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TO DEVELOP COMPUTATIONAL INTELLIGENCE TECHNIQUE BASED WOOD DEFECTS CLASSIFICATION SYSTEM

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Abstract - *In this paper presents a new classification algorithm to the problem of identifying Wood Defects in wood industries. 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 (WHT) Walsh Hadamard Transform coefficients. The Efficient classifiers based on Modular neural Network (MNN).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 MNN Neural Network comprising of hidden layers 2 with 19 PE's organized in a typical topology is found to be superior (98.57 %) 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.*

Key Words*: *Wood defects, Computational Intelligence MatLab, Neuro Solution Software, Microsoft excel, MNN Neural network, WHT Transform Techniques

1. INTRODUCTION

Quality of wooden products is heavily dependent on wood strength. Presence of any defect in wood may reduce the wood strength and thus the quality of wooden products. From strength's perspective, elasticity and stiffness of the wood plate are the important properties that are also affected

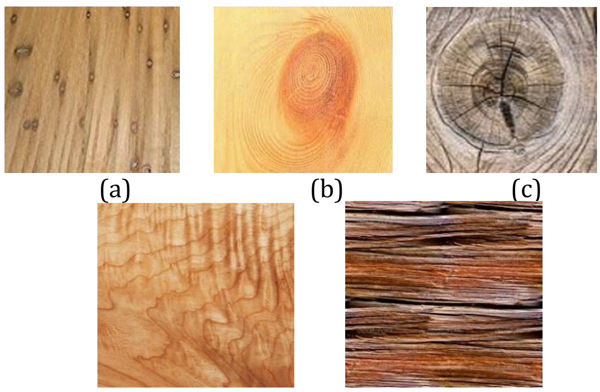
In common practice, the wood defects are detected manually by visual inspection. Manual inspection is a not only a slow process, also, it is extremely difficult to ensure 100% inspection, thus, making the quality control less reliable. Automatically detection of wood defects by not relying on human expertise and experience is the solution for the objectivity and repeatability problem. Computational intelligence technique based inspection systems are in great focus nowadays because of their capability to save inspection time by quick or timely detection of defects, thus improving the reliability of quality control process. This paper aims to present a computational intelligence technique based approach using trained neural network for classification of five sort of different defects in wood.

Researchers have developed systems for automatically detecting and identifying defects in wood. Such systems generally involve the use of image processing techniques, feature extraction to capture the essential characteristics of all defects and a classifier to recognise these defects. Artificial intelligence provides an efficient approach to the identification and quantification of the wood damages.

In this paper, MNN base on ANN is used to solve the objectivity and repeatability of wood defects classification. MNN is a simple ANN's model for automatically adjust learning parameters. In our experiment, to develop algorithm 158 different wood defect images With a view to extract features from the images after using matlab, an algorithm proposes (WHT) Walsh Hadamard Transform coefficients. MNN is the popular strategy for classification problems. This paper is organized as follows in the next section brief overview of wood defect analysis is discussed. In section II, the Methodology of work of automatic wood defects classification system is described in details. Section III demonstrated the result of the experiments. In the last section, conclusions and future work are presented.

1.1 BRIEF OVERVIEW OF WOOD 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).

2. 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 important thing is off the highlights, and in addition, the coefficient of the pictures will be deleted .Bearing in mind that the ultimate goal is to highlight the high points, WHT is the transform will be used.

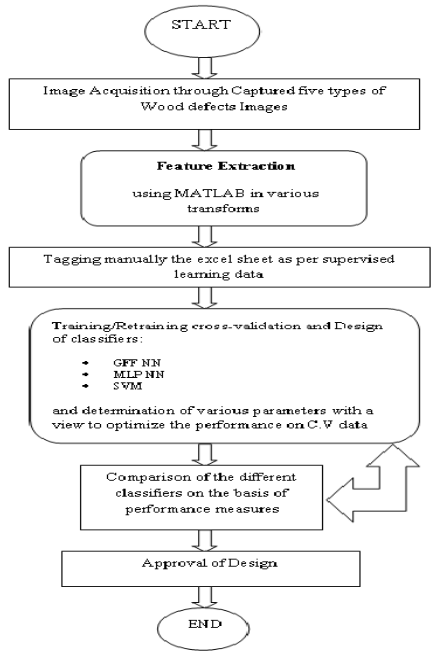


Fig.2 Methodology of work

2.1 NEURAL NETWORK

Following Neural Network are tested:

MODULAR NEURAL NETWORK (MNN)

Modular Neural Network is actually a modular feed forward neural network which may be a special category of MLP NN. It doesn't have full interconnectivity between their layers. Therefore, a smaller number of connection weights could also be required for an equivalent size MLP network with reference to an equivalent number of processing elements. In view of these facts, the training time is accelerated. There are some ways so as to segment a MNN into different modules. MNN processes its inputs with the assistance of various parallel connected MLPs and therefore the outputs of those MLP are recombined to supply the results. This neural network is made up of a variety of network modules, and with a particular topology, a structure inside the topological, in order to improve the properties of each of the sub module.

The following topology depicted in Fig.2.2 of the MNN has produced the simplest classification results.

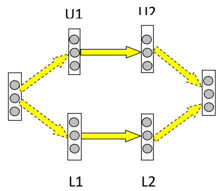


Fig. 3 Topology of a Modular Neural Network

This topology is suggested on the idea of experimental evidences, testing and performance measures.

2.2 LEARNING RULES OF NEURAL NETWORK

Ability to learn is one of the key features of neural network. Learning rules are algorithms for finding suitable connection weights W and other network parameters to minimize the cost function (Error) of the given example. Every processing element that has an adaptive parameter must change it according to some pre-specified procedure in order to produce an output that is as close as possible to the desired output. Back propagation is the most commonly used form of learning. The weights are changed based on their previous values and correction terms. The learning rule is the means by which the correction term is estimated. Extent of correction to be applied to the weights is decided by the user, once the particular rule is selected. It all depends upon the learning rate, whether it is small or high. For small learning rate, learning takes a long time whereas if it is set too high, the adaption diverges and weights are unusable.

- **MOMENTUM (MOM):**

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

$w_{ij}(n+1)=w_{ij}(n)+\eta\delta_i(n)\,x_j(n)+\eta[w_{ij}(n)-w_{ij}(n-1)]$ .... (1)

Where, η denotes the momentum constant. Typically, η should be set between 0.5 and 0.9. This is called momentum learning thanks to the shape of the last term, which resembles the momentum in machines. It's a solid way to speed up learning. Being a strong method to hurry up learning, it's 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.

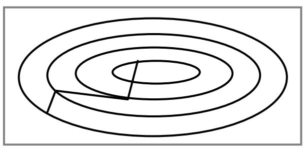


Fig 4: Path to the minimum with line search methods

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

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

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 (QP) may be a heuristic modification of the quality back propagation algorithm. Fahlman introduced QP in 1998. QP isn't essentially faster than back propagation albeit for a few applications it's going to prove faster. QP is more susceptible to instability and may stick to local minimum than back propagation. QP changes the network weights after each case. It is a batch update algorithm. It computes the typical gradient of the error surface across all the cases before updating the weights at the top of an epoch.

QP works with the assumption that the error surface is locally quadratic, with the axes of hyper-ellipsoid error surface associated with the weights. If this is true, then the minimum of the error surface can be found after only a couple of epochs. Certainly, the assumption is not generally valid, but if it is close to true, the algorithm can converge to the minimum very quickly. On the first epoch, the weights are changed using same rule as the back propagation, based upon the local gradient and the learning rate. On successive epochs, the quadratic assumption is used to obtain the minimum.

The basic QP formula has a number of limitations. If the error surface is not concave, the algorithm can deviate from the desired value. If gradient changes a little or not at all, Then the changes can be extremely large. If the zero error is encountered, a weight will stop changing permanently. On the first epoch, QP updates weights similar to back propagation. Subsequently, weight changes are calculated using the quick propagation equation.

$$\Delta w(t) = \frac{s(t)}{s(t-1)-s(t)}\Delta w(t-1) \quad .... (4)$$

The system is numerically unstable if s(t) is extremely close, equal or greater than s(t-1). Since (t) is expressed along the direction of weight gradient, such conditions can only occur if the slope becomes constant, or becomes steeper. In such cases, the weight update formula is

$$\Delta w(t) = \varepsilon\alpha\Delta w(t-1) \quad .... (5)$$

Where α denotes on acceleration constant

- **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.

$$\Delta\eta_i(n) = \begin{cases} K & s_i(n-1)\Delta w_i(n) > 0 \\ -\beta\eta_i(n) & s_i(n-1)\Delta w_i(n) < 0 \\ 0 & Otherwise \end{cases} \quad \text{....... (6)}$$

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:

$$\nabla w_i(n-1) = \eta_i \nabla w_i + \rho\Delta w_i(n) \quad \text{.... (7)}$$

3. SIMULATION RESULTS

3.1 COMPUTER SIMULATION

The MNN neural system has been simulated for 158 distinct images of five types of wood defect images out of which 128 were utilized for training reason and 30 were utilized for cross validation. The simulation of best classifier along with the confusion matrix is shown below:

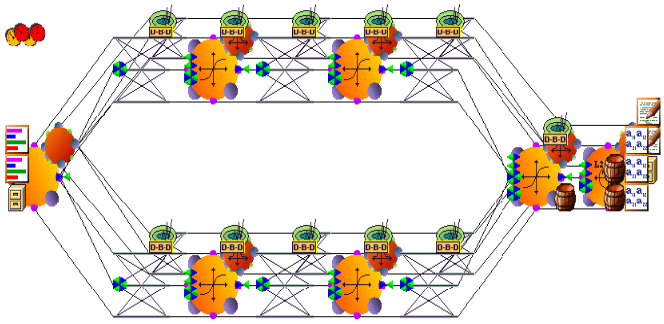


Fig .5 MNN1 neural network trained with DBD learning rule

3.2 EXPERIMENTAL RESULTS

The obtained Training Report Results of the Best Classifier are as shown below:

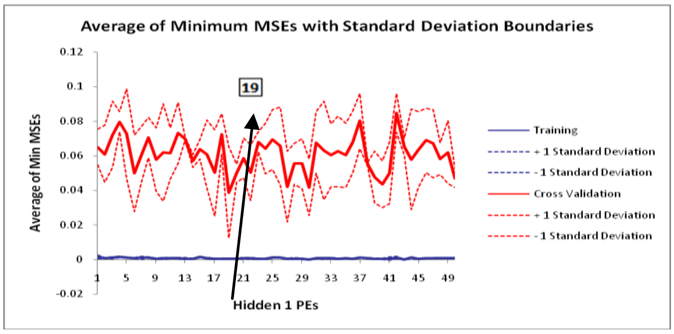


Fig. 6: Average of Minimum MSEs with Standard Deviation Boundaries

Table 1: Training and cross validation Report of the Best Classifier MNN Top 1-DBD

Best Networks	*Training*	*Cross Validation*
Hidden 1 PEs	45	19
Run #	2	2
Epoch #	1000	1000
Minimum MSE	2.66855E-05	0.009156998
Final MSE	2.66855E-05	0.009156998

To assess the performance of our proposed 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 -2: Confusion matrix on CV data set

Output/Desired	WORM HOLES	SOUND KNOTS	ROUGHNESS	ROTTEN KNOTS	CURLY GRAIN
WORM HOLES	4	0	0	0	0
SOUND KNOTS	0	7	0	1	0
ROUGHNESS	0	0	6	0	0
ROTTEN KNOTS	0	0	0	6	0
CURLY GRAIN	0	0	0	0	7

Table -3: Confusion matrix on Training data set

Output / Desired	WORM HOLES	SOUND KNOTS	ROUGHNESS	ROTTEN KNOTS	CURLY GRAIN
WORM HOLES	16	0	0	0	0
SOUND KNOTS	0	29	0	0	0
ROUGHNESS	0	0	23	0	0
ROTTEN KNOTS	0	0	0	30	0
CURLY GRAIN	0	0	0	0	29

Here Table- 1 and Table -2 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 128 WHT coefficients and 7 features of images. The result of the automatic classification performed by MNN is shown in table III and table IV respectively, which compares the accuracy of classifier.

Table -4: Accuracy of the network on CV data set

PERFORMANCE	WORM HOLES	SOUND KNOTS	ROUGHNESS	ROTTEN KNOTS	CURLY GRAIN
MSE	0.028509416	0.022664045	0.003629806	0.015900088	0.00511296
NMSE	0.253681008	0.129643735	0.023254957	0.090952288	0.029247348
MAE	0.083522965	0.065552387	0.031882138	0.069337452	0.038487306
Min Abs Error	0.002659109	0.000198513	0.000549895	0.000511187	0.000447735
Max Abs Error	0.667267765	0.727445199	0.193848108	0.392171926	0.345106802
r	0.887408104	0.934309298	0.988325479	0.954221167	0.985560606
Percent Correct	100	100	100	85.71428571	100

Table -5: Accuracy of the network on training data set

PERFOR MANCE	WORM HOLES	SOUND KNOTS	ROUGHNESS	ROTTEN KNOTS	CURLY GRAIN
MSE	0.000339057	0.000369619	0.000267306	0.000389345	0.000565984
NMSE	0.003079193	0.00209767	0.001802414	0.002157987	0.003212091
MAE	0.014325232	0.013673569	0.012580188	0.015846032	0.01684421
Min Abs Error	5.49552E-05	7.85886E-06	6.32283E-05	0.000432123	1.71249E-06
Max Abs Error	0.047821355	0.054306144	0.046689151	0.049656389	0.053999749
r	0.998673758	0.999101087	0.999173814	0.999027863	0.998695085
Percent Correct	100	100	100	100	100

Here Table III and Table IV Contain the C.V and Training result and show the 98.57 % percent accuracy.

4. CONCLUSIONS

In this paper, The Efficient classifiers based on Modular neural Network (MNN) were applied to the wood quality automatic detection. The dataset of 158 different wood defect images With a view to extract features from the images after using matlab, an algorithm presents (WHT) Walsh Hadamard Transform coefficients .Experiment result shows that MNN gives the best performance compared to other. From the results obtained it concludes that the MNN Neural Network with DBD (delta bar delta) and hidden layer -2 with processing element 19 gives best results of 100% in Training while in Cross Validation it gives 97.14% so overall result is 98.57%. 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. These systems may also be realized in hardware system on chip after through validation and the systems can be deployed in different wood industries.

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