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Wood defects classification using laws texture energy measures and supervised learning approach

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ABSTRACT

Machine vision based inspection systems 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 feed-forward 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 feed-forward 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 feed-forward back propagation neural network. Mean Square 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.

1. Introduction

Wood strength plays a vital role in quality of wooden products. Wood defects, such as knots, affect the wood strength that results in poor quality wooden products. Existence of wood knots may also affect the paint quality, therefore, aesthetically making the product not very attractive. In context of strength, it affects the mechanical properties, such as, elasticity, stiffness.

Generally, detection of wood defects is done manually by a human inspector, which is a tedious and time consuming, and labor intensive process. Moreover, it does not guarantee detection with higher repeatability and accuracy, hence, affects the quality control process. Machine vision based inspection systems are highly considered nowadays to ensure more accurate, precise and timely detection of defects in order to achieve more reliable quality control.

As wood is a highly textured material and wood defects, especially knot defects appear as a darker region embedded in the wood texture, therefore, main challenge lies in the separation of these knot defects from the rest of the texture. Various techniques such as Gray Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP) analysis, region detection techniques are in common practice to distinguish wood knot defects from the rest of the wood texture. These techniques have also been employed in medical imaging for diagnosis of different diseases. Law's Texture Energy Measures (LTEM) is a technique, widely used in other fields such as medical imaging, for cancer and liver disease diagnosis. The use of LTEM is also reported to detect texture based defects in materials, such as, for ceramics and steel [1,2]. However, this has never been used for wood knot defect detection. This motivates the authors to apply this technique for wood knot defect detection. Moreover, wood texture is a combination of spots, ripples and edges, etc. and many of the wood defects such as sound and dry knots appear in the form of spots. LTEM has five 1D kernels that are Level, Edge, Spot, Wave, and Ripple; therefore, any 2D convolution of these kernels can be applied to extract wood defects that are present in the wood texture. Therefore, main contribution of this paper is to present a novel texture based classification of wood knot defect using LTEM. LTEM is proposed for the very first time in the literature for feature extraction of wood knot defects. However, the motivation behind using GLCM based features is to benchmark LTEM results against the GLCM that is a standard approach to detect wood knot defects. The defect classification is then

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done using back-propagation neural networks. The LTEM results are then compared with GLCM based feature extraction and classification using the same classifier by varying the number of neurons in the hidden layer. A detailed technological survey is provided in the next section.

2. Technological survey

Various techniques have been proposed in this regard. The approaches that are found in literature for vision based wood defect detection mainly differ in terms of texture and non-texture based analysis and use of supervised and unsupervised learning for defect classification. Longuetaud et al. [3] developed a new algorithm for non-destructive extraction of knots in trees using a non-texture based approach. CT images of wood were used for experimentation. Knots were detected in 3D, moreover the algorithm also gave measurements for knot diameter as it involved the use of 3D distance transform and 3D connex components. 85% detection rate was achieved by using the algorithm. However, the proposed approach was labor intensive and semi-automatic in a sense as it required operator's involvement to detect the exact location of the knot boundaries. Sarigul et al. [4] used CT 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. Mu and Qi [5] proposed a non-texture based approach to recognize patterns of different defects of wood using supervised learning approach. Hu invariant moments is used for feature extraction and back-propagation neural network is used for classification. Proposed approach showed impressive results to recognize grubhole defect, however, the same approach showed less accuracy for knot and rot defects. Mohan et al. [6] proposed a non-texture based approach using supervised classification of wood defects. The Proposed work involves feature extraction by using Hilbert transform and feature reduction by Gabor filter and in the end optimized neural network is used as classifier for defects classification. Wang et al. [7] proposed a non-texture based approach for wood defects detection based on supervised wavelet neural network. An ultrasonic device was engaged for recognition and the analysis of internal wood defects by using wavelet transform and back-propagation neural network. The proposed approach was useful to detect internal wood defects only and unable to cater for external wood defects.

Yuce et al. [8] used a texture-based approach to detect wood veneer defects. 17 different features such as median gray-level, mode gray-level, standard deviation, kurtosis, skewness, were included in the feature set. Principal Component Analysis (PCA) was used to reduce the feature set. Backpropagation neural networks were then used for classification task. Results were analyzed and the identification of best ANN configuration was done by Taguchi method. Conners et al. [9] developed automated inspection system for locating and identifying defects on wood surface using texture and tonal measures. The authors 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 similar approach was proposed by França and Gonzaga [10]. The authors improved the classification of wood plates by developing a method that relies on two neural networks. Both of the neural networks worked with only a single input feature. A greater discriminating power was given to the system as compared to human inspectors when the fallout of the neural network were combined through a fuzzy logic to extract features for the classification of wood plates. Kim and Koivo [11] proposed image processing based approach for the classification of defects that were present on the surface of dusty wood boards using texture information. Initially, thresholding was applied on the image data. Shrinking and expanding were then applied on the thresholded images to get more enhanced defect regions. As a result of it, the image data is divided into two regions that were dark and bright. The priori knowledge about the defect location was used to identify the dark region whereas texture features are used to classify bright regions by using Bayesian classifier. However, the proposed approach was sensitive to the presence of dust on the samples as well as lighting conditions. Zhang et al. [12] proposed a technique using three-leveled, dual-tree complex wavelet transform for surface defect detection and texture analysis of wood. Ruz et al. [13] proposed a texture-based approach to classify wood defects by using automated visual inspection system (AVI). The work involves the segmentation of images by using fuzzy min-max neural network. Gray Level Co-occurrence Matrix (GLCM) was used for feature extraction. 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 (PSVM) which yield 91% classification accuracy. However, the proposed approach was confused to differentiate between the stain and clear wood categories. Using color image segmentation, Ruz and Estévez [14] also proposed another technique using fuzzy min-max neural network. The proposed method involved image segmentation to detect wood defects. The dataset used consists of wooden board images containing 10 defect types in order to analyze the performance of proposed neural network. The technique showed remarkable results for all types of defects except stain defects. Cavalin et al. [15] proposed texture based approach to detect wood defects. Monochromatic sensors were used instead of color sensors to achieve cost effectiveness. Support Vector Machines (SVM) and neural networks were used as a learning models. The technique was able to detect small defects such as cracks and spots, however, the results were slightly affected by contrast information. Zhang et al. [16] also used SVM, Local Binary Pattern (LBP), and Dual-Tree Complex Wavelet Transform (DTCWT) to classify wood defects. Wang et al. [17] proposed recognition of Wood Texture by using Gray Level Co-occurrence Matrix features and then applied Back Propagation (BP) Neural network for classification. The proposed technique was computationally expensive. A PSO trained neural network for wood defects detection using GLCM based features is proposed by the authors of this paper [18]. Yong Hua and Jin Cong [19] used texture features to identify the defects in wood. The authors proposed a hybrid approach by combining Tamura and GLCM based features to classify wood defects using back-propagation neural networks. However, the hybrid approach showed less accuracy when compared to individual use of GLCM and Tamura based features as inputs to the backpropagation neural network. Shahnorbanun et al. [20] used a Spiking Learning Vector Quantization (S-LVQ) network for features extraction to classify wood defects. Supervised learning vector quantization algorithm was used to train the S-LVQ network. Spiking neurons were used instead of common neurons as a processing elements in this network. Yu and Kamarthi [21] used wavelet coefficients of wood knot images as input features to multilayer perceptron and Probabilistic Neural Network (PNN) for wood defect detection. They proposed a clustering based approach to segregate wavelet coefficients that were computed from wood image dataset in order to classify different wood knot defects.

Mahram et al. [22] proposed a method in which feature extraction was done by using gray-scale co-occurrence matrix, statistical moment functions and local binary systems together. SVM and k-Nearest Neighbours are used as classifiers. The authors claimed 100% accuracy for two different combinations using the proposed approach.

In contrast to most of the approaches explained above that used supervised learning, Kauppinen et al. [23] used a non-segmenting approach for defects detection in which classification of defects is done by using self-organizing maps (SOM). However, two types of defects were detected using the proposed approach, sound knot defects being one class and rest of the defects as other class. Also, Niskanen et al. [24]

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. Silven et al. [25] proposed a new approach for the inspection of wood using unsupervised learning. The authors used Local Binary Pattern (LBP) that are second order texture features to classify wood defects such as shake, pitch pocket, and sound knot. The method employed unsupervised clustering and relies on Self-Organizing Maps (SOM) to detect and recognize wood defects. However, the major drawback of SOM based approaches is that SOM being an unsupervised learning strategy is less accurate as compared to supervised learning, such as, backpropagation neural network.

Apart from the approaches discussed above, other miscellaneous types of techniques have also been reported in the literature. Todoroki et al. [26] used a non-texture based approach for detection of wood knots. The authors used a set of digital images of veneer sheet. Algorithm based on two phases was proposed for detection. The first phase involved global thresholding that was utilized for image segmentation by using morphological operations to isolate knots. The second phase used red component and gray scale segmented images and adaptive thresholding was applied for more enhanced segmented knots. Red component images showed more accurate results than gray scale images. Funck et al. [27] compared performance of 9 different algorithms for wood defects detection. In this regard, approaches such as clustering with region growing, compass gradient mask, and entropy edge, were compared. Radovan et al. [28] improved the classification of wood defects by developing a machine vision system in which automated inspection of wood boards was performed for the detection and classification of both biological and mechanical defects. Baradit et al. [29] developed a microwave system for knot detection in wood.

The proposed technique involves laws texture energy measures as texture feature extraction method to detect different wood knot defects. Laws texture energy measures has never been applied on wood as texture feature extraction method to detect wood defects. Different researchers have used laws texture energy measures as texture feature extractor in different areas including biomedical. Dheeba et al. [30] proposed computer aided design (CAD) for the detection of abnormalities in breast. 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. Setiawan et al. [31] 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. Elnemr [32] 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. [33] 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. Valavanis et al. [34] 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. [35] used Laws texture energy measures for feature extraction of liver images. Habib et al. [1] 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. [2] 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. The next section clarifies the background theory.

3. Background theory

3.1. Gray level co-occurrence matrix

GLCM is a frequently used technique that is used in texture analysis of images. By definition co-occurrence matrix is a framework that is characterized over an image to be the distribution of co-occurred values at a given offset. Mathematically, an n × m image I can be used to define a co-occurrence matrix C, given by an offset (Δx, Δy), as shown in equation:

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

The value of the image intensity are given by i and j for the image I, whereas the spatial position is defined by p and q. The direction and the distance d used for the computation of matrix are the parameters on which the offset (Δx, Δy) rely.

Contrast, Homogeneity, Energy, Entropy, Correlation and Dissimilarity are the important texture features that can be obtained by using Grey-Level Co-occurrence Matrix.

3.2. 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 masks. 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]

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 Fig. 1.

Therefore by convolving 1-D convolutional kernel 16 two dimensional masks are produced as shown in Table 1.

Preprocessing of image for removing the illumination effects

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

Fig. 1. Example of convolution for creating 2-D mask of E5L5.

Table 1
16 2-D masks.

	L5	E5	S5	R5
L5	L5L5	E5L5	S5L5	R5L5
E5	L5E5	E5E5	S5E5	R5E5
S5	L5S5	E5S5	S5S5	R5S5
R5	L5R5	E5R5	S5R5	R5R5

Table 2
Nine final energy maps.

L5E5/E5L5	R5R5
L5R5/R5L5	L5S5/S5L5
E5S5/S5E5	E5E5
S5S5	E5R5/R5E5
S5R5/R5S5	

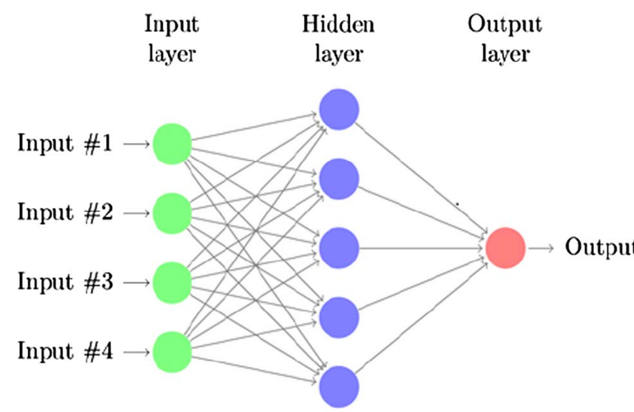

Fig. 2. Neural network model [36].

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 15×15 window. After the preprocessing, each of these sixteen 5×5 masks are applied to the preprocessed image, producing sixteen filtered images. Each texture energy map is a full image after producing the texture energy maps, nine 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 nine final energy maps are shown below in Table 2.

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

3.3. Neural networks

Artificial neural network is a mathematical model that consists of various interconnected nodes that are called neurons. In its simple form, it consists of three layers known as input, hidden, and output layers respectively. The input layer takes the input feature vector denoted by $\boldsymbol{In} = [i_1, i_2, i_3, \ldots, i_n]$ as inputs and then passes it to the intermediate layer. The inputs to the intermediate layer are amplified by a factor known as weights denoted by $\boldsymbol{W_{ij}} = [w_1, w_2, w_3, \ldots, w_n]$.

The hidden layer then calculates the sum of all inputs as given by Eq. (2).

$$y = \sum (\boldsymbol{W}_{\boldsymbol{ij}}^{T} \times \boldsymbol{i}_{\boldsymbol{i}}) + \boldsymbol{b} \tag{2}$$

Here $\boldsymbol{W_{ij}}$ represents the weight of a neuron i in the input layer connected to a neuron j in the hidden layer, whereas, $\boldsymbol{b} = [b_1, b_2, b_3, \ldots, b_n]$ represents the bias that is defined as the weight of a neuron that has always assigned a constant value '1'. Fig. 2 depicts a simple three layered neural network (see Fig. 3).

The summed output of Eq. (2) is then fed to an activation function. Activation functions are of many types, Eq. (3) represents the activation function.

$$\psi(y) = \frac{1}{1 + e^{-y}} \tag{3}$$

Here ψ represents the outcome of a neuron in middle layer. The output ψ of every neuron present in the hidden layer is then again amplified by multiplying it with another set of weight vector $W_{jk} = [w_1, w_2, w_3, \ldots, w_n]$, where, k can be an interconnected neuron in the output layer. The same process is repeated with the neurons in the output layer. The activation function of the neurons in the output layer may differ from the neurons in the hidden layer or it can be similar to that of neurons in the hidden layer. Mean Square Error is then calculated that provides the difference between desired or target and actual output of the neuron. It is provided by Eq. (4).

$$MSE = \frac{1}{N} \sum_{i=1}^{N} = (fx1(\pi_i;x) - y_i)^2 \tag{4}$$

In Eq. (4) $\lambda(\pi_i;x)$ represents the target output and N denotes number of samples. The neural network weights affiliated with the input vector are changed according to equation

$$\boldsymbol{W_k} = \boldsymbol{W_{k-1}} + \Delta \boldsymbol{W_k} \tag{5}$$

4. Dataset

Standard dataset of wood knot defects available at the website of university of Oulu, Finland are used in this paper. The dataset utilized as a part of this study contain about 395images of different knot defects. The dataset summary is shown in Table 3.

Sample images for each knot defect are shown below in Fig. 4. First row comprises samples images for dry knot, second row contain images for horn knot, and the third one contain images for leaf knot, fourth row comprises sample images for sound knot and fifth row comprises images for edge knot from the wood database.

Fig. 3. Sample of wood database [37].

Table 3
Summary of the wood database used for this work.

Class of defects	Number of images
Sound knot	179
Dry knot	69
Edge knot	65
Leaf knot	47
Horn knot	35
Total	395

5. Proposed technique

Fig. 4 depicts the flowchart of the proposed technique using GLCM based features. The technique uses four distinct features that are Energy, Contrast, Correlation, and Homogeneity for a feed-forward back propagation neural network that is used as a classifier. The algorithm first divides the data into three sets that are used for training, validation and testing respectively. The algorithm then adjust its weights to minimize mean squared error in order to optimize its performance for the classification task.

Similarly, for LTEM features based classification the flowchart of the proposed technique is shown in Fig. 5.

6. Experimentation

Firstly gray level co-occurrence matrix (GLCM) based experimentation was performed. Images from the database were converted to gray scale as shown below in Fig. 6.

Four GLCM based features including contrast, correlation, energy and homogeneity were extracted from the gray scale images. These feature were used as an input feature to back propagation neural network for classification of wood knot defects.

Secondly Laws texture energy measures (LTEM) based experimentation was performed. LTEM was applied on 395 sample images containing different wood knot defects. For each image of wood knot defect we get nine texture energy maps. Therefore after applying laws texture energy measure on 395 images of wood knot defects we get a total of 3555 texture energy maps, nine texture energy maps respect to a single image. For example for a particular sample of dry sample shown below we get the following nine texture energy maps are shown in Fig. 7.

The first image 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 image 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 image is the combination of S5E5/E5S5. The fourth image is of similar combination that is of S5S5. This images particularly detects spots. The fifth image is the combination of R5R5. It indicates ripples in the image. The sixth image 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

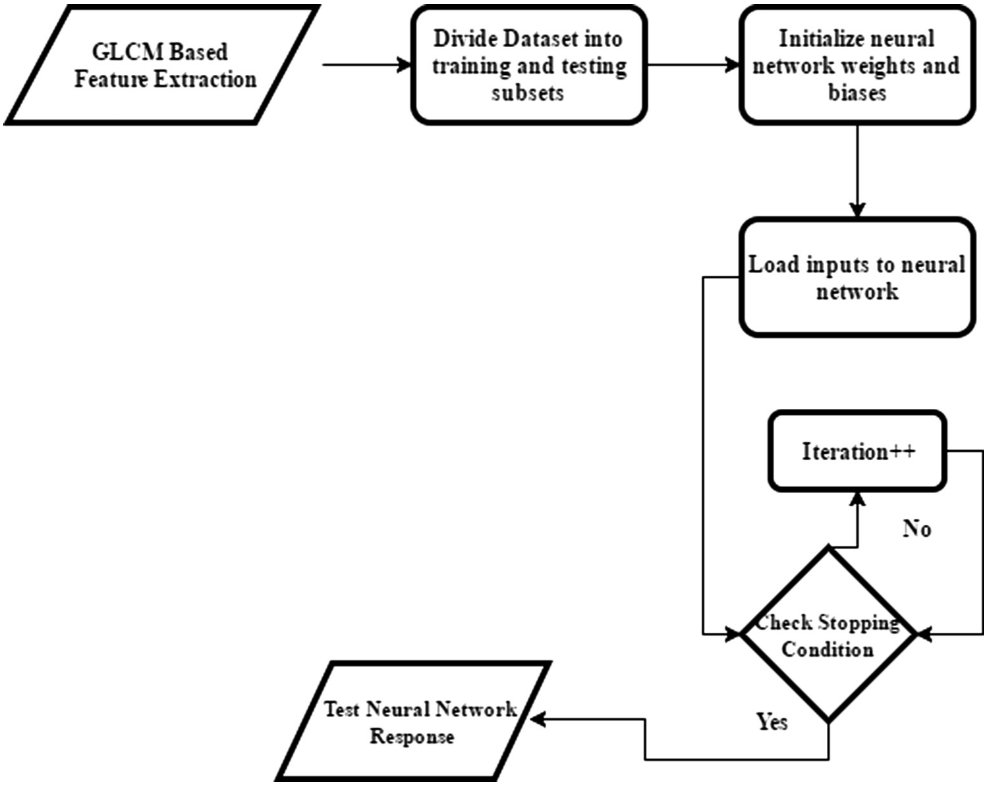

Fig. 4. Algorithm flowchart for GLCM.

seventh image is the 2D image that is the combination of E5E5. The eight image is the mean R5E5/E5R5 & the ninth image is the mean S5R5/R5S5. The sample images used for our experimentation are knot defects in wood so those texture energy maps were consideredfor feature extraction for a particular knot defect that shows more prominent results for that knot defect. Therefore first, fourth, sixth & seventh texture energy map obtained after applying laws texture energy measures on all samples of different wood knot defects were consideredfor all knot defects because they give us relatively more information related to edges and spots in the particular wood defect images, the detection of spots and edges are important because knot is a particular imperfection in the wood the rest of the texture energy maps that were obtained after the applying LTEM are neglected.

These four texture energy maps were itself used as a feature and

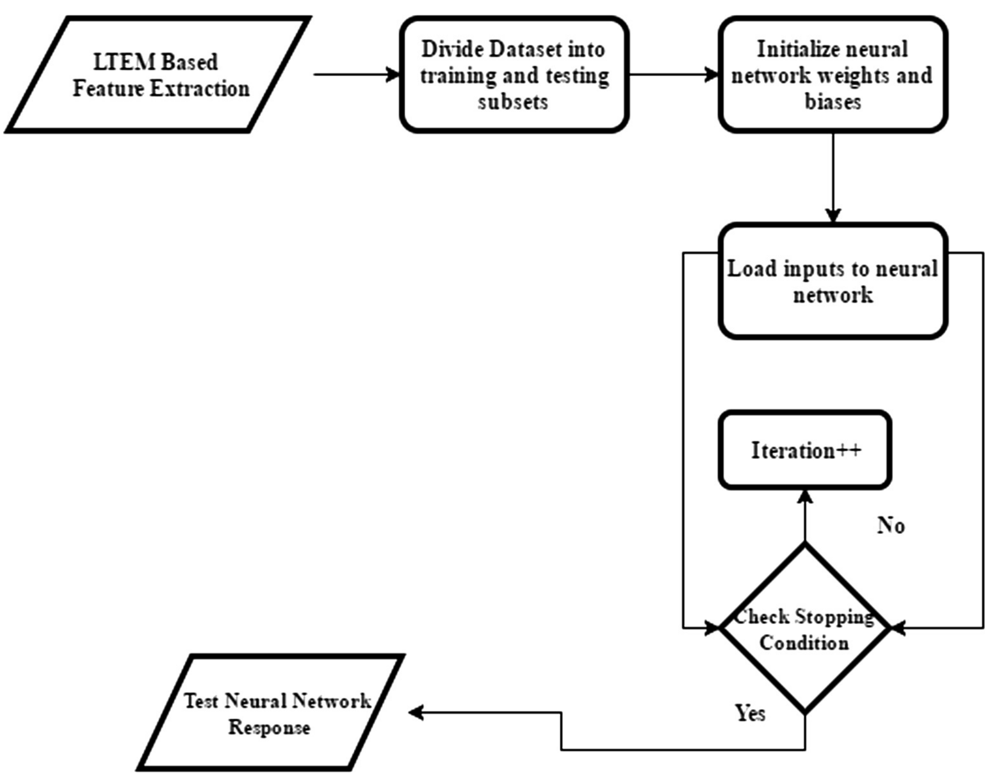

Fig. 5. Algorithm flowchart for LTEM.

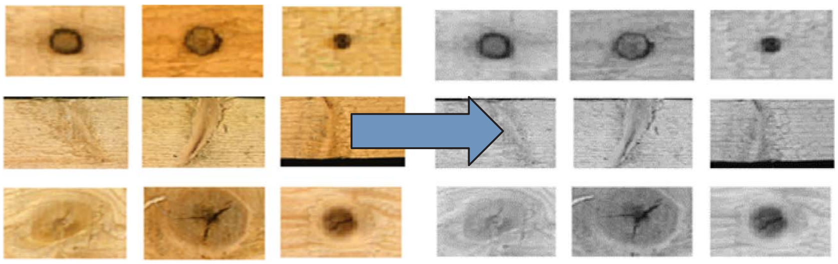

Fig. 6. Images conversion to gray scale.

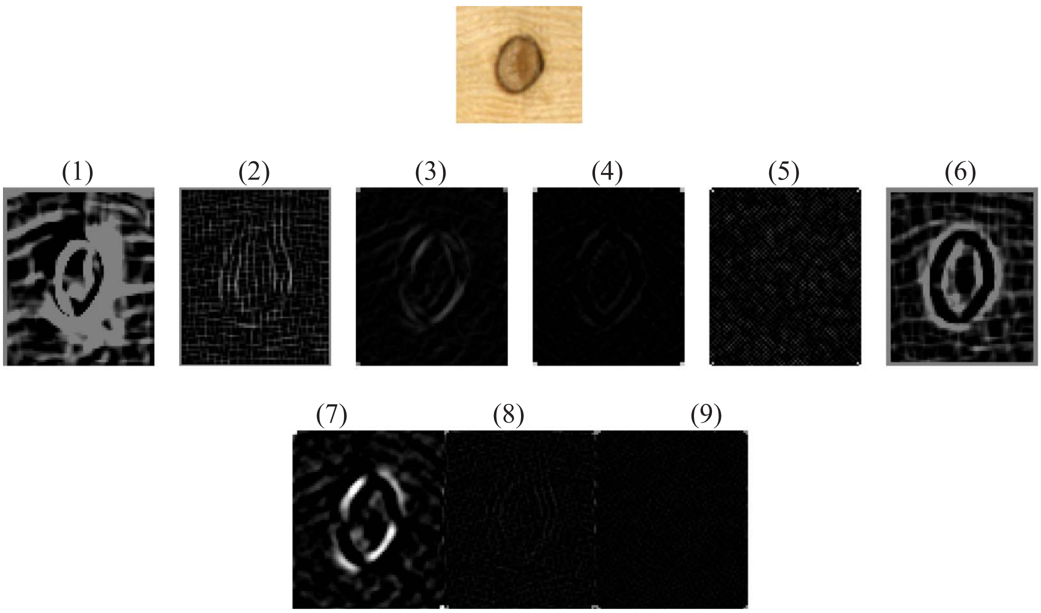

Fig. 7. Nine texture energy maps for a particular image of dry knot.

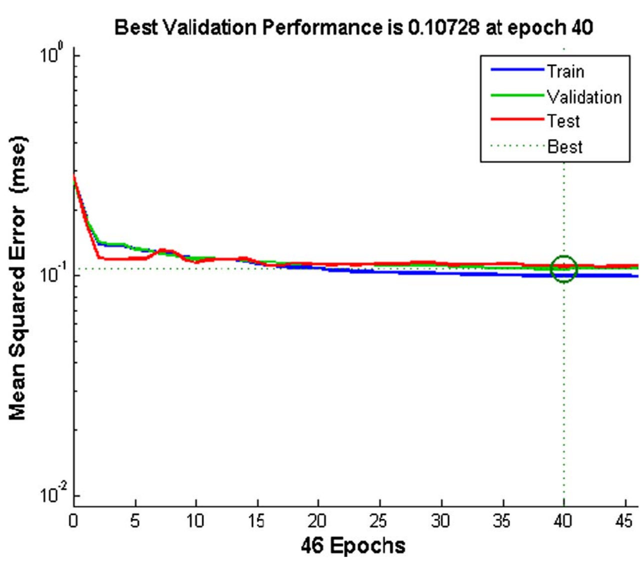

Fig. 8. MSE graph of back-propagation neural network for GLCM.

average energy of these four texture energy maps was calculated. The average energy obtained from four texture energy maps was used as an input feature for back propagation neural network for classification of wood knot defects.

7. Results and discussion

Feed-Forward back-propagation neural networks are used as a classification tool to predict the wood defects. The network is trained using4 input, and 5 output neurons while neurons in the hidden layer are varied to get the best performance. The dataset contain 395 images, for which there are two feature sets. The first feature set contains GLCM based feature whereas the second feature set contain LTEM based features. For both feature sets 70% of the whole data used to train the neural network while 15% of the data is used as testing data and 15% data is used for validation.

The best performance of the neural network for GLCM based feature set comes with 15 hidden layer neurons where MSE for the training data is 0.10728. Training curve of neural network trained with 15 hidden layer neurons using GLCM based feature set is shown below in Fig. 8.

The overall performance of the neural network by using 15 neurons

Table 4
Performance of BPNN using 15 neurons and GLCM features.

Input dataset	No. of neurons		Dry knot	Horn knot	Leaf knot	Sound knot	Edge knot
		Precision	63	63	29	66	56
GLCM	15	Recall	36	63	26	86	42
		F score	46	63	27	75	48
		Accuracy	85	93	84	74	85

Table 5
Performance of BPNN using 30 neurons and LTEM features.

Input dataset	No. of neurons		Dry knot	Horn knot	Leaf knot	Sound knot	Edge knot
		Precision	72	68	71	82	70
LTEM	30	Recall	71	71	51	88	68
		F score	71	69	59	85	69
		Accuracy	90	94	92	86	90

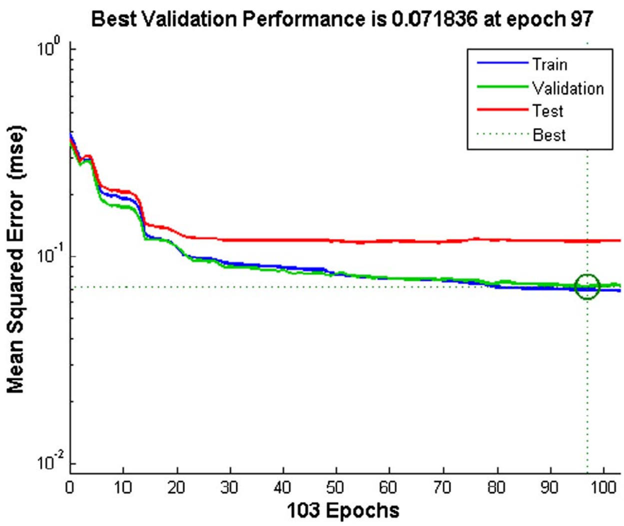

Fig. 9. MSE graph of back-propagation neural network for LTEM.

Table 6
Comparison of results on the basis of overall classification accuracy.

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

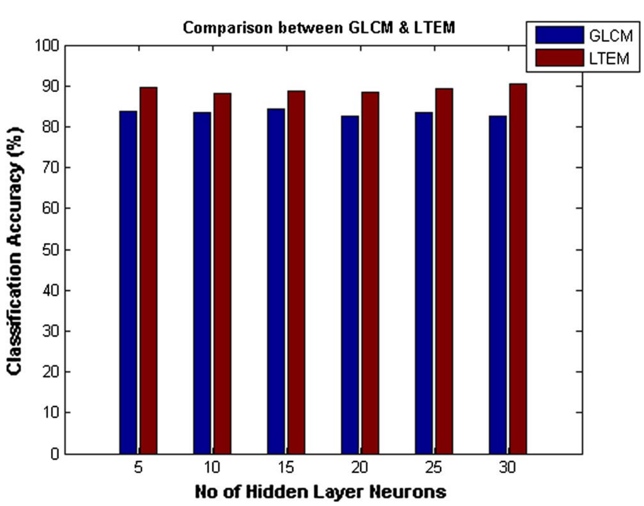

Fig. 10. Performance comparison between GLCM and LTEM based classifiers.

in the hidden layer and GLCM based input features is shown in Table 5. In case of multi-class problems accuracy standalone is not an accurate measure, therefore, for individual classes, along with accuracy other parameters such as precision, recall and F Score are calculated and presented in Table 4.

It can be seen from Table 4 that sound knot shows the highest precision, recall, and F-Score values, whereas, horn knot shows the highest individual class accuracy of 93%. The reason for this high accuracy may be because of the availability of small dataset of horn knot, therefore, less samples are used for testing that yield in higher accuracy.

The best performance of the neural network for LTEM based feature set comes with 30 hidden layer neurons where mse for the training data is 0.071836. Training curve of neural network trained with 30 hidden layer neurons using LTEM based feature set is shown below in Fig. 9.

The overall performance of the neural network by using 30 neurons in the hidden layer and LTEM based input features is shown in Table 5.

Similarly, like in case of GLCM based features, it can be seen from Table 5 that sound knot shows the highest precision, recall, and F-Score values, whereas, horn knot shows the highest individual class accuracy of 94%.

Moreover, comparison of the performance of back propagation neural network using gray level co-occurrence matrix (GLCM) and laws texture energy measures (LTEM) based feature with different number of hidden layer neurons is shown in Table 6.

It can be seen from the table that initially, the overall accuracy is increased by increasing number of neurons for both GLCM and LTEM. However, there is a drop in accuracy for both GLCM and LTEM when the number of neurons was increased to 20. LTEM trained neural networks showed best performance at 30 neurons with an overall accuracy of 90.5%. In general, it is difficult to correlate number of hidden neurons and accuracy as the accuracy is dependent up on various other factors such as dataset, learning rate of the neural network. However, better results may be achieved by minimizing the training error using some optimization algorithm such as, Genetic Algorithm (GA). A more clear picture for the performance comparison between GLCM and LTEM based back-propagation neural network with different number of hidden layer neurons is shown in Fig. 10. Figure shows the comparison between overall average classification accuracy for both GLCM and LTEM based classifier using different number of hidden layer neurons.

Comparison between performance of classifiers using GLCM and LTEM based input using different neurons in the hidden layer shows that LTEM based classifier shows better performance as compared to GLCM based classifier. Table 7 summarizes some of the state-of-the-art approaches that are explained in the literature review for wood defect classification.

If we see the summary of approaches that are presented in Table 7 then it can be easily concluded that:

1. The proposed LTEM based approach shows good results with 90.5% accuracy that is consistent with many approaches that are presented for wood defects classification in literature review showing accuracies around 90% or above. Hence the proposed approach is reliable to be considered as a new addition to the existing approaches for wood defect detection.
2. Specific to detection of wood knot defects and the utilization of same dataset, the proposed approach is comparable to Yu and Kamarthi [21] and Mahram et al. [22] in a sense that both approaches used the same dataset for classification of wood knot defects.

Table 7
Comparison of different approaches for wood defect classification.

	Approach	Dataset	Defect types	Accuracy
Longuetaud et al. [3]	3D connex components + 3D distance transform	CT images of seven set of squared beams of Silver Fir and Norway Spruce	Knots	85%
Sarigul et al. [4]	Morphological operators + NN	643 CT images of Red Oak logs	Knots, Splits, Bark, Decay	85.1%
Mu and Qi [5]	Hu-invariant moments + BPNN	Training Dataset = 80 samples	Knot, Rot, Grub Hole	86.7%
Mohan et al. [6]	Hilbert transform + Gabor + Naïve Bayes/MLP/ optimized NN	400 images containing 100 images each for 4 defects	Sound Knot, Dry Knot, Horn Knot and Edge Knot	79% (Naïve Bayes)86% (MLP)91% (optimized NN)
Wang et al. [7]	Wavelet + ANN	Ultrasonic signals from 275 Elm specimens of wood defects	Single hole, double hole, triple hole, split, knot and no defect specimen	At least 90%
Yuce et al. [8]	PCA + BPNN + Taguchi Analysis	CCD images of wood defects from plywood boards	Bark, Pin Knots, Roughness, Worm Holes, Streak, Splits, Sound Knots, Rots, etc.	80%
Conners et al. [9]	Tonal measures + Texture measures using a sequential Classifier	500 wood boards containing one or more defects	Knots, mineral streak, decay, stane, wane, splits and checks, grub holes and holes, dark and light bark.	63.13% (Tonal measures + sequential Classifier) 75.96% (Texture measures + sequential classifier) 88.33% (Tonal and Texture Measures + sequential classifier)
Ruz et al. [13]	FMMIS + GLCM + SVM/MLP	550 test wood images containing 11 defects (University of Chile database)	Birdseye, pockets, wane, split, stain, blue stain, pith, dead knot, live knot and hole	82.79% (FMMIS + GLCM with SVM)81.735% (FMMIS + GLCM with MLP)SVM Pair-wise classification (91.739%)
Rizwan et al. [18]	GLCM + PSO Optimized BPNN	90 Images containing 3 defects categories (University of Oulu database)	Dry knot, Horn Knot, Sound Knot	78.26%
YongHua and JinCong [19]	Tamura Features + BPNN GLCM + BPNN	300 samples of wood defects containing 3 defects categories	Wood dead festival, wood live festival, wood poles	90.67% (Tamura + BPNN)91.33% (GLCM + BPNN)92.67% (GLCM + Tamura + BPNN)
Yu and Kamarthi [21]	Cluster based wavelet features + PNN/MLP DWT + PNN/MLP	329 images of different knot defects from University of Oulu database	Sound knot, horn knot, encase knot, leaf knot, edge knot	91% (Cluster based wavelet + PNN) 87.7% (Cluster based wavelet + MLP)87% (DWT + PNN)83.1% (DWT + MLP)
Mahram et al. [22]	Different combinations of GLCM, Statistical Measures, LBP with SVM and KNN classifiers	329 images of different knot defects from University of Oulu database	Sound knot, horn knot, encase knot, leaf knot, edge knot	100%(GLCM + LBP + KNN) 100%(GLCM + LBP + SVM)
Proposed approach	LTEM + BPNN GLCM + BPNN	395 images of different knot defects from University of Oulu database	Sound knot, dry knot, edge knot, leaf knot, horn knot	90.5% (LTEM + BPNN)84.3% (GLCM + BPNN)

3. The proposed approach performed better than the cluster based wavelet approach proposed by Yu and Kamarthi [21] in three cases and showed accuracy of 90.5% as compared to the accuracy of 91% in one case that Yu and Kamarthi determined for a combination of cluster based wavelet and probabilistic neural network. Similarly, as compared to Mehram et al. [22] claimed 100% accuracy, the results of the proposed approach are more realistic and reliable as the proposed approach uses a larger dataset of 395 images as compared to the works by Yu and Kamarthi [21] and Mehram et al. [22] that employ 325 images for wood knot defect classification. Size of dataset affects overall accuracy, therefore, results using larger dataset are considered more realistic as with larger datasets, it is possible to present more samples for testing to make conclusion regarding accuracy of the system.
4. It can also be concluded by observing the results from Table 7 that hybridization of features especially with GLCM yield better results. Therefore in future, GLCM features and LTEM features can be combined to verify any improvements in classify accuracy.

In a nutshell, the work presents a novel method in which texture based features are used to classify five wood defects; sound knot, dry knot, edge knot, leaf knot, and horn knot successfully. The proposed technique is benchmarked against a well-established GLCM based feature extraction and classification approach. LTEM based feature extraction and classification showed promising results as compared to widely reported GLCM based method. Hence, the presented work is a new contribution in the area of texture based wood defect detection and classification. The paper in comparison to others pays special attention to aesthetics that is closer to visual perception of humans. It presents a new combination of texture features and neural networks. The neural networks used for classification is a well-established approach for defect classification. However, the use of back-propagation neural network is justified by the fact that at the moment as scope of the paper is limited to texture based feature extraction and classification. In future, it is aimed to improve the results by using deep learning approaches for feature extraction, and classification.

8. Conclusion

The paper presents a novel approach for classification of wood defects. The proposed method firstly extracts gray level co-occurrence matrix based features from 395 samples of different wood defects and secondly extracts laws texture energy measures based features from 395 samples of different wood defects. Feed-forward backpropagation neural network is used to classify the defects using firstly GLCM based features and secondly by laws texture energy measures based features. The proposed technique shows promising results for wood defects classification. Mean Square Error of the network for training dataset is found to be0.10728, whereas overall accuracy is found to be 84.3% using 15 hidden layer neurons and glcm based feature set whereas mean square error of the network for training dataset is found to be 0.0718 and 90.4% overall accuracy is achieved using laws texture energy measures based feature set. Future work involves further investigation of other machine learning techniques for wood defects classification such as deep learning.

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