WOOD DEFECTS CLASSIFICATION USING GENERALIZED FEED-FORWARD NEURAL NETWORK

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***Abstract*: In this paper a new classification algorithm is proposed for the Wood Defects. In order to develop algorithm 158 different wood defect images With a view to extract features from the images after using matlab, an algorithm proposes (FFT) Fast Fourier Transform coefficients. The Efficient classifiers based on Generalized Feed-Forward Neural Networks (GFF NN). A separate Cross-Validation dataset is employed for correct evaluation of the proposed classification algorithm with reference to important performance measures, like MSE and classification accuracy. The Average Classification Accuracy of GFF Neural Network comprising of hidden layers1 with 50 PE's organized in a typical system is found to be superior (97.5 %) for Training. Finally, optimal algorithm has been developed on the idea of the simplest classifier performance. The algorithm will provide an effective alternative to traditional method of wood defects analysis for deciding the best quality wood.**

Index Terms: **MatLab, Nero Solution Software, Microsoft excel, GFF Neural network, FFT Transform Technique**s

I. INTRODUCTION

The wood classification is a problem that is present in many industrial contests such as the furniture industries and the wood panel production. Different woods have different aspects, properties, and costs. Proper collection of wood type is very important to ensure that the final product has the necessary features and characteristics. For example, within the production of wood panels, the wood type influences the number of the glue that has got to be utilized in the panel to ensure the right mechanical properties. On the opposite side, the glue features a great impact on the final cost of the panel and affects the general environmental impact. In the paper industry, wood type affects the final amount of cellulose in paper, hence the quality of paper.

In the production process, if the value and just-in-time delivery represent the 2 lines of the proper angle, the standard should be the hypotenuse that completes the proper triangle of the method. It means the standard is that the most vital parameter despite the rise in one or both of the opposite parameters (geometrical fact). Scientifically, a process internal control means conducting observations, tests and inspections and thereby making decisions which improve its performance. Because no production or manufacturing process is 100% defect-free (this applies particularly where natural materials, as textile ones, are processed), the success of a wood milling process is significantly highlighted by its success in reducing wood defects.

Defects develop in growing tree and timber. Some defects are characteristic of both living and felled trees (cracks, rot, and wormholes). Wood processing impairment is produced during the purchase, transport, and operation of woodworking machinery. The seriousness of defect is determined by its type, size, and location, as well as by the purpose for which the wood is to be used. Thus defects undesirable in some type of timber may be disregarded or even valued in other. For example, illicit grain is not acceptable for resonant wood, it is acceptable for commercial timber, and it is very valuable for timber.

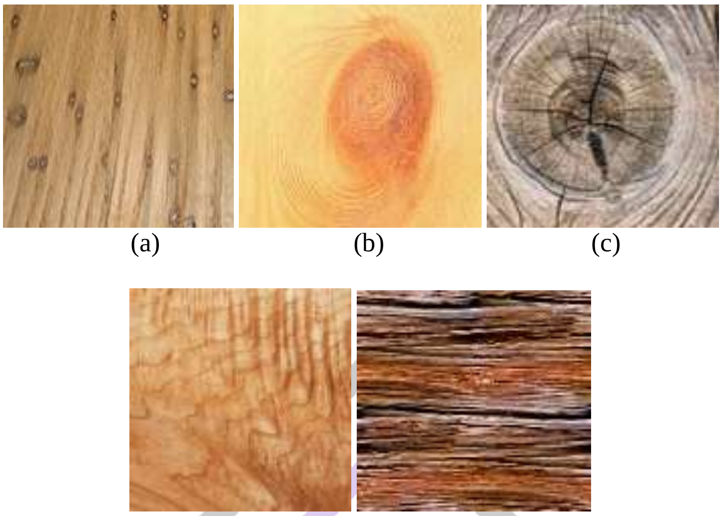
From the first beginning, the human dream is to enhance the manufacturing techniques to realize optimum potential benefits as quality, cost, comfort, accuracy, precision and speed. To imitate the big variety of human functions, technology was the magic stick that advanced humanity from manual to mechanical then from mechanical to automatic. The rare existence of automated wood inspection may be attributed to the methodologies, which are often unable to cope with a wide variety of wood defects, yet a continued reduction in processor and memory costs would suggest that automated wood defect inspection has potential as a cost effective alternative. The wider application of automated wood defect inspection would seem to offer a number of potential advantages, including improved safety, reduced labour costs, the elimination of human error and/or subjective judgment, and therefore the creation of timely statistical product data. Therefore, automated visual inspection is gaining increasing importance in wood industry.

The automated test program usually has a computer-based detection system. Because they're computer-based, these systems don't suffer the drawbacks of human visual inspection. Automated systems are able to inspect wood in a continuous manner without pause. Most of those automated systems are offline or off-loom systems. Therefore, for it to work better testing systems must be used online or where materials are used. An automated inspection system usually consists of a computer-based vision system. Because they are computer-based, these systems do not suffer the drawbacks of human visual inspection. Automated systems are able to inspect wood in a continuous manner without pause. Most of these automated systems are offline or off-loom systems. Therefore, to be more efficient, inspection systems must be implemented online or on-loom.

This paper presents a strategy in view of a trained generalized feed forward neural network that takes texture features like Average, Standard deviation, Entropy, Energy, Contrast, Correlation and Homogeneity as inputs and classifies wood defects. Utilization of a FFT trained neural network for this reason has never been tended to in the writing in this way. Next segment clarifies the strategy.

1.1 DEFECT ANALYSIS

In this paper, we've addressed five sorts of wood defect, which frequently occur in wood industries, Wormhole, Sound Knots, Rotten Knots, Curly grains, Roughness as shown below in figure. All of the defects are shown in Fig.1. All of them are discussed here below.



(a) (b) (c)

(d) (e)

Fig 1: Different types of defect occurred in knitted fabrics.
(a)Wormhole, (b) Sound Knots, (c) Rotten Knots, (d) Curly grains, (e)Roughness

• **Wormhole**: Fig. 1(a) shows the defect of wormhole. Worms are corridors and openings made from wood for insects. Insecticides usually cease after the bark has been removed and after the wood has dried or treated with antiseptics. Top worms don't affect the mechanical properties of wood. Deep holes disrupt the integrity of the wood and should reduce its strength. Worms often promote the event of wood fungus spots and wood rot.

•. **Sound Knots**: Fig. 1(b) shows the defect of Visible a knot is a component of a branch that's made from wood. Knots come from wood and disrupt their uniform structure. They twist the grain and ring of the year and weaken the wood when it's pulled by weeds and bent. On the opposite hand, knots increase the strength of a wood that's pressed with a twist or cut from a distance.

• **Rotten Knots**: Fig. 1(c) shows the defect of Rotten Knots. Knots are cut or broken from limbs or branches of shoots, green or dead, protruding, flowing, or pressed, but with exposed sound or rotten wood. When the exposed wood is felt, the knot "sounds", if rotten, "unheard of".

• **Curly grains**: Fig. 1(d) shows the defect of Curly grains. Curly grain is common in most species and is additionally referred to as Burl grain, burly grain, fiddle back or figure wood. The various causes of burl grains include the location of knots, bark cambium crust damage, and genetic predisposition. Curly grain is usually a desired characteristic for specialty products, but are often difficult to machine. Curly grains are considered as defective because it causes a discount within the strength of wood.

• **Roughness**: Fig. 1(d) shows the defect of Roughness. Hardness describes the potential for good in a mechanical environment. These irregularities are often determined by measuring the peak, width and shape of peaks and valleys produced by woodworking operations and anatomical structural properties. The measurement could also be administered during a plane (2D) or a given area (3D).

II. RESEARCH METHODOLOGY

It is characterization of five types of wood defect images Using Neural Network Approaches. Information procurement for the proposed classifier intended for the order of wood defect images. The most essential unrelated highlights and in addition coefficient from the images will be removed .keeping in mind the end goal to separate highlights FFT transform will be utilized.

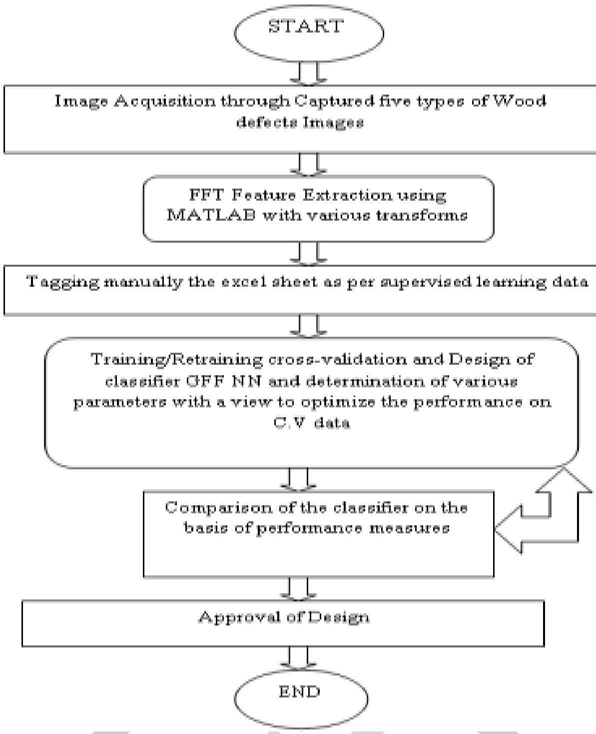


Fig.2 Methodology of work

2.1 NEURAL NETWORKS

Following Neural Networks are tested:

GENERALIZED FEED-FORWARD NEURAL NETWORKS (GFF NN):

Theoretically, MLP can solve any problem that can be solved by a standard feed network. In practice, however, generalized feed-forward networks often solve the matter far more efficiently. Without describing the matter, it suffices to mention that a typical MLP requires many times more training epochs than the generalized feed-forward network containing an equivalent number of processing elements. The following network depicted in Fig.2.2 of the GFF has produced the best classification results.

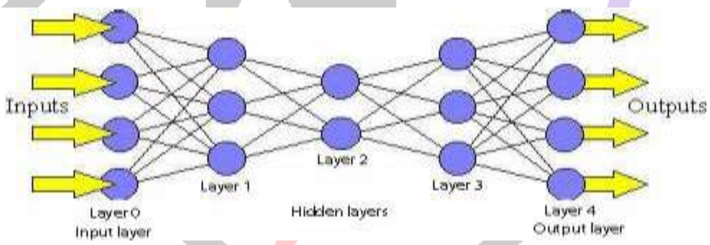


Fig .3 A feed-forward network

Feed-forward networks have the following characteristics:

1. Perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers haven't any reference to the external world, and hence are called hidden layers.
2. Each perceptron in one layer is connected to each perceptron on subsequent layer. Hence information is consistently "fed forward" from one layer to subsequent, and this explains why these networks are called feed-forward networks.
3. There is no interaction between percepetons in the same layer.

One perceptron can split points into two equally divided regions. Now allow us to extend the discussion into the separation of points into two regions that aren't linearly separable. Consider the following network:

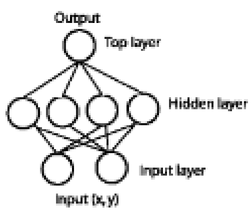


Fig 4: A feed-forward network with one hidden layer.

The same (x, y) is fed into the network through the perceptrons within the input layer. With four perceptrons that are independent of every other within the hidden layer, the purpose is assessed into 4 pairs of linearly separable regions, each of which features a unique line separating the region.

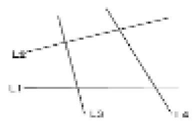
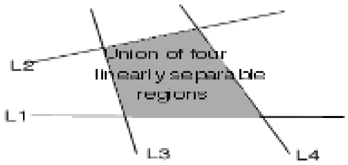


Fig.5: lines each dividing the plane into 2 linearly separable regions.

The top perceptron performs logical operations on the outputs of the hidden layers in order that the entire network classifies input points in 2 regions which may not be linearly separable. For instance, using the AND operator on these four outputs, one gets the intersection of the 4 regions that forms the centre region.



. **Fig 6**: Intersection of 4 linearly separable regions forms the centre region

By varying the amount of nodes within the hidden layer, the amount of layers, and therefore the number of input and output nodes, one can classification of points in arbitrary dimension into an arbitrary number of groups. Hence feed-forward networks are commonly used for classification.

2.2 LEARNING RULES USED

- **Momentum (MOM)**

Momentum learning rule is an improvement over the straight gradient-descent search in the sense that a memory term, i.e., the past increment in the weight, is set to speed up and stabilize convergence. In momentum learning, the equation to update the weight becomes

$$w\_ij\ (n+1)=w\_ij\ (n)+n\delta\_i\ (n)\ x\_j\ (n)+\eta[w\_ij\ (n)-w\_ij\ (n-1)\ ] \qquad \text{.... (1)}$$

Where, η denotes the momentum constant. Typically, η should be set between 0.5 and 0.9. This is called momentum learning due to the form of the last term, which resembles the momentum in machines. It's a solid way to speed up learning. Being a robust method to speed up learning, it is recommended as a default search rule for network with nonlinearities.

- **Conjugate Gradient(CG)**

The basic idea of the line search is to begin with gradient-descent direction and search for minimum along the line, that is, $w(n+1) = w(n) + \lambda(n)s(n)$ Where $\lambda(n) = J[w(n) + \lambda s(n)]$ .... (2)

There has been a problem with the gradient direction that it is sensitive to the eccentricity of the performance surface (caused by the Eigen value spread), so following the gradient is not the quickest path to the minimum. Alternatively, one can compute the optimal step size at each point, which corresponds to a line search.

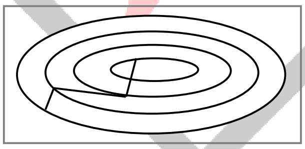


Fig.7: Path to the minimum with line search methods

It can be proved that successive direction have to be perpendicular to each other as displayed in Figure 6 and path to the minimum is intrinsically a zigzag path. This procedure can be improved if weight is cut across the zigzag. The formulation becomes

$$s^{new} = -\nabla J^{new} + \alpha s^{old} \qquad \text{.... (3)}$$

Where, α denotes a dynamically computed parameter that compromises between the two directions. This is called a conjugate method. For quadratic performance surfaces, the conjugate algorithm preserves quadratic termination and can reach the minimum in D step, where D denotes the dimension of the weight space.

- **Quick propagation(QP)**

Quick propagation (Quick prop) is one among the foremost effective and widely used adaptive learning rules. There is just one global parameter making a big contribution to the result, the e-parameter. Quick-propagation uses a group of heuristics to optimize Back-propagation; the condition where e is employed is when the sign for the present slope and former slope for the load is the same.

- **Delta bar Delta(DBD)**

Delta-Bar-Delta algorithm is an adaptive step-size procedure for searching a performance surface. Step size and intensity are adjusted according to previous PE error values. If the present and past weight updates are both of an equivalent sign, the training rate is increased linearly. The reasoning is that if the load is being moved within the same direction to decrease the error, then it'll get there faster with a bigger step size. If the updates have different signs, this is often a sign that the load has been moved too far. When this happens, the learning rate decreases geometrically.

$$\Delta\eta_i(n) = \begin{cases} K & s_i(n-1)\Delta w_i(n) > 0 \\ -\beta\eta_i(n) & s_i(n-1)\Delta w_i(n) < 0 \\ 0 & \text{Otherwise} \end{cases} \quad \text{................ (4)}$$

Where: $S_i(n) = (1-\lambda)\nabla w_i(n-1) + \lambda S_i(n-1)$

K= Additive constant
B= Multiplication constant
λ= Smoothing factor
Weights update Equation:

$$\nabla w_i(n-1) = \eta_i \nabla w_i + \rho \Delta w_i(n) \quad \text{.... (5)}$$

III. Simulation Results

3.1 COMPUTER SIMULATION

The GFF neural system has been simulated for 158 distinct images of five types of wood defect images out of which 141 were utilized for training reason and 17 were utilized for cross validation. The simulation of best classifier along with the confusion matrix is shown below:

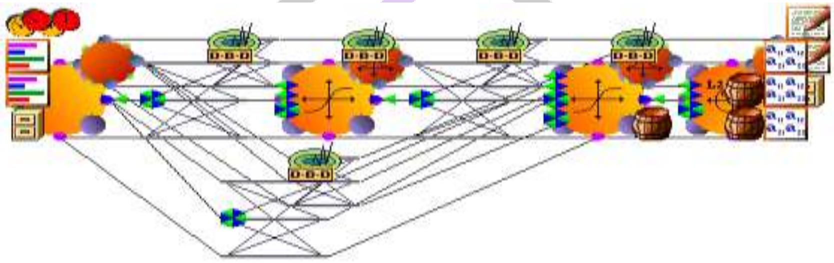


Fig.7 GFF neural network trained with DBD learning rule

3.2 RESULTS

To assess the performance of our presented model, we used confusion matrix. This measurement is often used for classification evaluation model. By using confusion matrix, accuracy of the classifier can be calculated

Table I. Confusion matrix on CV data set

Output / Desired	WORM HOLES	SOUND KNOTS	ROUGHNESS	ROTTEN KNOTS	CURLY GRAIN
WORM HOLES	2	0	0	0	0
SOUND KNOTS	0	3	0	0	0
ROUGHNESS	0	0	3	0	0
ROTTEN KNOTS	0	0	0	4	0
CURLY GRAIN	0	1	0	0	4

TABLE II. Confusion matrix on Training data set

Output / Desired	*WORM HOLES*	*SOUND KNOTS*	*ROUGHNESS*	*ROTTEN KNOTS*	*CURLY GRAIN*
WORM HOLES	18	0	0	0	0
SOUND KNOTS	0	32	0	0	0
ROUGHNESS	0	0	26	0	0
ROTTEN KNOTS	0	0	0	33	0
CURLY GRAIN	0	0	0	0	32

Here Table I and Table II Contend the C.V as well as Training data set.

This paper uses MATLAB and neuro solution tool to conduct the experiment. The coefficients and features are extracted from these wood defects images and transferred to linked excel sheet through MATLAB program where 64 FFT coefficients and 7 features of images. The results of the automatic classification performed by MNN is shown in table III and table IV respectively, which compares the accuracy of classifier

TABLE III. Accuracy of the network on CV data set

PERFORMANCE	WORM HOLES	SOUND KNOTS	ROUGHNESS	ROTTEN KNOTS	CURLY GRAIN
MSE	0.021541314	0.076108807	0.023343543	0.022052113	0.051905004
NMSE	0.207514656	0.422989331	0.160625811	0.122558859	0.288472041
MAE	0.077498733	0.155084644	0.089273392	0.106280072	0.12372768
Min Abs Error	0.001852376	0.003091255	0.003128399	0.004806392	0.003729119
Max Abs Error	0.526368254	0.863496087	0.456836895	0.316063015	0.621651314
r	0.897331176	0.804221044	0.932282467	0.954555519	0.882037415
Percent Correct	100	75	100	100	100

TABLE IV. Accuracy of the network on training data set

PERFORMANCE	WORM HOLES	SOUND KNOTS	ROUGHNESS	ROTTEN KNOTS	CURLY GRAIN
MSE	0.000432824	0.000610786	0.000515322	0.000669814	0.000724285
NMSE	0.003886622	0.003481376	0.00342646	0.003736414	0.004128297
MAE	0.01482805	0.017676383	0.016275261	0.019396258	0.0199827
Min Abs Error	0.000181604	0.000172233	2.80195E-05	0.00012146	5.35193E-05
Max Abs Error	0.055369779	0.05552602	0.05552959	0.054834789	0.05536072
r	0.998319125	0.998602386	0.998550729	0.99851205	0.998385972
Percent Correct	100	100	100	100	100

Here Table III and Table IV Contain the C.V and Training result and show the 97.5% percent accuracy.

IV. CONCLUSION AND FUTURE WORK

From the results obtained it concludes that the GFF Neural Network with DBD (delta bar delta) and hidden layer 1 with processing element 50 gives best results of 100% in Training while in Cross Validation it gives 95% so overall result is 97.5%. For further improvement, feature selection strategy needs to be added to wood quality automatically detection. The accuracy of the system can be further improved with the use of five types of Wood Defects images through rigorous training and cross validation.

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