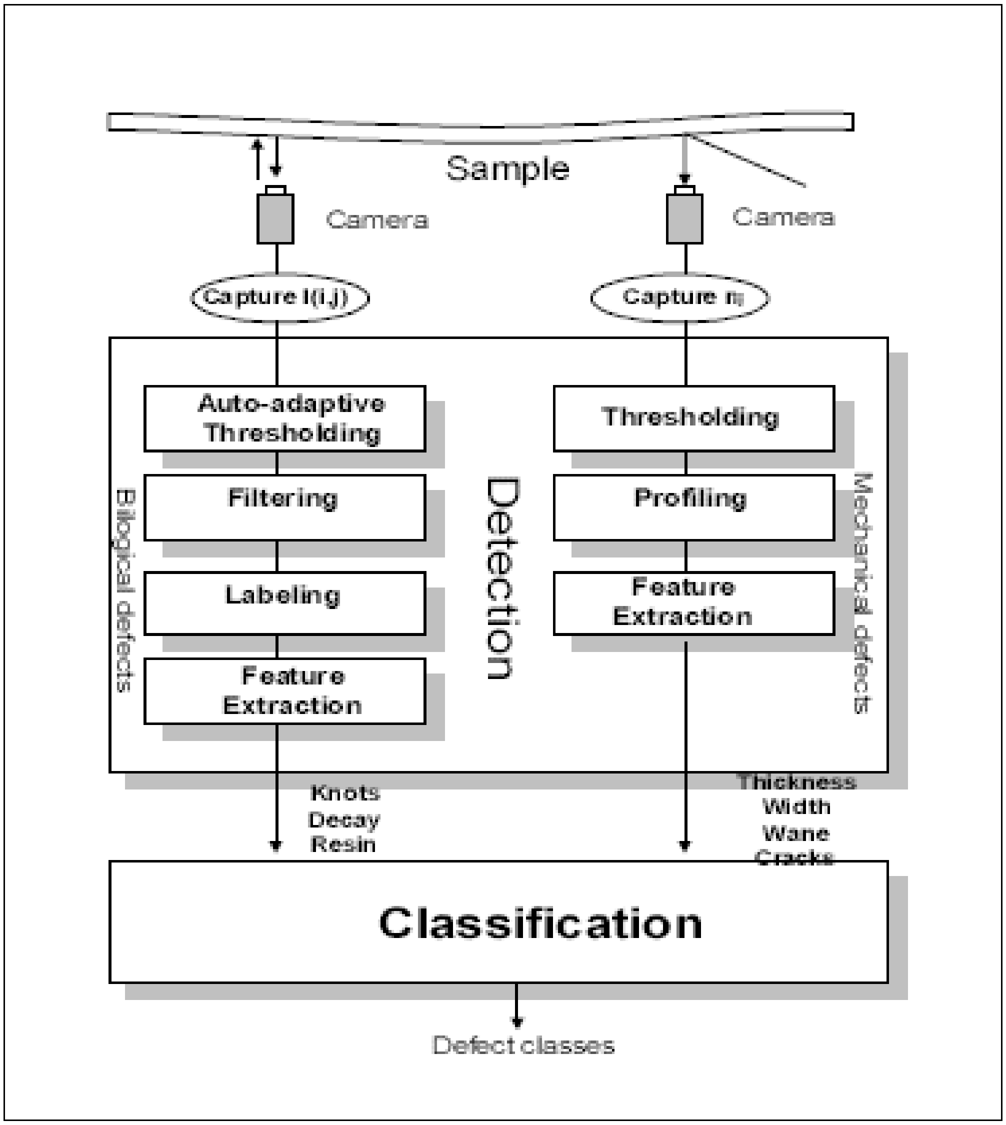

Figure 2.15: Steps for detection of biological and mechanical defects [32]

Parallel operation were performed for detection of both mechanical and biological defects. Processing of images was done by using series of operations as shown in figure 2.15. Fuzzy logic was used for classification of biological defects and rule-based approach was used for classification of mechanical defects. Another technique was proposed by yu and kamarthi [33] to detect wood defects using standard wood database available at university of oulu website. They used 2-D discrete wavelet transform for extraction of features. These features were used as input features by probalistic neural network and multi-layer perceptron neural network to predict wood defects.

Our Proposed work involved feature extraction by using gray level co-occurrence matrix and laws texture energy measures. Laws texture energy measure was never been applied on wood to extract features for wood defects classification. Different researcher had used laws texture energy measures as texture feature extractor in different areas. A review of a technique utilizing laws texture energy measures is given in [34].

Dheeba et al. [34] used laws texture energy measures for feature extraction. He proposed computer aided design (CAD) for the detection of abnormalities in breast. Computer aided design for abnormalities detection system is shown in figure 2.16. He used standard mammogram database images for experimentation which were digitized to higher resolution. Thresholding was applied to the digitized images as preprocessing technique in order to restrict the images to region of interest. Law's Texture Energy Measures was used for feature extraction. The LTEM features were used as an input to classifier for classification. The wavelet transform is used in combination with neural network for classification, the proposed classifier is wavelet neural network (WNN) whereas particle swarm optimization (PSO) was used to train the WNN. Accuracy of 93.67 % was achieved for classification.

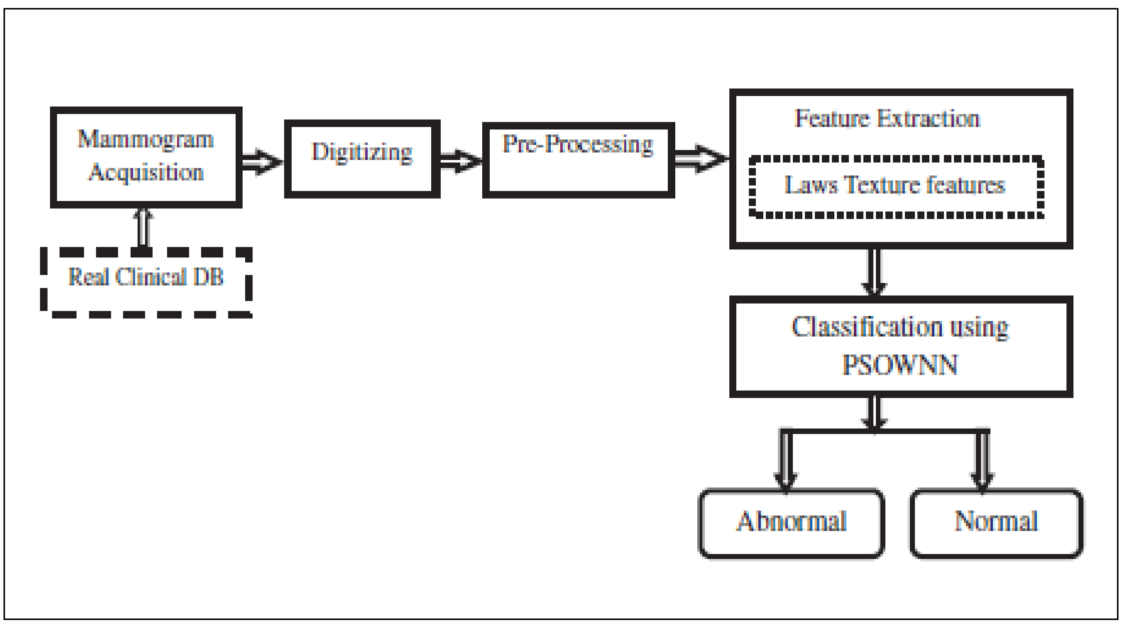

Figure 2.16: Computer aided design for abnormalities detection in breast [34]

Setiawan et al. [35] proposed mammogram classification in which texture feature extraction is done by using Law's Texture Energy Measures and Artificial Neural Network (ANN) is used for classification. He used a standard database from mammographic image analysis society consisting of 327 images. Firstly images were cropped to region of interest (ROI) then feature extraction was performed by using laws texture energy measures in the end a back-propagation neural network are used to classify images. Classification was performed in two steps by using two neural networks. Classification between normal and abnormal class was performed in first step and in the second step abnormal class was classified between benign and malignant class. Accuracy of 93.90 % was achieved by using laws texture energy measures (LTEM) for classification between normal and abnormal class whereas 83.30% accuracy was achieved by LTEM for classification between benign and malignant class. Comparison of laws texture energy measures and gray level co-occurrence matrix (GLCM) based classification was also performed. Accuracy of 72.20 % was shown for normal and abnormal class by GLCM whereas only 53.60 classification accuracy was achieved by using GlCM for benign-malignant class.

Elnemr [36] applied LTEM on lung CT images for their statistical analysis for cancer and water lung detection. Firstly the image contrast is enhanced by using Weiner filter and histogram equalization then Law's Texture Energy Measures is applied for texture feature extraction. Rachidi et al. [37] used Law's Texture Energy Measures for the texture analysis of Bones. He used radiographs obtained from X-ray device for experimentation. Firstly radiographs were used to restrict images to region of interest by using anatomical terminology secondly LTEM was applied to extract texture features. Another technique based on laws texture energy measures for features extraction was proposed in [38].

Valavanis et al. [38] used different texture feature extraction techniques including Laws texture energy measures for the texture analysis of hepatic tissue using computed tomography images. The texture features were used by neural network for classification. Back propagation was used to train the neural network. Wu et al. [39] used Laws texture energy measures for feature extraction of liver images.

Habib et al. [40] uses computer vision for inspection of defects in Ceramic tiles. The proposed technique utilizes Law's Texture Energy Measures (LTEM) for texture feature extraction and texture feature description in the end energy values of LTEM are used for classification of defects. Bama et al. [41] proposed inspection of steel products based on LTEM by using Scanning Electron Microscopy images. Firstly discrete wavelet Transform is applied on the training images then law's mask are applied on the resultant sub images so that better classification accuracy is achieved. Secondly law's masks are applied on testing images. Feature values of entropy, mean, skewness, standard deviation and kurtosis are extracted for both training and testing images in the end feature values of both set of images are used for assessment of accuracy.

2.2 THESIS AIMS AND OBJECTIVES

The scope of the research is quite broad, however, according to level of research and based on the literature review, the thesis aims and objectives can be defined as follows

I. To devise a technique based on texture analysis for wood defect detection
II. To classify different wood defects using a machine learning based approach
III. To develop a user friendly software interface for implementation and demonstration of the proposed technique.

2.3 Summary

This chapter describes

- Different techniques have been used by researchers for wood defects detection generally divided into two categories; direct methods and indirect method.
- Indirect methods involves machine vision based inspection systems which uses different feature extractors and feature classifiers for wood defects detection.
- Gray level co-occurrence matrix, tamura texture and Hilbert transform are the most widely used texture feature extraction methods for wood defects detection.
- Different supervised and unsupervised learning algorithms including neural networks and self-organizing maps have been used as classifiers for wood defects classification.

CHAPTER 3

TOOLS AND TECHNIQUES

This chapter explains the techniques used to fulfill the scopes of thesis as well as the background theory related to them. The Chapter is divided into two main sections; explaining the different paradigms of feature extraction techniques, and back propagation neural network.

3.1 FEATURE EXTRACTION TECHNIQUES

One of the most vital aspects of pattern analysis is feature extraction. Object characteristics range from confusion to coarseness and the like. At any given moment, classification relies more on these feature than uniformity of intensity as is the case with wood defects, which has varying degrees of distribution and types. The selection of features for classification is made even more difficult by fact that the extraction of texture characteristics of defects in their entirety is a remote possibility.

3.1.1 GRAY LEVEL CO-OCURENCE MATRIX

Texture analysis relies heavily on GLCM based features. Gray level intensities in an image determine the GLCM, which is then used to extrapolate statistical features. Co-occurrence matrix is a framework that illustrates how co-occurred values are distributed at a particular offset in an image. To illustrate this mathematically, the following equation 3.1 can be used: an n × m image I can be used to define a co-occurrence matrix C, given by an offset (Δx, Δy).

$$C_{\Delta x,\Delta y}\ (i,j) = \sum_{p=1}^{n} \sum_{q=1}^{m} \begin{cases} 1, if\ I(p,q) = i\ \ and\ I(p+\Delta \mathrm{x}, \mathrm{q}+\Delta \mathrm{y}) = \mathrm{j} \\ 0, otherwise \end{cases} \tag{3.1}$$

Image intensity for an Image I is illustrated by i and j, on the other hand p and q define the spatial position. The offset (Δx, Δy) relies on the distance and direction signified by d parameter, which is used for matrix computation.

Gray Level Co-occurrence Matrices (GLCM) was put forth by Haralick et.al. [42] in 1973 and stands to this date as the most prominent and earliest methods of texture feature extraction. According to Haralick, fourteen textural features measured from the probability matrix, can be used to extract characteristics of texture statistics of remote sensing images. Contrast, correlation, energy, homogeneity, sum entropy, difference entropy, local homogeneity, average, variance, inertia, cluster shade, cluster prominence are the statistical features that were extrapolated by making use of gray level co-occurrence matrices. Following notation was used for different statistical features as shown in table 3.1. Z is for gray level, λ is the mean value of Q, $\boldsymbol{\lambda}_x$ and $\boldsymbol{\lambda}_y$are means where S_x and S_y are standard deviations of Q_x and Q_y. Q_x(i) is the ith entry in the marginal-probability matrix obtained by summing the rows of Q(i, j).

Notations	Formulas
$Q_x(i)$	$\sum_{j=0}^{Z-1} Q(i,j)$
$Q_y(j)$	$\sum_{i=0}^{Z-1} Q(i,j)$
λ_x	$\sum_{i=0}^{Z-1} i\ Q_x(i)$
λ_y	$\sum_{j=0}^{Z-1} j\ Q_y(j)$
S_x^2	$\sum_{i=0}^{Z-1} (Q_x(i) - \lambda_x(i))^2$
S_y^2	$\sum_{j=0}^{Z-1} i\ (Q_y(j) - \lambda_y(j))^2$
$Q_{x+y}(k)$	$\sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1} Q(i,j)$
$Q_{x-y}(k)$	$\sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1} Q(i,j)$

Table 3.1: Notations for GLCM features [43]

Another term of Angular Second Moment is Uniformity or Energy. Angular Second Moment is defined as sum of squares of the entries in GLCM. Homogeneity of an image can be measured by using angular second moment.

Angular second moment can be mathematically defined by equation 3.2.

$$\text{Angular Second Moment} = \sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1}[\mathrm{Q(i,j)}]^2 \qquad (3.2)$$

Local homogeneity is reflected through Inverse Difference Moment (IDM). Uniformity in local gray level and spike in inverse GLCM cause a rise in IDM and can be mathematically expressed by equation 3.3.

$$\text{Inverse Difference Moment} = \sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1}\frac{1}{1+(i-j)^2}\mathrm{Q(i,j)} \qquad (3.3)$$

Entropy is the information required about the image for image compression. It gauges information loss or message transmitted through a signal, additionally; it also measures information about the image, whereas mathematical equation for entropy is given below by equation 3.4.

$$\text{Entropy} = -\sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1}\mathrm{Q(i,j)} \times \log[Q(\mathrm{i,j})] \qquad (3.4)$$

Correlation is a term used to express the measure to which gray levels of neighboring pixel are linearly dependent on each other. Digital Image Correlation, an optical method, uses image registration and tracking to accurately measure 2D and 3D changes in an image. The mathematical equation (3.5) for correlation is given below

$$\text{Correlation} = \sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1}\frac{[i\ \times \mathrm{j}] \times \mathrm{Q(i,j)} - [\lambda_x \times \lambda_y]}{\mathrm{S}_x \times \mathrm{S}_y} \qquad (3.5)$$

Contrast, 0 for a constant image, portrays the contrast of intensity between neighboring pixels in an image. Contrast is defined mathematically as by equation 3.6.

$$\text{Contrast} = \sum_{n=0}^{z-1} n^2\, [\sum_{i=1}^{Z}\sum_{J=1}^{Z}\mathrm{Q(i,j)}] \quad \text{where } |\,\mathrm{i} - \mathrm{j}\,| = \mathrm{n} \qquad (3.6)$$

GLCM variance performs the same function as variance. It makes use of the mean value and the deviation around the mean value of cell values in GLCM and mathematically given by equation 3.7.

$$\text{Variance} = \sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1}(\mathrm{i} - \lambda)\mathrm{Q(i,j)}^2 \qquad (3.7)$$

Similarly other important statistical features that are calculated by gray level co-occurrence matrices are shown mathematically in table 3.2.

Features	Formulas
Sum Average	$\sum_{j=0}^{2Z-2} \mathrm{i}\, \mathrm{Q}_{x+y}(i)$
Sum Entropy	$-\sum_{I=0}^{2Z-2} \mathrm{Q}_{x+y}(i) \log(\mathrm{Q}_{x+y}(i))$
Difference Entropy	$-\sum_{I=0}^{Z-1} \mathrm{Q}_{x+y}(i) \log(\mathrm{Q}_{x+y}(i))$
Inertia	$\sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1} (\mathrm{i}-\mathrm{j})^2 \times \mathrm{Q}(\mathrm{i},\mathrm{j})$
Cluster Shade	$\sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1} (\mathrm{i}+\mathrm{j} - \lambda_x - \lambda_y)\text{^}3 \times \mathrm{Q}(\mathrm{i},\mathrm{j})$
Cluster Prominance	$\sum_{i=0}^{Z-1}\sum_{J=0}^{Z-1} \left(\mathrm{i}+\mathrm{j} - \lambda_x - \lambda_y\right)^4 \times \mathrm{Q}(\mathrm{i},\mathrm{j})$

Table 3.2: GLCM Features [43]

GLCM, an important factor in classification, are used to estimate the motion in videos. In addition to real time pattern recognition applications ranging from the health industry to the military.

3.1.2 LAWS TEXTURE ENERGY MEASURES

Laws texture energy measures (LTEM) is used for the texture feature extraction of images. This approach uses local masks for generating different texture features for detecting different types of texture. Amount of variation is measured by texture-energy approach developed by laws within a fixed window. There is a set of 1-D convolutions kernels which are of length 5 that are convolved to get the 2-D convolution kernels. The 1-D convolution kernels are shown below

L5 (Level)	=	[	1	4	6	4	1	]
E5 (Edge)	=	[	-1	-2	0	2	1	]
S5 (Spot)	=	[	-1	0	2	0	-1	]
W5 (Wave)	=	[	-1	2	0	2	1	]
R5 (Ripple)	=	[	1	-4	6	-4	1	]

Purpose of 1-D kernels is described by their names. Center-weighted local average is given by L5, spots are detected by S5, ripples are detected by R5 similarly edges are detected by E5 and W5 is used to find wave. The convolution of horizontal 1-D kernel with vertical 1-D kernel gives a 2-D convolution mask. Convolution of E5 and L5 for computing a 2-D mask of E5L5 is shown in figure 3.3.

$$\begin{bmatrix} -1 \\ -2 \\ 0 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix} = \begin{bmatrix} -1 & -4 & -6 & -4 & -1 \\ -2 & -8 & -12 & -8 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 8 & 12 & 8 & 2 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

Figure 3.1: Example of convolution for creating 2-D mask of E5L5

Therefore by convolving 1-D convolutional kernel 25 two dimensional masks are produced which are shown below.

	L5	E5	S5	R5	W5
L5	L5L5	E5L5	S5L5	R5L5	W5L5
E5	L5E5	E5E5	S5E5	R5E5	W5E5
S5	L5S5	E5S5	S5S5	R5S5	W5S5
R5	L5R5	E5R5	S5R5	R5R5	W5R5
W5	L5W5	E5W5	S5W5	R5W5	W5W5

Table 3.3: 2-D Masks for LTEM

Preprocessing of image for removing the illumination effects involves a moving window operation around the image and local average is subtracted from each pixel in first step. The class of imagery defines the window size; natural scenes uses a 15 x 15 window. After the preprocessing, each of the twenty five 5 x 5 masks are applied to the preprocessed image, producing twenty five filtered images. Each texture energy map is a full image after producing the twenty five energy maps, fourteen final maps are produced by combining symmetric pairs. For example the vertical edge content is measured by using L5E5 whereas horizontal edge content is measured by E5L5 therefore the total edge content will be the mean of E5L5/L5E5 similarly L5R5 shows vertical Ripple content whereas R5L5 gives horizontal ripple content. The mean of these two will be the total ripple content. The fourteen final energy maps are shown below

L5E5/E5L5	E5R5/R5E5
L5R5/R5L5	S5R5/R5S5
E5S5/S5E5	L5W5/W5L5
S5S5	E5W5/W5E5
R5R5	S5W5/W5S5
L5S5/S5L5	R5W5/W5R5
E5E5	W5W5

Final processing gives fourteen energy maps images that are used to extract different features. Texture energy is computed by using a set of fourteen 5 x 5 convolution masks.

3.2 FEATURE CLASSIFICATION TECHNIQUES

Classification is a process of making decision that how accurate our results are. Machine learning technique is proposed for classification of wood defects by using features extracted from different feature extraction techniques that were used as inputs to supervised learning algorithm for classification of wood defects. This techniques include neural network with supervised learning, algorithms.

3.2.1 NEURAL NETWORKS

Artificial neural network, a computational model, is based on interlinked neurons. Consisting of a number of neurons, these act as individual processing units. Channel known as Dendrites are used to input information into the system. This information is then used by the neural network to enhance by a particular amplification factor called synapses and sum by dendrites. This is then further processed by neurons through an activation factor that computes the weighted sum and comes up with an output depending on the model. Amplification factor known as synapses or weights and are summed together by the processing unit. Then the weighted sum is further processed by the neuron which contains an activation function that takes the weighted sum and produces an output depending upon its model. The activation function's standard form largely depends upon the nature and architecture of the neural network. The architecture of the neural network is classified into two types, depending on the learning paradigms i-e supervised learning and unsupervised learning. In the first category namely supervised learning, the output is pre-determined and with that in mind the neural network is used for classification purposes. On the other hand, in unsupervised learning the output is undetermined with similar data being clustered together into classes on the basis of similarity. Neural Networks; utility as classification tools can be harnessed to great effect to identify defect in wood articles. For this purpose, back-propagation network from supervised learning have been explored in further detail

For the most part, feed forward neural network architecture has three layers, input layer I, hidden layer j and lastly output layer k. The learning data $\varrho=\{(Xk,Tk)\}k=1E$ is extrapolated from the pattern space where each sample relates an input vector $Xk \in \mathbb{R}n$ and $Tk \in \mathbb{R}p$, where Tk is a desired vector response to an input Xk. Usually, the amount of neurons in input layer is equal to the input feature, while the number of output layer is determined by the number of output classes desired. Hidden layer neurons can be chosen based on the performance of the neural network.

The feed forward network structure is shown in figure 3.2.

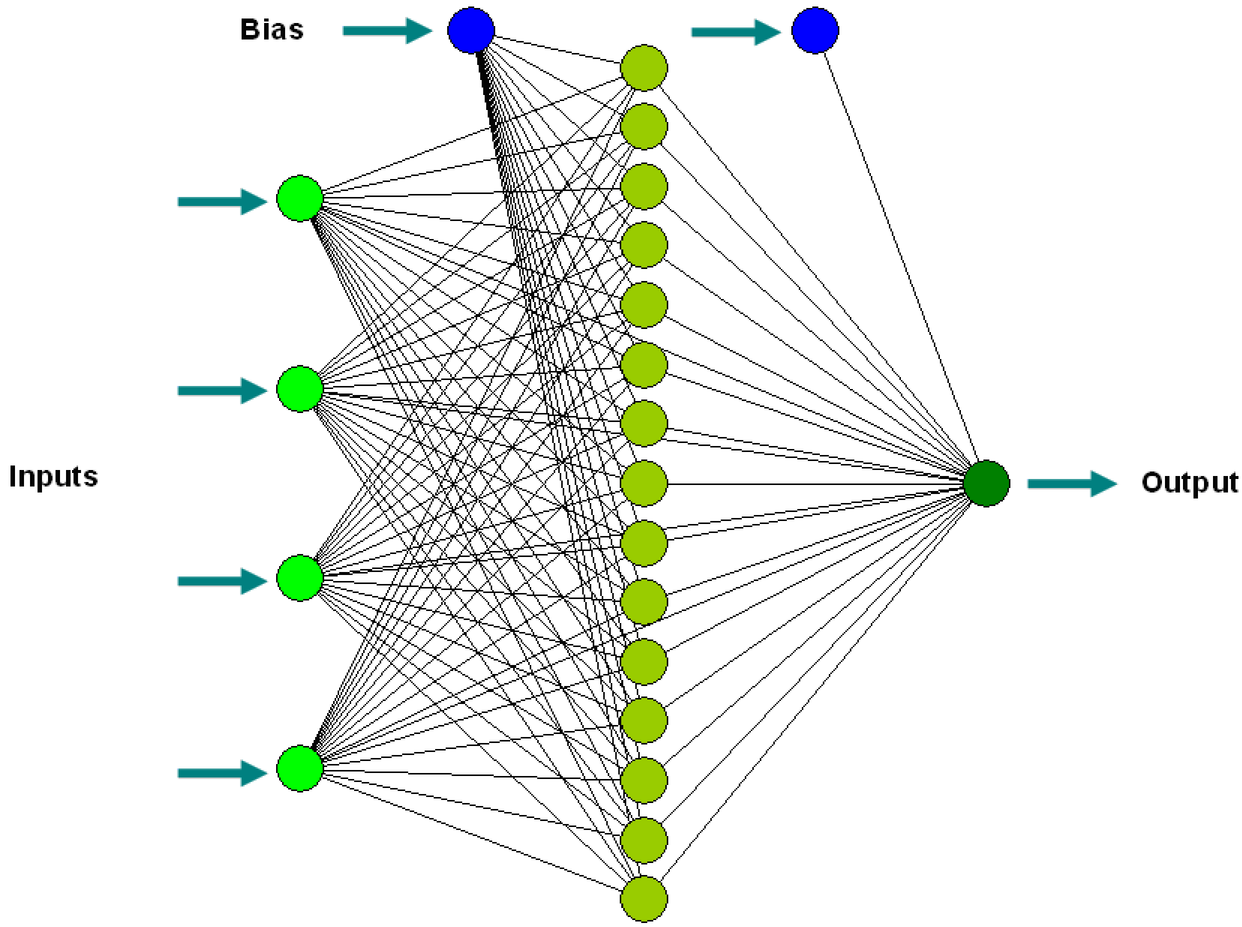

Figure 3.2: Feed Forward Neural Network Structure [44]

The neurons present in the input layer are used to pass the input parameters to a particular neural network, the input is expressed mathematically as: $\boldsymbol{In} = [i_1,\ i_2,\ i_3, \ldots, i_n]$. The amplification factor expressed as $\boldsymbol{W_{ij}} = [w_1,\ w_2,\ w_3, \ldots, w_n\ ]$ is then multiplied to the input. This is then further processed by passing the amplified input to the neurons present in the hidden or middle layer. As illustrated by the equation 3.8.

$$y = \sum(\boldsymbol{W_{ij}^T} \times \boldsymbol{i_i}) + \boldsymbol{b} \qquad (3.8)$$

Where the weight of input layer i is denoted by W_{ij} to the middle layer neuron j. $\boldsymbol{i_i}$ is input feature vector; While the bias is denoted by $b = [b_1,\ b_2,\ b_3, \ldots, b_n\ ]$ with a constant input 1. The consequent result is then added to each neuron in the middle layer as illustrated in equation 3.8. ***yi*** is the output sum against the input presented in the input layer.

The activation function expressed below in equation 3.9 is used to calculate the output of each hidden or middle layer neuron.

$$\boldsymbol{\psi}(\boldsymbol{y}) = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{y}}} - \mathbf{1} \qquad (3.9)$$

Where ψ is the output of the middle layer neuron.

A new set of weights $W_{jk} = [w_1,\ w_2,\ w_3, \ldots, w_n\ ]$ is then used to multiply the output ψ of each middle layer neuron. These weights serve the purpose of connecting the hidden layer neurons to the output layer neurons. Once weight multiplication is achieved then the activation function, expressed above by equation 3.2, can again be utilized to calculate the output of the neurons in the output layer. Mean square error is used by feed forward neural network to update its weights. The difference between expected or target and actual output of the neuron is provided by the calculation of the Mean Square Error. It is provided by the equation 3.10 given below.

$$\boldsymbol{MSE} = \frac{\mathbf{1}}{\boldsymbol{N}}\sum_{i=1}^{N}(\lambda(\tau_i; x)\text{-}y_i)^2 \qquad (3.10)$$

Where λ (;) the output target of input feature vector, y_i is neural network output and N denotes number of samples.

The neural network weights affiliated with the input vector are changed according to equation 3.11.

$$\boldsymbol{W_k} = \boldsymbol{W_{k-1}} + \Delta\boldsymbol{W_k} \qquad (3.11)$$

Researcher these days are using a number of different algorithms, such as gradient descent method, gradient descent with momentum and levenbern-Marquardt (LM), all of which are back propagation algorithms, to a great extent. We have used scaled conjugate backpropagation.

3.2.2 Proposed Algorithm For Feature Classification

The proposed algorithm depicting the utilization of neural network by proposed technique is shown in figure 3.3. Firstly different texture feature extractor will be used to extract different features. The extracted features are used by the back propagation neural network to test the performance.

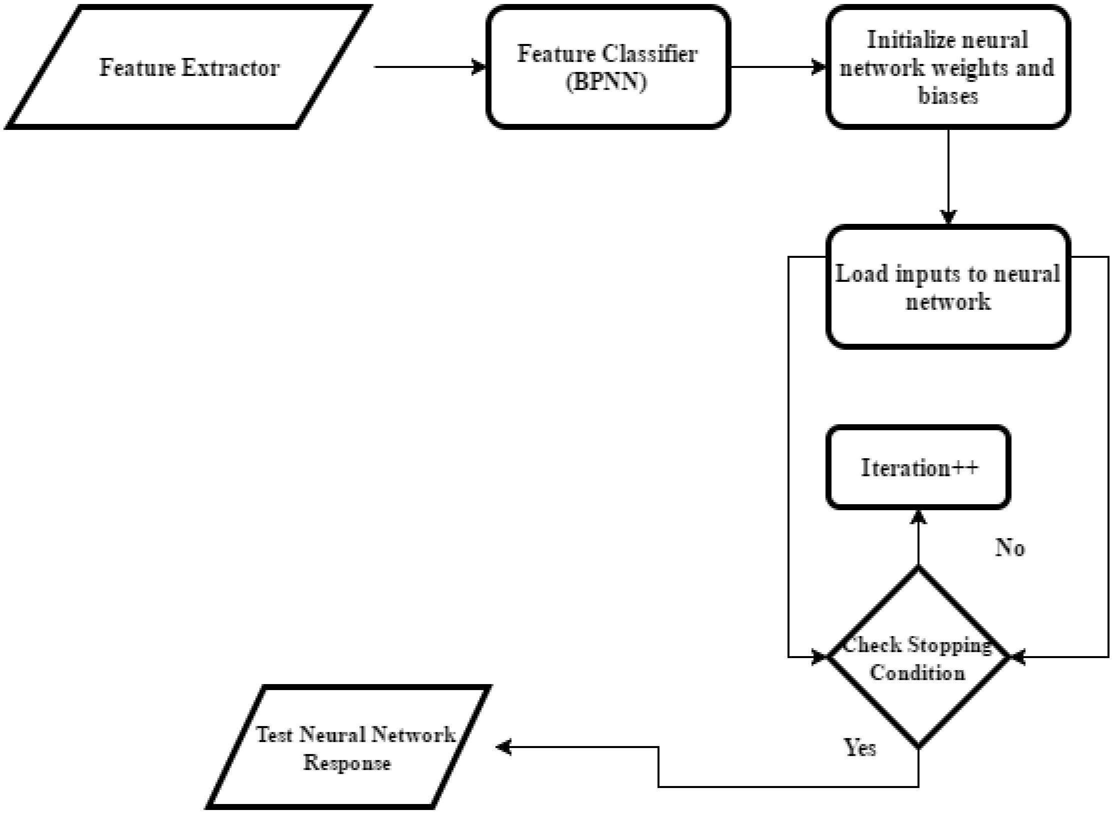

Figure 3.3: BPNN based feature classification algorithm flowchart

3.3 Summary

This chapter describes

- Gray level co-occurrence matrix is one the most prominent texture feature extraction method. Different statistical features including mean, variance, entropy, energy and homogeneity can be extracted by using gray level co-occurrence matrix.
- Laws texture energy measures is another texture feature extraction method that generates texture energy maps for texture feature extraction.
- Neural network are the widely used computational models and can be used as classifiers

CHAPTER – 4

EXPERIMENTATION

4.1 Dataset

Standard dataset available at the University of Oulu, Finland website for wood knot defects is used for the experimentation. Dataset contains 395 images for different wood knot defects namely dry knot, horn knot, leaf knot, sound knot and edge knot [45]. The summary of dataset details are shown in table 4.1.

Class of Defects	No. of images
Sound Knot	179
Dry Knot	69
Edge Knot	65
Leaf Knot	47
Horn Knot	35
Total	395

Table 4.1: Summary of Wood Database

Different samples of wood knot defects are shown in figure 4.1. First column is for dry knot, Second is for horn knot, third is for leaf knot, fourth is for sound knot and the last one is for edge knot.

Figure 4.1: Samples of Knot defects from Oulu Wood Database [45]

4.2 GLCM based algorithm for feature extraction

Feature extraction based algorithms are developed to detect wood knot defects. In order to detect different knot defects the wood database available at university of oulu website was used. The wood database contains 395 samples of different wood knot defects. The proposed algorithms relies on gray level co-occurrence matrix and laws texture energy measures for feature extraction. Firstly gray level co-occurrence matrix based feature extraction was performed. The summary of the steps performed for extraction of GLCM features is shown in figure 4.2.

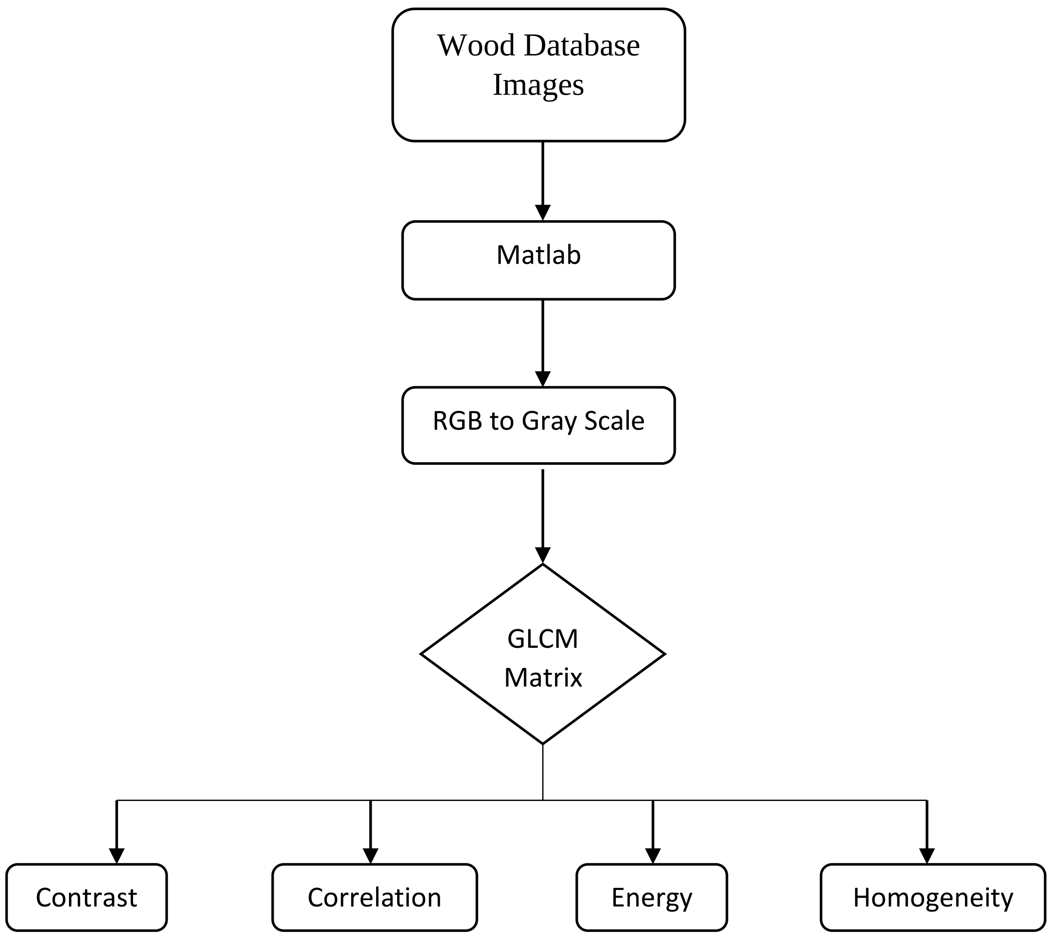

Figure 4.2: Feature extraction based on GLCM

Contrast, Correlation, Energy and Homogeneity are extracted as features from gray scale images by using gray level co-occurrence matrix (GLCM).

4.3 LTEM based algorithm for feature extraction

Secondly laws texture energy measures (LTEM) was applied on the standard dataset available at the university of oulu website to extract features from laws based energy maps. The summary of the steps performed for extraction LTEM based feature extraction is shown in figure 4.3.

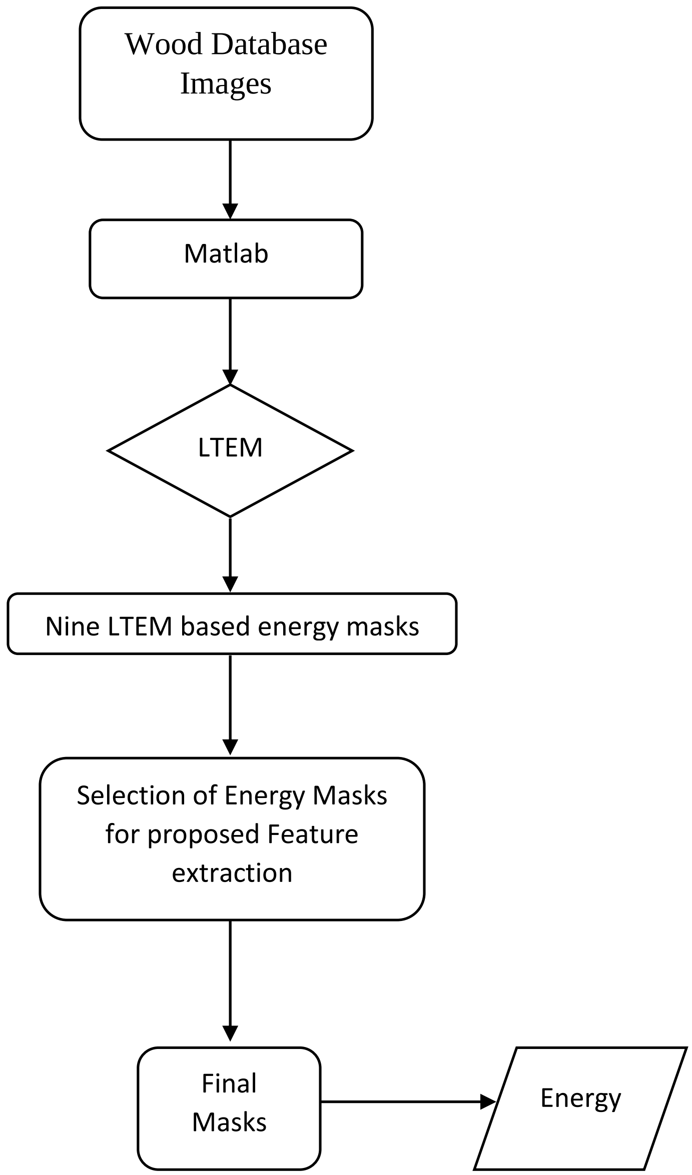

Figure 4.3: Feature extraction based on LTEM

Firstly one dimensional kernels namely level (L5), spot (S5), Edge (E5) and ripple (R5) are convolved with each other giving sixteen two dimensional masks. These sixteen two dimensional masks are then convolved with the images from the database, for each image we get sixteen laws texture energy maps. In the next step symmetric pairs from the laws texture energy maps are combined producing nine final laws texture energy maps. So finally nine laws texture energy maps are produced with respect to a single image from the wood database, as we have 395 images in wood database so after applying laws texture energy measures on our database we get a total of 3555 texture energy maps, 9 texture energy maps with respect to a single image. As we have five defect categories namely dry knot, horn knot, leaf knot, sound knot and edge knot so for each defect category a particular sample of defect and the nine texture energy maps produced after applying laws texture energy measures on that sample of defects are shown below. Firstly for a particular sample of dry knot the 9 texture energy maps produced and the combination of two dimensional masks against these maps are shown in figure 4.4.

Figure 4.4: Nine laws texture energy maps for a sample of dry knot

The final nine laws texture energy maps obtained for a particular sample of horn knot and the combination of two dimensional masks against these nine texture energy maps are shown in figure 4.5.

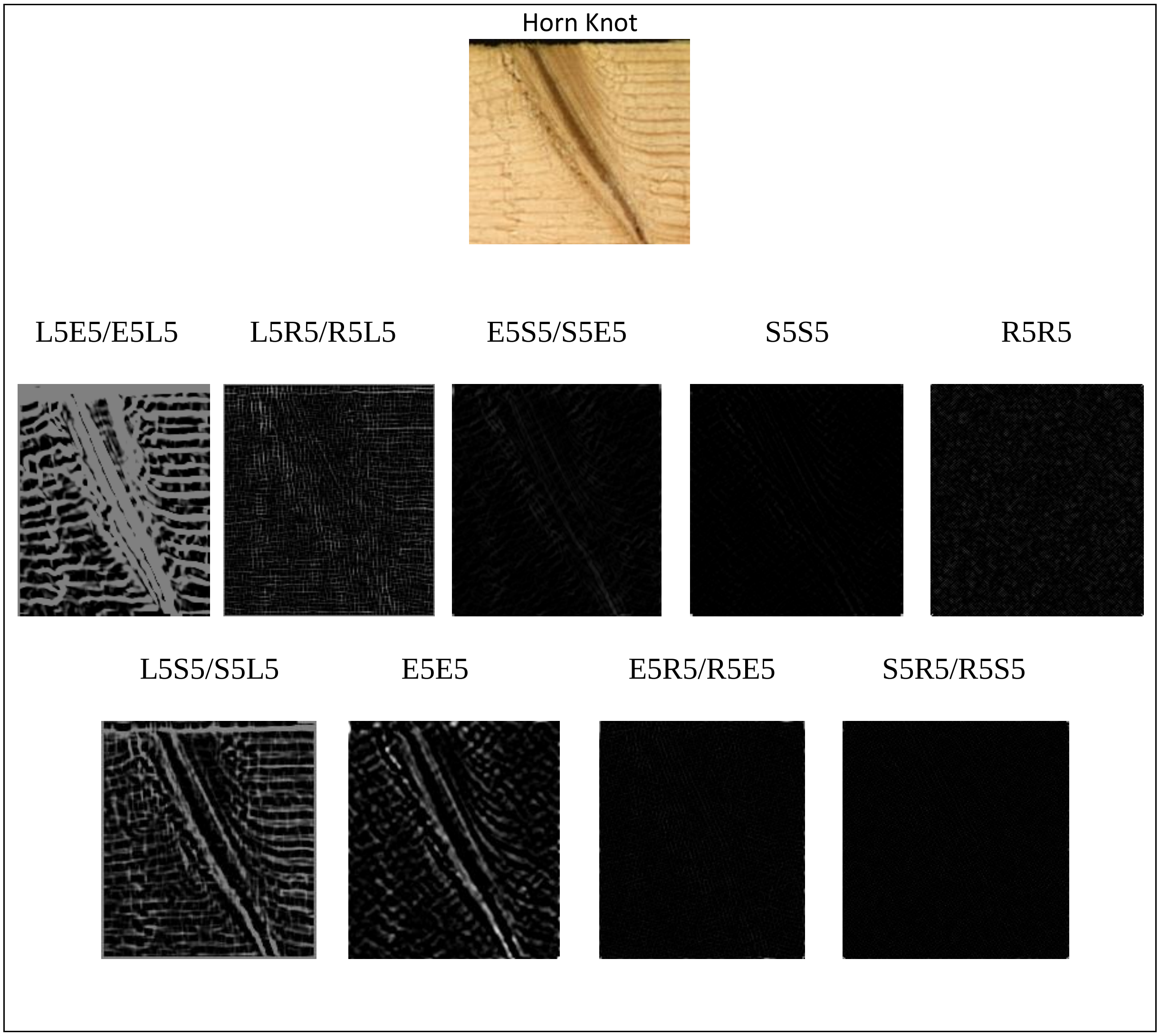

Figure 4.5: Nine laws texture energy maps for a sample of horn knot

The first texture energy map is the combination of E5L5/ L5E5. Vertical edge content is measured by using L5E5 whereas horizontal edge content is measured by E5L5. Therefore the total edge content will be the mean of E5L5/L5E5. The second texture energy map is the combination of R5L5/L5R5. L5R5 shows vertical Ripple content whereas R5L5 gives horizontal ripple content. The mean of these two will the total ripple content. The third texture energy map is the combination of S5E5/E5S5. The fourth texture energy map is of similar combination that is of S5S5. This map particularly indicates spots. The fifth texture energy map is the combination of

R5R5. It indicates ripples in the image. The sixth texture energy map is the combination of S5L5/L5S5. Vertical spot content is measured by using L5S5 whereas horizontal spot content is measured by using S5L5. So total spot content will the mean of S5L5/L5S5. The seventh texture energy map is the 2D image that is the combination of E5E5. The eight texture energy map is the combination of R5E5/E5R5 & the ninth texture energy map is the combination S5R5/R5S5. The final nine texture energy maps for a particular sample of leaf knot and the combination of two dimensional masks against these maps are shown in figure 4.6.

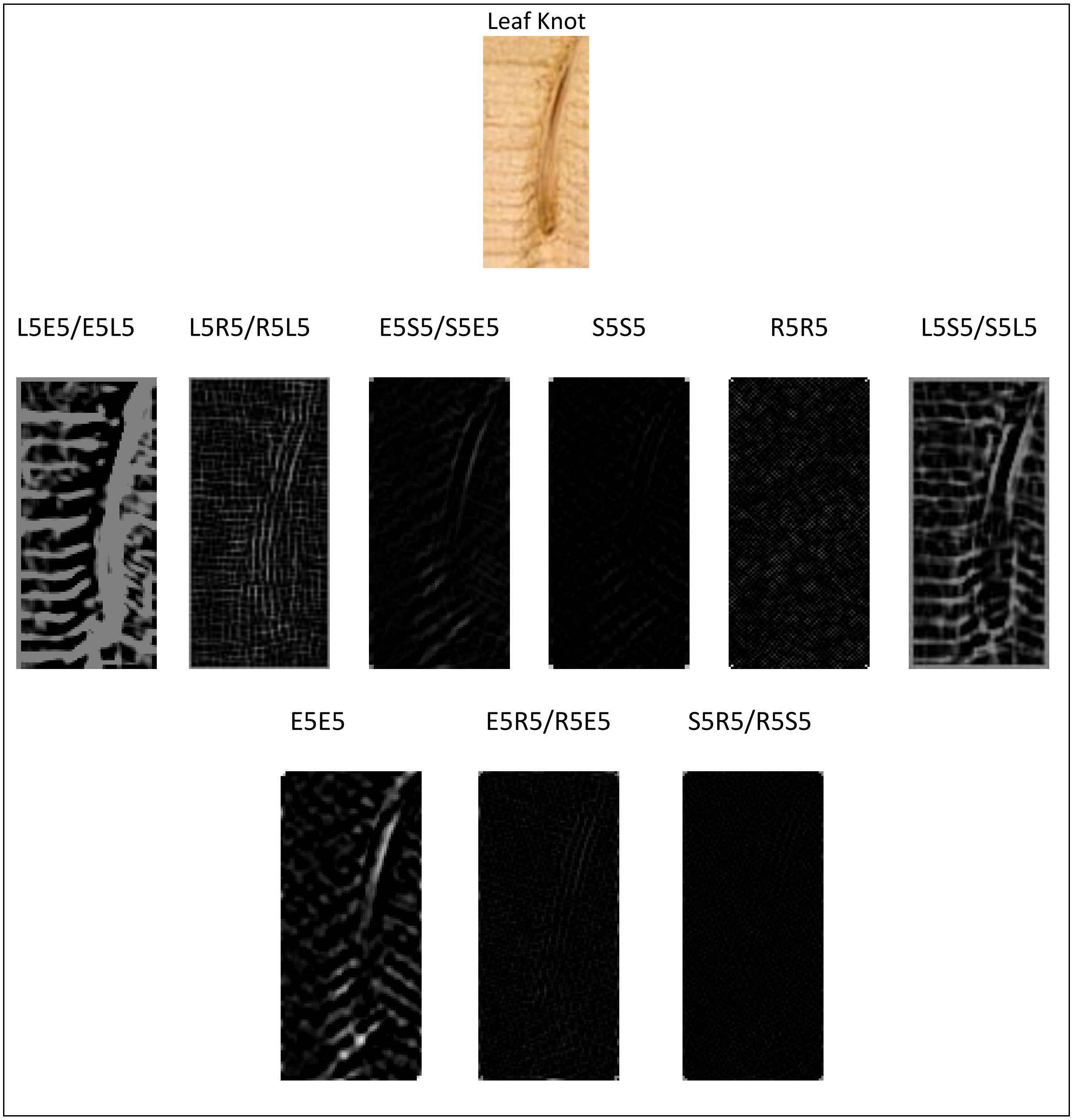

Figure 4.6: Nine laws texture energy maps for a sample of leaf knot

The nine texture energy maps for a particular image of sound knot and the combination of two dimensional masks against these maps are shown in figure 4.7.

Figure 4.7: Nine laws texture energy maps for a sample of Sound knot

The combination of two dimensional masks against the final texture energy maps are the same as obtained for other type of knots. Similarly the final nine texture energy maps for a particular sample of edge knot and the combination of two dimensional masks against those maps is shown on the next page in figure 4.8.

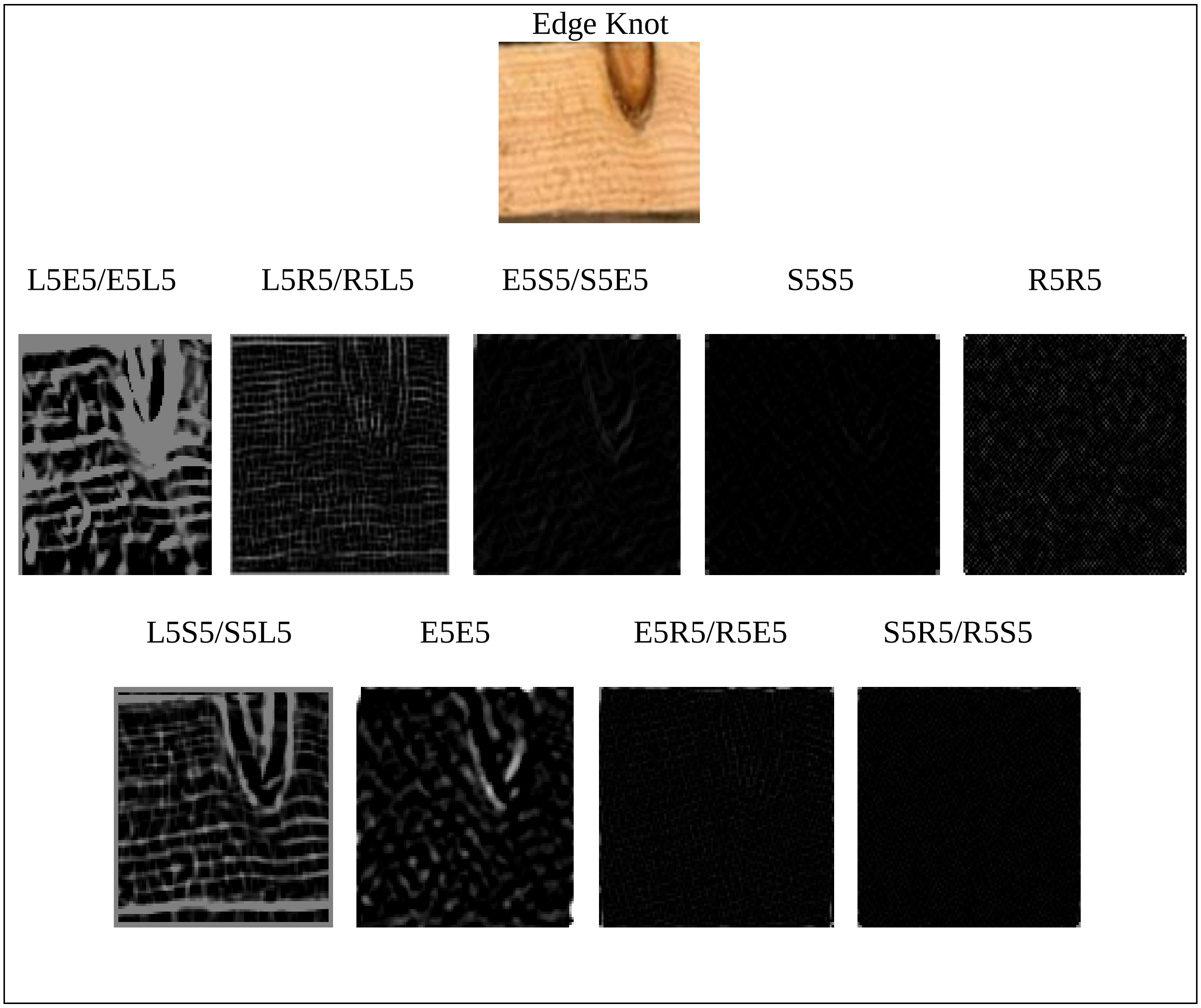

Figure 4.8: Nine laws texture energy maps for a sample of Edge knot

Selection of final masks for feature extraction involves a windowing operation. A 3×3 window by using operations of mean and standard deviation was applied on 9 texture energy maps. After that four texture energy maps were selected for feature extraction. The maps for combination of L5E5/E5L5, S5S5, L5S5/S5L5 and E5E5 were selected and average energy of these four maps was extracted. This energy was used as input feature to classifier for prediction of defects. The features extracted from GLCM and LTEM were used as inputs to neural network for classification of wood defects.

4.4 Experimentation flowchart

The summary of the proposed technique for wood defect detection is shown in figure 4.9.

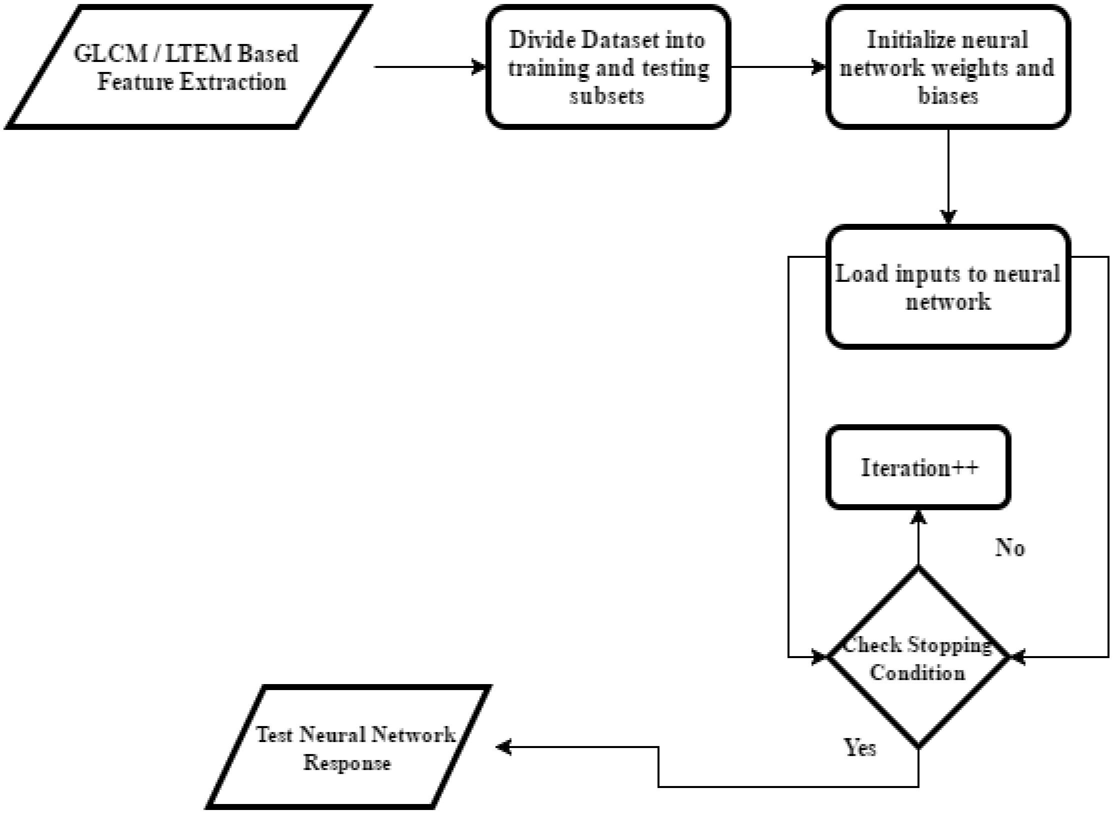

Figure 4.9: Flow chart for the proposed technique

4.5 Summary

This chapter describes

- Wood database containing 395 images of different knot defects namely dry knot, horn knot, leaf knot, sound knot and edge knot is used for experimentation and implementation of proposed technique
- Gray level co-occurrence matrix is used to extract different features namely contrast, correlation, energy and homogeneity from the gray scale images of the wood database.
- Laws texture energy measures is used to generate laws based energy maps for each sample of wood knot defects and then four selective texture energy maps for each wood knot sample are selected and the energy of these maps is calculated.

CHAPTER – 5

RESULTS AND DISCUSSION

This chapter presents the results of the research. A detailed discussion on performance of machine learning algorithm used as classifier for wood defects is given in the chapter. Results of the algorithm are also included in the chapter.

5.1 NEURAL NETWORKS

The feedforward back propagation neural network is used for classification of different knot defects. The information moves only in the forward direction in feed forward network. No loops are present in the network. The data from input nodes goes to the hidden nodes and then from the hidden nodes goes to the output nodes. As mentioned earlier, machine learning algorithm is selected in order to classify wood defects on the basis of gray level co-occurrence matrix (GLCM) and laws texture energy measures (LTEM) based features. The algorithm used as a classifier is back-propagation neural network (BPNN). Two separate datasets are used. First dataset contain GLCM based features that are contrast, correlation, energy and homogeneity and second dataset contain energy calculated from selective laws energy masks. The feature from both dataset were used as input to the neural network. Classification of the neural network depends on the chosen features.

First experiment was conducted by using GLCM dataset as input to neural network. GLCM dataset contain four distinct features including contrast, correlation, energy and homogeneity that are obtained from 395 samples of different wood knot defects that are dry knot, horn knot, leaf knot, sound knot and edge knot. The GLCM dataset is divided into three separate datasets, dataset A, dataset B, dataset C used for training, validation and testing purposes. Dataset A is used for training, dataset B is used for validation and dataset C is used for testing purposes. 70% samples used for training purpose, 15% used for validation purpose and remaining data used for testing. The architecture of neural network consists of 4 neurons in the input layer, 1 neuron in the output layer while neurons in the hidden layer are varied to check the performance. Neural network is trained until the minimum value of validation error is found. Precision, recall, f score and average accuracy were calculated to judge the performance of neural network having 5 neurons in the hidden layer by using confusion matrix. The performance of the neural network by using 5 neurons in the hidden layer for different types of knot defects is shown in the table 5.1.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
GLCM	5	Precision	0.7	0.48	0.24	0.64	0.54
		Recall	0.30	0.66	0.09	0.89	0.42
		F Score	0.42	0.56	0.13	0.74	0.47
		Accuracy	0.86	0.91	0.86	0.72	0.85

Table 5.1: NN Performance with GLCM inputs using 5 hidden layer neurons

The overall average accuracy using 5 hidden layer neurons is found to be 83.76 %. Further testing involves changing the number of neurons in the hidden layer to 10. Changing the number of neurons from 5 to 10 in hidden layer have a slight effect on the overall accuracy of the network. The overall average accuracy decreases by 0.2 % and found to be 83.57 % moreover the performance of the neural network by using 10 neurons in the hidden layer is shown in the 5.2.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
GLCM	10	Precision	0.64	0.53	0.35	0.66	0.52
		Recall	0.32	0.54	0.34	0.85	0.37
		F Score	0.43	0.53	0.34	0.74	0.43
		Accuracy	0.85	0.92	0.85	0.73	0.84

Table 5.2: NN Performance with GLCM inputs using 10 hidden layer neurons

The accuracy of the neural network is increased by 0.73 % when the number of the neurons in the hidden layer are increased to 15 and the overall average accuracy is found to be 84.3 % using 15 neurons in the hidden layer. The overall performance of the neural network by using 15 neurons in the hidden layer is shown in table 5.3. More over for 15 hidden layer neurons the horn knot gives the best individual class accuracy of 93.4 %.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
GLCM	15	Precision	0.63	0.63	0.29	0.66	0.56
		Recall	0.36	0.63	0.26	0.86	0.42
		F Score	0.46	0.63	0.27	0.75	0.48
		Accuracy	0.85	0.93	0.84	0.74	0.85

Table 5.3: NN Performance with GLCM inputs using 15 hidden layer neurons

Further performance of the neural network using glcm based features including contrast, correlation, energy and homogeneity as input by varying the number of neurons in hidden layers are shown below. The overall average accuracy decreases by 1.65 % when the number of hidden layer neurons are increased to 20 as compared to the overall average accuracy of 84.3 % with 15 hidden layer neurons. The overall average accuracy is found to be 82.65 % using 20 neurons in the hidden layer. The overall performance of the network using 20 neurons in hidden layer is shown in table 5.4.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
GLCM	20	Precision	0.63	0.5	0.33	0.63	0.47
		Recall	0.29	0.69	0.36	0.87	0.11
		F Score	0.40	0.57	0.34	0.73	0.18
		Accuracy	0.85	0.91	0.84	0.71	0.83

Table 5.4: NN Performance with GLCM inputs using 20 hidden layer neurons

Similarly the performance of the network with 25 hidden layer neurons and 30 hidden layers is shown in table 5.5. The overall average accuracy increases by 0.91 % with 25 hidden layer neurons when compared with the performance of the network with 20 hidden layer neurons and found to be 83.56 %. However the accuracy decreases again by 0.84 % with 30 hidden layer neurons and found to be 82.72 %.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
GLCM	25	Precision	0.66	0.5	0.44	0.65	0.41
		Recall	0.32	0.45	0.17	0.88	0.44
		F Score	0.43	0.47	0.25	0.75	0.42
		Accuracy	0.85	0.91	0.88	0.73	0.81
GLCM	30	Precision	0.61	0.54	0.30	0.63	0.37
		Recall	0.30	0.57	0.08	0.86	0.40
		F Score	0.40	0.55	0.12	0.72	0.38
		Accuracy	0.85	0.92	0.87	0.72	0.79

Table 5.5: NN Performance with GLCM inputs using 25 and 30 hidden layer neurons

The neural network trained with 15 hidden layer neurons gives the best overall classification accuracy for GLCM based input features. Neural network is trained until the minimum validation error is achieved. So the minimum validation error of the network using 15 neurons in hidden layer was found to be 0.10728. Training curve of back-propagation neural network is presented in figure 5.1.

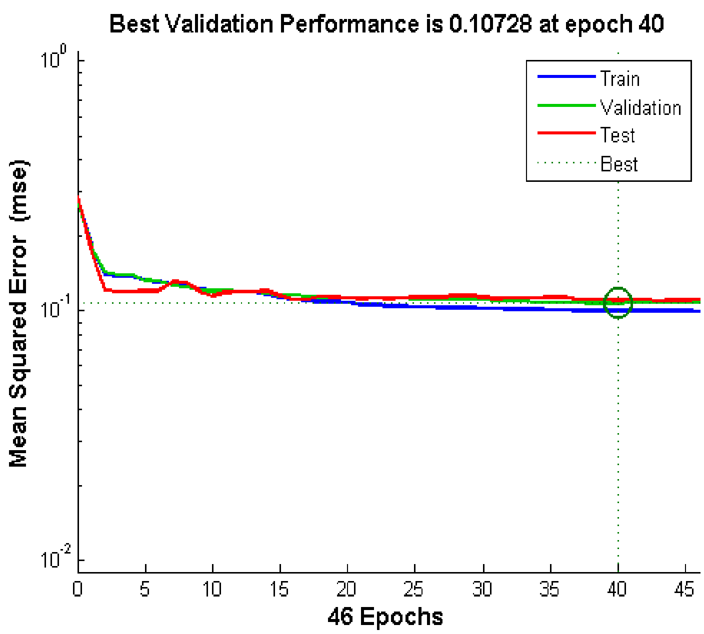

Figure 5.1: Training curve of back-propagation neural network with GLCM inputs

The performance of the neural network for different classes of wood knot defects by using glcm based input features is judged by using confusion matrix as shown in figure 5.2.

		Actual Class				
		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
Predicted Class	Dry Knot	25	0	0	13	2
	Horn Knot	1	22	9	1	2
	Leaf Knot	2	6	12	9	13
	Sound Knot	39	2	15	153	21
	Edge Knot	2	5	11	3	27

Figure 5.2: Confusion matrix for wood knot defects using GLCM features

Confusion matrix given in figure 5.2 shows the overall prediction for different wood knot defects using 15 neurons in the hidden layer. The number of true positive for each class are highlighted by blue colour. The overall average classification accuracy for detection of wood knot defects was found to 84.3 % using GLCM based input features. Figure 5.3 shows individual class accuracy.

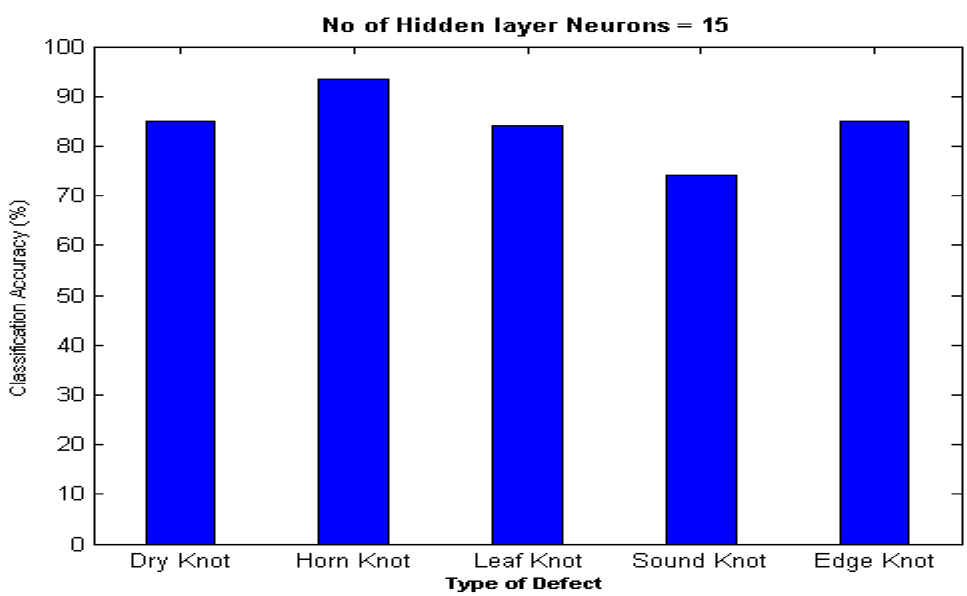

Figure 5.3: Accuracy plot for different classes using 15 hidden neurons and GLCM input.

Second experiment was conducted by using LTEM dataset as input to neural network. LTEM dataset contains energy calculated from the four selective laws energy masks that are obtained by applying LTEM on each of the 395 samples of different wood knot defects that are dry knot, horn knot, leaf knot, sound knot and edge knot. The LTEM dataset is divided into three separate datasets, dataset A, dataset B, dataset C used for training, validation and testing purposes. Dataset A is used for training, dataset B is used for validation and dataset C is used for testing purposes. 70% samples used for training purpose, 15% used for validation purpose and remaining data used for testing. The architecture of neural network consists of 4 neurons in the input layer, 1 neuron in the output layer while neurons in the hidden layer are varied to check the performance similar to the architecture of neural network using GLCM based features as input. Neural network is trained until the minimum value of validation error is found. Precision, recall, f score and accuracy were calculated to judge the performance of neural network having 5 neurons in the hidden layer by using confusion matrix. The performance of the neural network by using 5 neurons in the hidden layer and LTEM based features as input for different types of knot defects is shown in the table 5.6. The overall average accuracy using 5 hidden layer neurons is found to be 89.57 %.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
LTEM	5	Precision	0.68	0.63	0.79	0.82	0.65
		Recall	0.68	0.74	0.23	0.89	0.75
		F Score	0.68	0.68	0.35	0.85	0.69
		Accuracy	0.89	0.94	0.90	0.86	0.89

Table 5.6: NN Performance with LTEM inputs using 5 hidden layer neurons

The neurons in hidden layer are changed to 10 to further check the performance of the neural network using LTEM based input features. When the neurons in the hidden layer are increased to 10 there is a decrease in the classification accuracy by 1.53 % as for 5 hidden layer neurons the overall average classification accuracy is 89.57 % whereas the overall classification accuracy decreases to 88.04 % when the number of neurons in the hidden layer are increased to

10. The overall performance of the neural network by using 10 hidden layer neurons and LTEM based input features is judged by different parameters as shown in table 5.7.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
LTEM	10	Precision	0.76	0.91	0.51	0.76	0.59
		Recall	0.49	0.29	0.43	0.91	0.77
		F Score	0.59	0.43	0.46	0.82	0.66
		Accuracy	0.88	0.93	0.88	0.83	0.87

Table 5.7: NN Performance with LTEM inputs using 10 hidden layer neurons

The performance of the neural network by using 15 hidden layer neurons and 20 hidden layer neurons and LTEM based feature as input is shown in Table 5.8. When the neurons in the hidden layer are increased to 15 from 10 there is an increase in the overall classification accuracy by 0.8% and the overall classification accuracy using 15 hidden layer neurons is found to be 88.85 % however the classification accuracy again decreases by 0.4 % when then number of hidden layer neurons increased to 20 where it is found to be 88.45 %.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
LTEM	15	Precision	0.71	62	0.69	0.76	0.67
		Recall	0.57	0.74	0.23	0.92	0.69
		F Score	0.63	0.67	0.35	0.83	0.67
		Accuracy	0.88	0.94	0.90	0.83	0.89
LTEM	20	Precision	0.74	0.59	0.55	0.77	0.62
		Recall	0.57	0.74	0.13	0.92	0.69
		F Score	0.64	0.66	0.21	0.84	0.65
		Accuracy	0.89	0.93	0.88	0.84	0.88

Table 5.8: NN Performance with LTEM inputs using 15 and 20 hidden layer neurons

The overall classification accuracy increases to 89.45 % when the number of hidden layer neurons are increased to 25 moreover it further increases to 90.5 % when the number hidden layer neurons are set to 30. The overall performance of neural network with LTEM based inputs using 25 and 30 hidden layer neurons is shown in table 5.9.

Input Dataset	No of Neurons		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
LTEM	25	Precision	0.84	0.60	0.56	0.77	0.69
		Recall	0.61	0.69	0.19	0.93	0.77
		F Score	0.71	0.64	0.28	0.84	0.73
		Accuracy	0.91	0.93	0.89	0.84	0.91
LTEM	30	Precision	0.72	0.68	0.71	0.82	0.70
		Recall	0.71	0.71	0.51	0.88	0.68
		F Score	0.71	0.69	0.59	0.85	0.69
		Accuracy	0.90	0.94	0.92	0.86	0.90

Table 5.9: NN Performance with LTEM inputs using 25 and 30 hidden layer neurons

The neural network trained by using 30 hidden layer neurons gives the best overall average classification accuracy of 90.5 % for different wood knot defects namely dry knot, horn knot, leaf knot, sound knot and edge knot by using LTEM based input features. Neural network is trained until the minimum validation error is achieved. So the minimum validation error of the network using 30 neurons in hidden layer was found to be 0.07183. Training curve of back-propagation neural network using LTEM based features as inputs is presented in figure 5.4.

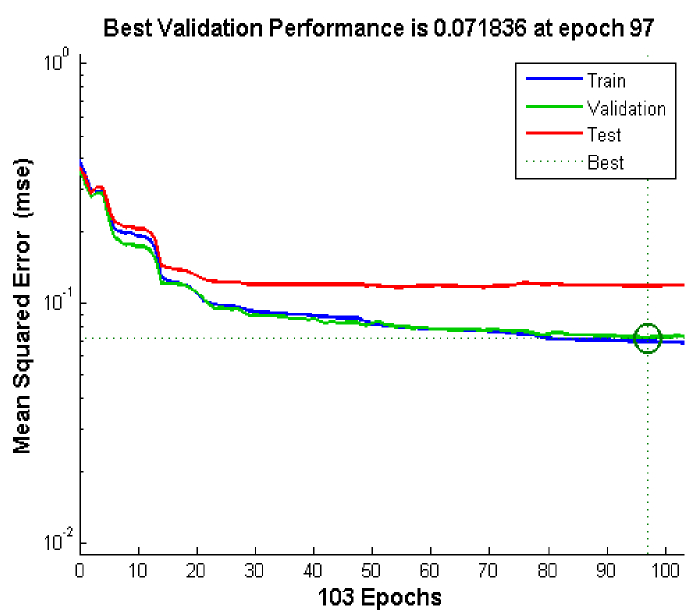

Figure 5.4: Training curve of back-propagation neural network with LTEM inputs

The performance of the neural network for different classes of wood knot defects by using LTEM based input features is judged by using confusion matrix as shown in figure 5.5.

		Actual Class				
		Dry Knot	Horn Knot	Leaf Knot	Sound Knot	Edge Knot
Predicted Class	Dry Knot	49	1	1	9	8
	Horn Knot	0	25	7	1	4
	Leaf Knot	2	0	24	8	0
	Sound Knot	12	1	13	158	9
	Edge Knot	6	8	2	3	44

Figure 5.5: Confusion matrix for wood knot defects using LTEM features

Confusion matrix given in figure 5.5 shows the best overall prediction for different wood knot defects. The number truly predicted samples of different wood knot defects are highlighted by blue colour. The best overall classification accuracy for detection of wood knot defects was found to be 90.5 % using LTEM based input features and 30 hidden layer neurons. Figure 5.6 shows the individual accuracy for each class using 30 neurons in the hidden layer.

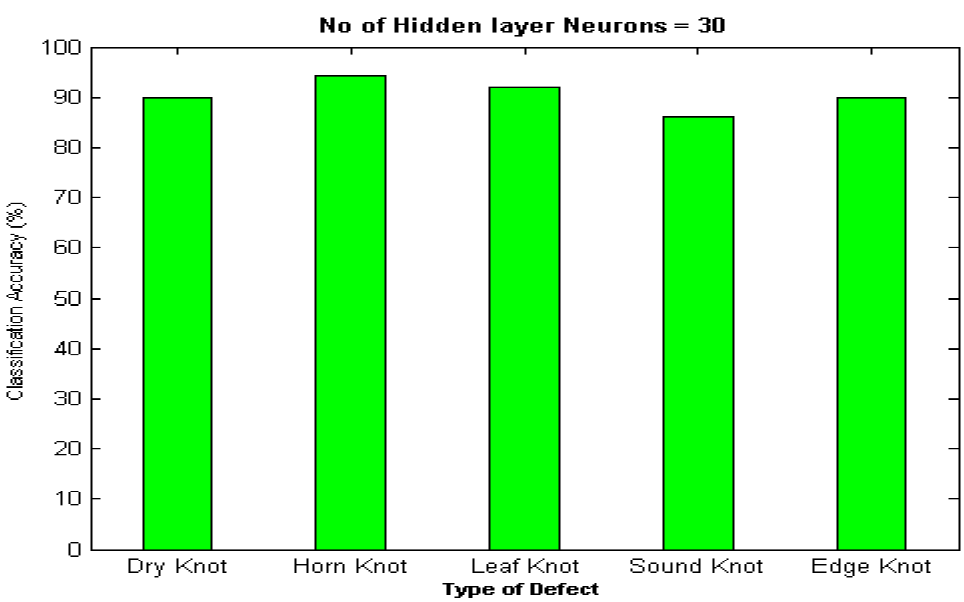

Figure 5.6: Accuracy plot for different classes using 30 hidden neurons and LTEM input

Laws texture energy measures (LTEM) based classifier outperform gray level occurrence matrix (GLCM) based classifier for wood knot defects detection. Classifier based on LTEM gives much better classification accuracy for woof defects detection as compared to GLCM based classifier for different architecture. Testing involves changing the number of hidden layer neurons for classifier which is in our case is back-propagation neural network (BPNN). More over laws texture energy measures has never been applied on wood for extraction of features to detect defects thus the proposed area of research is quite novel. Comparing the results of back-propagation neural network trained by using GLCM based features as input with another back-propagation neural network trained by using LTEM based input features by varying the number of hidden layer neurons gives further clarification.

Comparison of the results for back-propagation neural network using gray level co-occurrence matrix (GLCM) and laws texture energy measures (LTEM) is given in table 5.10.

No of hidden layer neurons	Overall Classification accuracy for wood database (%)	
	GLCM	**LTEM**
5	83.76	89.57
10	83.57	88.04
15	84.3	88.85
20	82.65	88.45
25	83.56	89.45
30	82.72	90.5

Table 5.10: Comparison of results on the basis of overall classification accuracy

More clearer picture for the performance comparison between GLCM and LTEM based back propagation neural network with different number of hidden layer neurons is shown in figure 5.7. Figure shows the comparison between overall average classification accuracy for both glcm and ltem based classifier using different number of hidden layer neurons.

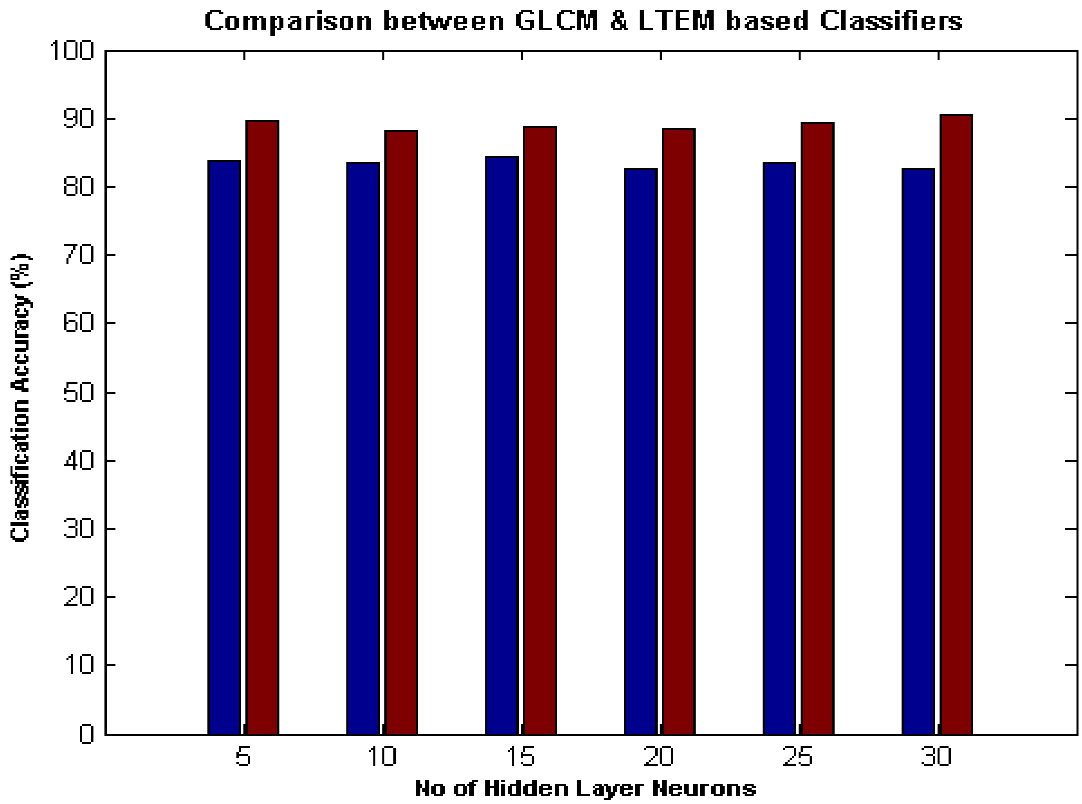

Figure 5.7: Performance comparison between GLCM and LTEM based classifiers

Comparison between best performance of classifiers using glcm and ltem based input for individual classes is shown in table 5.11.

Type of Defect	Classification accuracy for wood database (%)	
	GLCM	**LTEM**
Dry Knot	85	90
Horn Knot	93.4	94.4
Leaf Knot	84	92
Sound Knot	74	86
Edge Knot	85	90
Overall	84.3	90.5

Table 5.11: Best performance comparison for individual classes

More clearer picture of the best performance of classifiers using glcm and ltem based inputs is shown in Figure 5.8. The best performance for the classifier using glcm inputs comes with 15 hidden layer neurons whereas the best performance for the classifier using ltem inputs comes with 30 hidden layer neurons.

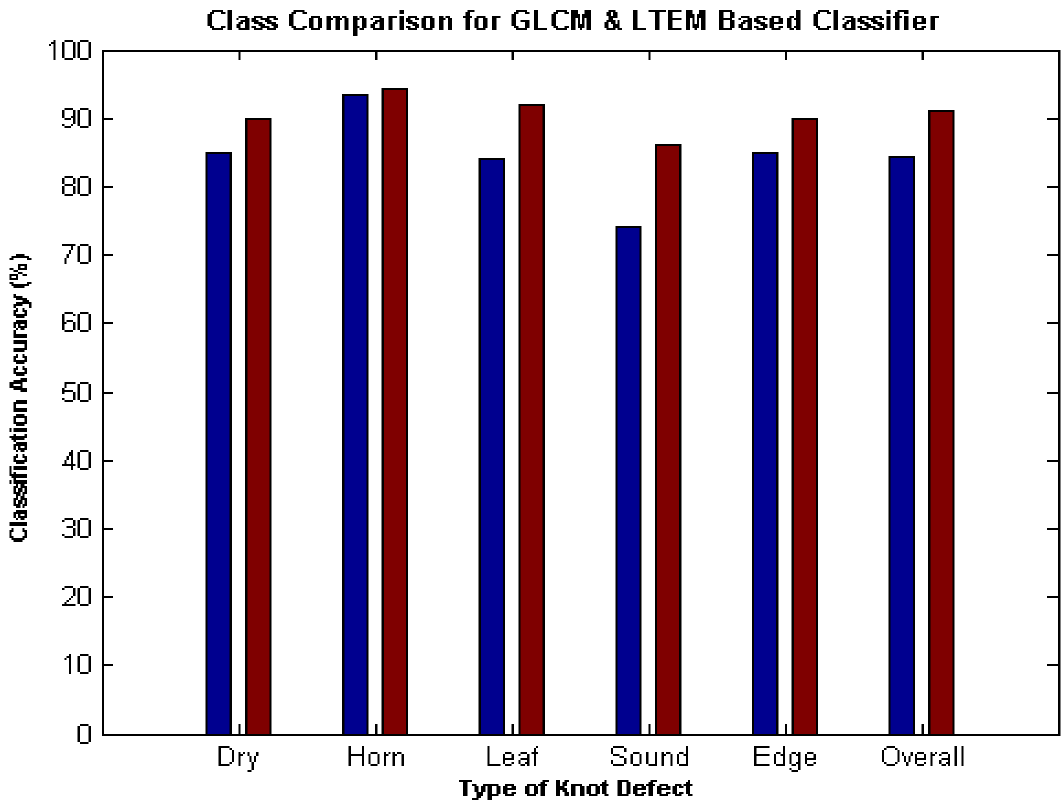

Figure 5.8: Best Performance comparison between GLCM and LTEM based classifiers

Moreover a GUI based interface for the implementation of the proposed technique is shown in Figure 5.9. The interface demonstrates the steps involve in the implementation of the proposed technique. Two texture feature extraction methods as mentioned earlier are used for texture feature extraction of wood defects images namely LTEM and GLCM as demonstrated in the GUI. BPNN is used as a classifier for the classification of different knot defects in wood.

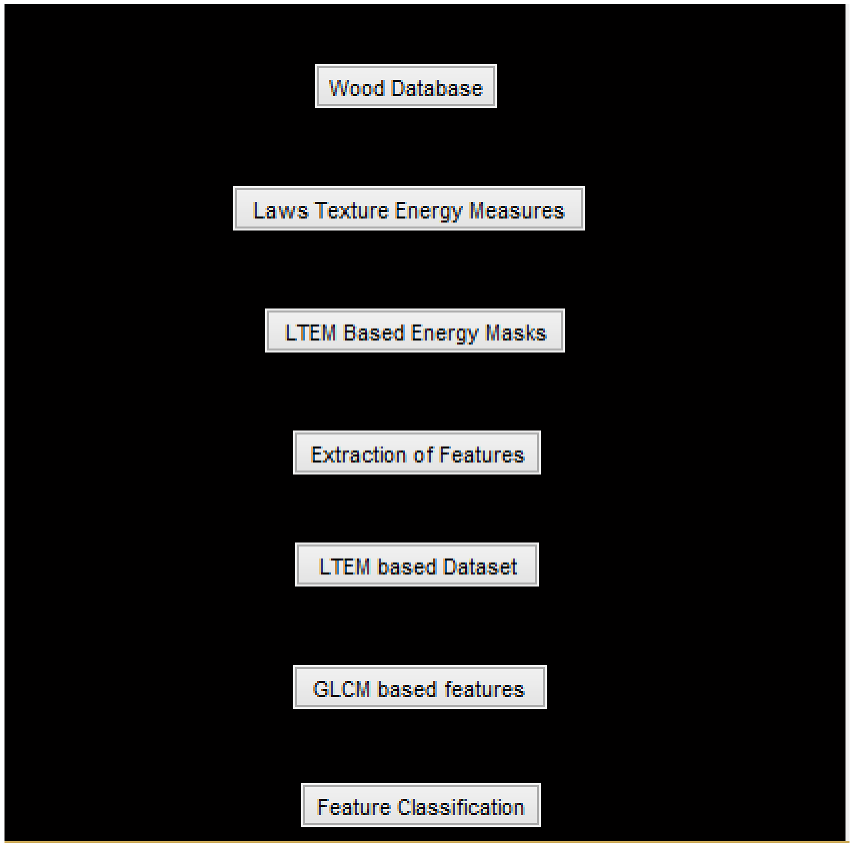

Figure 5.9: GUI for the implementation of proposed technique

5.2 Summary

This chapter describes

- Two feature sets based on gray level co-occurrence matrix based features and laws texture energy measures based features are used to as input features to neural network for classification of wood knot defects.
- Laws texture energy measures based classifier shows more prominent results than gray level co-occurrence matrix based classifier.
- Best classification accuracy of 90.5 % comes with 30 hidden layer neurons for laws texture energy measures based classifier whereas for gray level co-occurrence matrix based classifier the best classification accuracy is 84.3 % which comes with 15 hidden layer neurons.

CHAPTER - 6
CHALLENGES

Many researchers have proposed different machine vision based inspection systems for detection of wood defects. However, there are various challenges in implementation of the technique at industrial grade. One of the major challenge lies in the development of a rig for inspection and testing equipped with machine vision based camera. Wood normally comes in the form of planks that makes the industrial inspection of wood bit difficult. Therefore the challenge lies in the development of an inspection rig. For this purpose, there should be a conveyer driven mechanism provided with machine vision camera or there should be hand held scanner that is handy to use by local quality inspector. Moreover, a mobile inspection robot can also be a solution for more automated inspection of wood. Small size Quad rotors can also be a possible solution for quality inspection.

The other major challenge lie in the improvement of classification algorithm. Normally, a supervised learning approach as proposed in this thesis, requires big datasets and training. An unsupervised approach such as Self-Organizing map (SOM) can be used as an alternative to reduce training data requirements.

The challenge also lies in development of an extensive knowledge base of wood defects that contains variety of wood defects categories as well as knowledge from wood experts. For such a purpose an web-based tool should be developed that maintains a repository of wood defect images as well as it caters experts knowledge and opinions in this regards. Wood is a highly textured material therefore the area of feature extraction is also needed to be explored.

6.1 Summary

The chapter can be summarized as follows

- ❖ There are various challenges in the implementation of the proposed technique. Quality check measures needed to be introduced.
- ❖ Larger dataset needed to be required for more accurate classification.
- ❖ There is a need for extensive wood defect knowledge that also incorporates the expert's opinion.

CHAPTER – 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

The proposed work presents a novel approach for classification of wood defects. The proposed method was further divided into two stages namely feature extraction stage and feature classification stage. The feature extraction stage involves two feature extraction methods for texture feature extraction of wood defects namely gray level co-occurrence matrix and laws texture energy measures, firstly gray level co-occurrence matrix based features namely contrast, energy correlation and homogeneity are extracted from 395 samples of different wood knot defects and secondly Laws texture energy measures based features including energy a from laws texture energy maps of 395 samples of wood knot defects are extracted. The feature classification stage involves a feed-forward back propagation neural network which is used to classify the defects using gray level co-occurrence matrix and laws texture energy measures based features. The proposed technique using laws texture energy measures based features shows promising results for classification of wood defects as compared to gray level co-occurrence matrix based features. Mean Square Error of the network for training dataset for laws texture energy measures is found to be 0.0718, whereas, the overall average classification accuracy is found to be 90.5% using 30 neurons in the hidden layer whereas mean square error for training dataset for gray level co-occurrence matrix is found to be 0.10728 and 84.3 % overall average classification accuracy is achieved using 15 neurons in the hidden layer.

7.2 Future Work

Future work involves further investigation of different feature extraction techniques for texture feature extraction of wood defects images and investigation of different supervised and unsupervised learning techniques for the classification of wood defects. Moreover further examination of different wood defects other than knots can also done by using the proposed technique in the future.

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Completion Certificate

It is certified that the thesis titled **"Wood Defects Detection by Using Texture Analysis"** submitted by registration no. NUST201464534MCEME35514F, NS Muhammad Rizwan Qayyum of MS-82 Mechatronics Engineering is completed in all respects as per the requirements of MainOffice, NUST (Exam branch).

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