WOOD DEFECT IDENTIFICATION USING GENERALIZED FEED FORWARD NEURAL NETWORK

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Abstract- In this paper a new classification algorithm is proposed for the Wood Defect Identification Using Generalized Feed Forward Neural Network. In order to develop algorithm 50 captured wood defect images of plywood have been considered, With a view to extract features from the plywood captured images after image processing, an algorithm proposes (DCT) discreet cosine transformed 128 coefficients. The Efficient classifiers based on Generalized feed forward (GFF) Neural Network. A separate Cross-Validation dataset is used for proper evaluation of the proposed classification algorithm with respect to important performance measures, such as MSE and classification accuracy. The Average Classification Accuracy of GFF Neural Network comprising of one hidden layers with 8 PE's organized in a typical topology is found to be superior (100 %) for Training. Finally, optimal algorithm has been developed on the basis of the best classifier performance. The algorithm will provide an effective alternative to traditional method of plywood captured images analysis for Classify the six type plywood defect.
Keywords—Signal & Image processing, neural network, Transformed domain techniques, MATLAB, Microsoft Office Excel etc.

1.INTRODUCTION:

Wood is made up of many cells that were produced by the living tissues in the tree. The manner in which the cells develop and are organized has profound effects on the properties of wood. The anatomy of wood is also the basis for separating wood into categories or species.

Natural resources such as wood have become scarce and very expensive. Maximize the usage and reduce the rejection (losses) is a great challenge for the wood industry. The process to maximize the value of wood can be divided into three parts. Initially, the wood is taken to a sawmill and then one needs to decide whether the wood is more valuable as lumber, veneer, or chips. If it is for lumber, them the boards cut from it must be edged and trimmed. This is a process that requires someone to decide how to trim off effective parts and make the board as valuable as possible. Thereafter, someone must examine the board and give it a grade, based on the quality of the wood and presence of defects. Finally, someone cuts the lumber again to produce defect free dimension parts.

Defect develop in growing tree and timber. Some defect are characteristic of both living and felled trees (cracks, rot, wormholes). wood working defects are produced during the procurement, transport, and mechanical working of the wood. The seriousness of defect is determine 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, Cross grain is unacceptable in resonant wood, acceptable in commercial lumber, and highly valued in plywood.

The main defects of wood include knots, cracks, fungal damage ,warping, slanting, and worm holes. A knot is a part of a branch embedded in wood. Knots appearance of wood and disturb its uniform structure. They twist the grain and the annual rings and weaken the wood when it is pulled with the grain and when bent. On the other hand, knots increase the strength of wood that is compressed transversely or sheared longitudinally.

Therefore, the effective detection of wood defect information is particularly important. A new wood defect detection method an Efficient algorithm for Wood defect identification using neural classifier used in this Research for the detection of wood defect.

We have collected the 50 images of six type of defect plywood captured images. By using this plywood captured images an algorithm is developed which proposes two-dimensional (DCT) Discreet cosine transformed domain coefficients in addition to Average, Standard Deviation, Entropy, Contrast, Correlation, Energy, Homogeneity total coefficient i get in excel sheet by using matlab.

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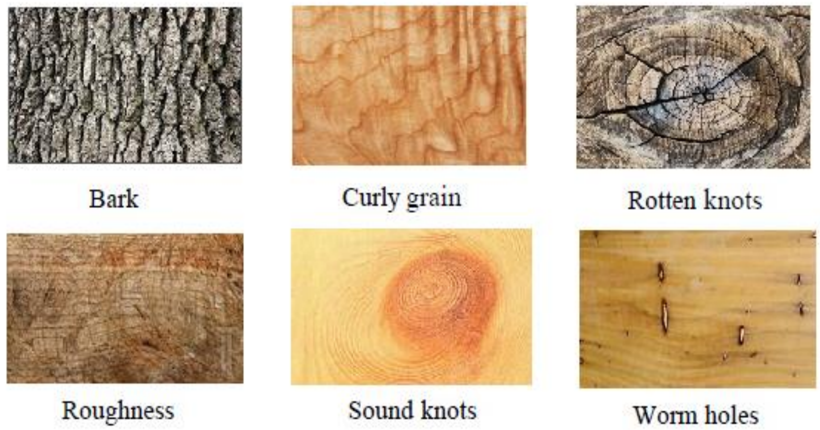

Figure 1:Plywood defect type, there are 6 distinct type defect that need to be identified by the neural network

2.Research Methodology:

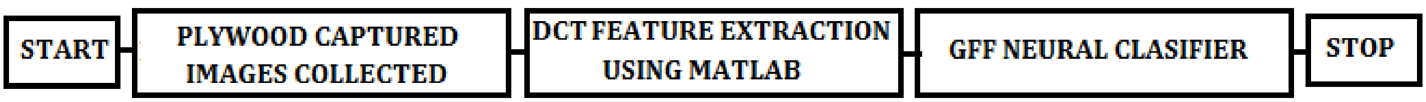

Figure2 Methodology of work

It this paper to study Wood Defect Identification Using Generalized Feed Forward Neural Network. Data acquisition for the proposed classifier designed for the Recognition of wood defect shall be in the form of plywood captured images. Image data will be Collected from the different- different sawmills .The most important un correlated features as well as coefficient from the images will be extracted .In order to extract features, statistical techniques, image processing techniques, DCT transformed domain will be used.

3.NEURAL NETWORKS

Following Neural Networks are tested: Feed-Forward Neural Networks

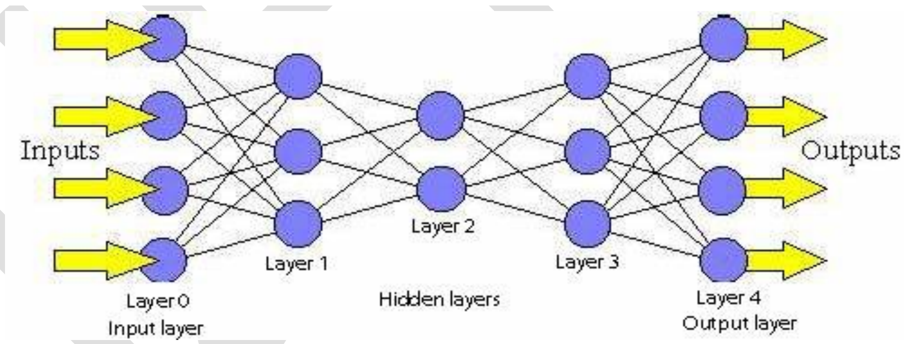

Figure 3 feed-forward network.

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 have no connection with the external world, and hence are called hidden layers.

2. Each perceptron in one layer is connected to every perceptron on the next layer. Hence information is constantly "fed forward" from one layer to the next., and this explains why these networks are called feed-forward networks.

3. There is no connection among perceptrons in the same layer.

A single perceptron can classify points into two regions that are linearly separable. Now let us extend the discussion into the separation of points into two regions that are not linearly separable. Consider the following network:

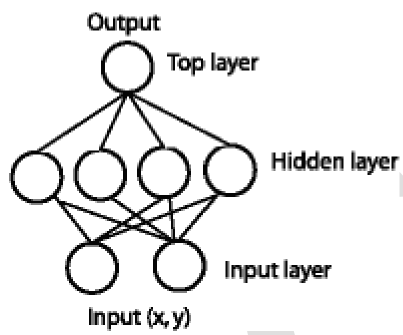

Figure. 3.2 A feed-forward network with one hidden layer.

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

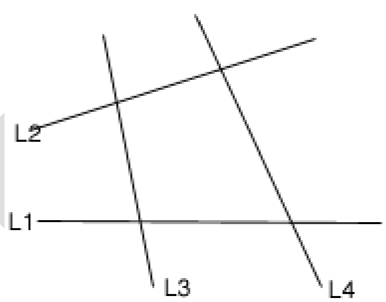

Figure 3.3 lines each dividing the plane into 2 linearly separable regions.

The top perceptron performs logical operations on the outputs of the hidden layers so that the whole network classifies input points in 2 regions that might 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 center region.

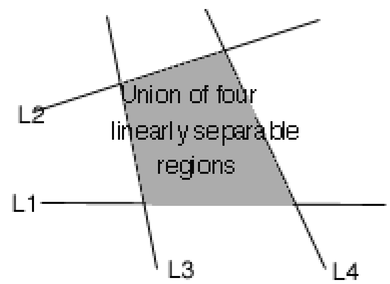

Figure3.4 Intersection of 4 linearly separable regions forms the center region.

By varying the number of nodes in the hidden layer, the number of layers, and 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.

4. Learning Rules used:

- ***Momentum***

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

- Conjugate Gradient

CG is the most popular iterative method for solving large systems of linear equations. CG is effective for systems of the form A=xb-A (1) where x _is an unknown vector, b is a known vector, and A _is a known, square, symmetric, positive-definite (or positive-indefinite) matrix. (Don't worry if you've forgotten what "positive-definite" means; we shall review it.) These systems arise in many important settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis, circuit analysis, and math homework.

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in n-space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector.

- Quick propagation

Quick propagation (Quickprop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimise Back-propagation, the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

- Delta by Delta

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

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5. RESULT

The GFF neural network has been simulated for 50 different images of plywood out of which 12 were used for training purpose and 12 were used for cross validation.

The simulation of best classifier along with the confusion matrix is shown below :

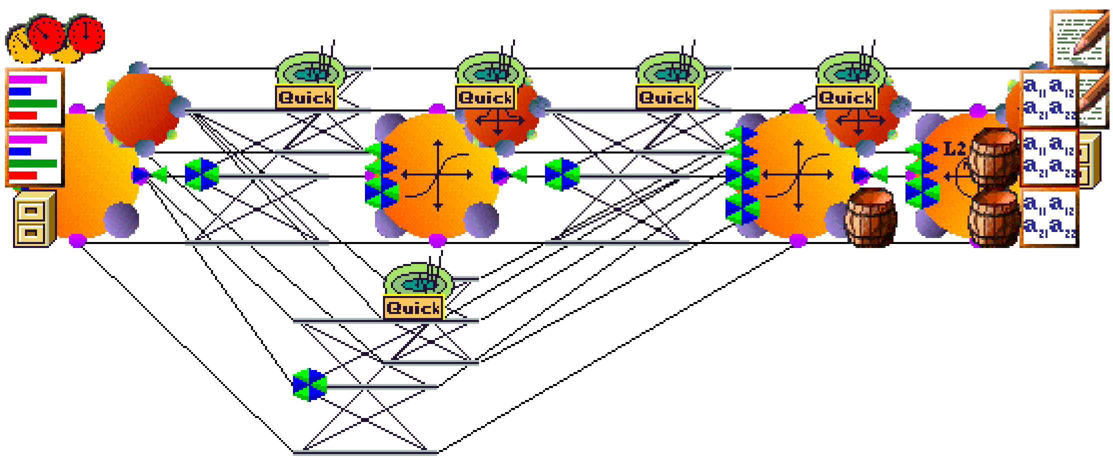

Fig.3.1 GFF neural network trained with QP learning rule

Output / Desired	NAME(WORM HOLES)	NAME(SOUND KNOTS)	NAME(ROUGHNESS)	NAME(ROTTEN KNOTS)	NAME(CURLY GRAIN)	NAME(BARK)
NAME(WORM HOLES)	1	0	0	0	0	0
NAME(SOUND KNOTS)	0	1	0	0	0	0
NAME(ROUGHNESS)	0	0	3	0	0	1
NAME(ROTTEN KNOTS)	0	0	0	1	0	1
NAME(CURLY GRAIN)	0	0	0	0	2	0
NAME(BARK)	0	0	0	1	0	1

Table I. Confusion matrix on CV data set

Output / Desired	NAME(WORM HOLES)	NAME(SOUND KNOTS)	NAME(ROUGHNESS)	NAME(ROTTEN KNOTS)	NAME(CURLY GRAIN)	NAME(BARK)
NAME(WORM HOLES)	4	0	0	0	0	0
NAME(SOUND KNOTS)	0	2	0	0	0	0
NAME(ROUGHNESS)	0	0	8	0	0	0
NAME(ROTTEN KNOTS)	0	0	0	7	0	0
NAME(CURLY GRAIN)	0	0	0	0	7	0
NAME(BARK)	0	0	0	0	0	10

TABLE II. Confusion matrix on Training data set

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

Performance	NAME(WORM HOLES)	NAME(SOUND KNOTS)	NAME(ROUGHNESS)	NAME(ROTTEN KNOTS)	NAME(CURLY GRAIN)	NAME(BARK)
MSE	0.07398213	0.006524388	0.239449026	0.154823869	0.05864414	0.158172086
NMSE	0.968493341	0.085410166	1.277061471	1.11473186	0.422237806	0.843584459
MAE	0.111414417	0.064973981	0.32941733	0.234875177	0.133033782	0.195991144
Min Abs Error	0.010544895	0.007503917	0.010263846	0.004744665	0.004879127	0.00489623
Max Abs Error	0.933000404	0.17389578	1.043488912	0.930368191	0.752958851	1.037152624
r	0.645112821	0.957759162	0.195902108	0.029740522	0.788597963	0.540613778
Percent Correct	100	100	100	50	100	33.33333333

TABLE III. Accuracy of the network on CV data set

Performance	NAME(WORM HOLES)	NAME(SOUND KNOTS)	NAME(ROUGHNESS)	NAME(ROTTEN KNOTS)	NAME(CURLY GRAIN)	NAME(BARK)
MSE	0.001431667	0.002349799	0.003854274	0.003374651	0.001789275	0.005900982
NMSE	0.015200937	0.047126525	0.023189881	0.022456203	0.011906514	0.030432208
MAE	0.031659477	0.042040336	0.041625525	0.0430089	0.038909737	0.047642133
Min Abs Error	0.001247344	0.007220327	0.000675769	0.004910652	0.008827058	0.003969832
Max Abs Error	0.055467508	0.15581342	0.240600975	0.226140374	0.081814073	0.387065849
r	0.995494137	0.980247978	0.988911016	0.988714387	0.995812127	0.984999253
Percent Correct	100	100	100	100	100	100

TABLE IV. Accuracy of the network on training data set

Here Table III and Table IV Contain the C.V and Training result.

6.CONCLUSION

This paper demonstrated how artificial neural networks(ANN)could be used to build accurate wood defect clasifier. In order to train the neural network we extract shape features from real plywood images that we captured at earlier time. We use Generalized Feed-Forward Network as classification. The result show that in training 100% accuracy but in cross-validation result rotten knots is 50% and bark is 33.33% is rest of 100% is not good.

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