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MACHINE LEARNING APPROACH FOR DAMAGE DETECTION IN COMPOSITE STRUCTURE USING DYNAMIC RESPONES

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Abstract: Structural Health Monitoring is a process of damage identification, localization, classification and prediction of remaining life of a structure. In this project, damage identification for the composite plates is carried out using machine learning techniques. Six composite plates of unidirectional glass-epoxy in cross-ply configuration is fabricated for the project. One plate is healthy, and five plates are damaged in the form of delamination at various locations and of various sizes. The frequency domain and time domain features are extracted from this dynamic response. These features then act as an input for data driven techniques for damage identification purpose. The machine learning techniques mostly include classification methods and supervised learning technique. A healthy and a damaged plate are used for training the classifier, whereas remaining four plates are used for identification purpose. The damage identification of four laminated beams is compared using decision tree and two ensemble methods namely Rotation Forest and Bagging with decision tree as the base classifier. It isobserved that the classification accuracy of ensemble methods is much higher than the decision tree classifier.

I. Introduction

Structural Health Monitoring is a process of damage identification, localization, classification and prediction of remaining life of a structure. In this project, damage identification for the composite plates is carried out using machine learning techniques. Six composite plates of unidirectional glass-epoxy in cross-ply [0/90/0/90] configuration are fabricated for the case study. One plate is healthy and five plates are damaged in the form of delamination at various locations and of various sizes. For the purposes of damage identification, dynamic responses of composite cantilever beams made from these plates are recorded using Laser Doppler Vibrometer. The frequency domain and time domain features are extracted from this dynamic response. These features then act as

an input for data driven techniques for damage identification purpose. The machine learning techniques mostly include classification methods and supervised learning technique, which are data driven techniques, used to identify damage in composite plates. A healthy and a damaged plate are used for training the classifier, whereas remaining four plates are used for identification purpose. The damage identification result of four laminated beams is compared using decision tree and two ensemble methods namely Rotation Forest and Bagging with decision tree as the base classifier. It is observed that the classification accuracy of ensemble methods is much higher than the decision tree classifier. Also these methods show significant improvement in the result for damage identification as compared to the single decision tree classifier.

II. Literature Review

The damage is defined as changes introduced into a system that adversely affects the current and future performance of the system. From the point of view of damage identification in structures and mechanical systems, the damage is defined as a change in the material and/or geometric properties of these systems, including changes to 1the boundary conditions and system connectivity, which adversely affect the current or future performance of these systems [1]. The presence of damage in the system changes the geometry as well as material properties such as changes in stiffness and energy dissipation properties of system. The changes in these properties alter the measured dynamic response of system and this is prime motive for most of the damage identification problem. A typical damage is shown in Figure 1.1.

Goals of SHM Technology

Goals of Structural Health Monitoring (SHM) are to develop techniques to detect damages in the given structure by monitoring global or local dynamic response to avoid possible catastrophic failures. In general, structures are designed for specific design criteria with a margin of safety, to account for the unknowns during the use of the structure. However all structures degrade after a finite life span as they are put into service. Processes such as corrosion, fatigue, erosion, wear and overloads degrade them until they are no longer fit for their intended use. Depending on the value of a structure, the cost of repairing varies

PATTERN RECOGNITION AND MACHINE LEARNING FOR SHM

Pattern Recognition (PR) refers to the assignment of labelling the objects. These objects are described in terms of features or attributes. Features are the characteristics of these objects and discriminate these objects into given classes in PR problem. Damage identification is regarded as a problem of pattern recognition. A pattern is in form of features vector or matrix. Patterns represent the different conditions and indicate whether the analysed structure is healthy or damaged. Machine learning is concerned with the design and development of algorithms that allow computers to bring out behaviour of a system based on empirical data. It is the study of methods for developing algorithms and programming computers to learn based on data. The data may be obtained from different sources such as from a set of sensors or from any other measuring system. The one of the goal of machine learning is to automatically learn to recognize patterns present in data set and make intelligent decisions based on this data set.

Regression

The regression is the construction of map between a group of continuous inputs variable and a continuous output variable on basis of set of samples. It is a technique of modelling and analyzing the dependent variable and one or more independent variable. The output of regression algorithm is one or more continuous variables. In SHM it is used for 9damage location problem where the diagnosis is the Cartesian coordinate of the damage and in severity assessment it could be the length of the crack. The algorithms discussed above are used in Structural Health Monitoring. The classification problem is used in this study for damage identification purpose. The various classification algorithms are available in machine learning literature such as linear classifiers (Fisher's linear discriminant, Logistic regression, Naive Bayes classifier, Perceptron), support vector machines, neural network, decision tree etc. the decision tree classifier is used in this study out of all the classifiers. The Pattern Recognition problem for damage identification is carried out using supervised learning as well as unsupervised learning as shown in

Figure 2.1. The decision regarding the selection of machine learning algorithm is made on the basis of availability of acquired data and problem in hand. Once algorithm is selected, a decision of healthy state of the system is taken.

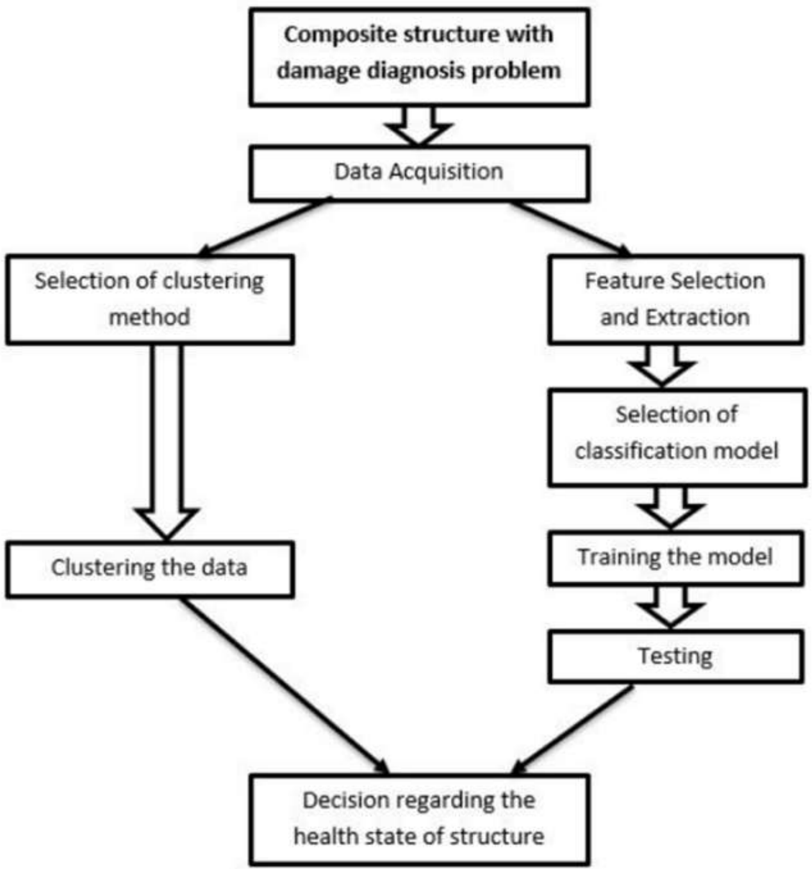

Fig. 2.1 Pattern Recognition Problem for Damage Identification

General approach to build a classification Model

The classification technique is a systematic approach to build the classification model from an input training set and class labels. Various classifiers include the rule-based classifiers, decision tree classifiers, support vector machines and neural network. Each classifier employs a learning algorithm to identify a model that fits the relationship between the features and class labels of input data. The generated model fits the input 11data as well as correctly predicts the class of unknown data never used in training purpose. The general approach for solving the classification problem is shown in Figure 2.2. The input required for classification problem is a training set characterized by using features and set of class labels. The training set is used to build a classification model. This model is applied to the test set which consists of records with unknown class labels.

Decision Tree

A decision tree is a hierarchical data structure applying the divide-and-conquer strategy. The learning algorithms build the tree from a given labelled training set. The goal is to create a model that predicts the value of a target variable based on several input variables. It is an efficient non-parametric method, which can be used for both classification and regression. In Classification tree, the output is the class labels to which the data belongs whereas in Regression tree the output is a real number.

Decision Tree Induction

To generate the decision tree one requires the induction algorithm. In decision tree learning various learning algorithms like ID3, C4.5 etc. are available. For our problem C 4.5 algorithm is used. The algorithm is explained in next section. A decision tree is a model used for supervised learning technique in which, a tree is learned by splitting the training set into subsets based on an attribute test condition. The splitting process is repeated on each derived subset in a recursive manner. The recursion is completed when the subset at a node has all the same value of the target variable, or when splitting no longer adds value to the predictions. This process is known as top- down induction of decision trees. A tree is composed of root node which is initial node in tree, internal nodes and leaf nodes or terminal nodes. Each leaf node is assigned a class label, whereas nonterminal node contains the attribute test condition to separate the data recursively. The classification tree induction is illustrated in Fig. 2.3.

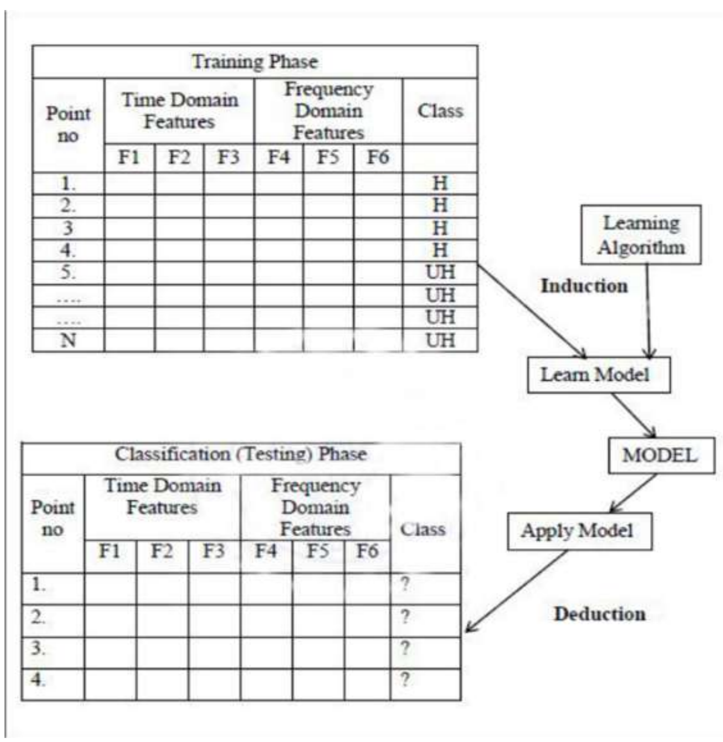

Fig 2.2 Approach for Building the Classification Model

At root node Feature 1 is selected and on basis of attribute/feature test condition, feature 1 is split into two subsets namely ≤ and second is >. The subset has feature 1 values ≤ is assign as leaf node whereas for another subset feature 2 is selected and again attribute test condition is applied. This tree growing process is continuing till all the records are classified. The division of records into subset is on basis of attribute test condition is explain in next section.

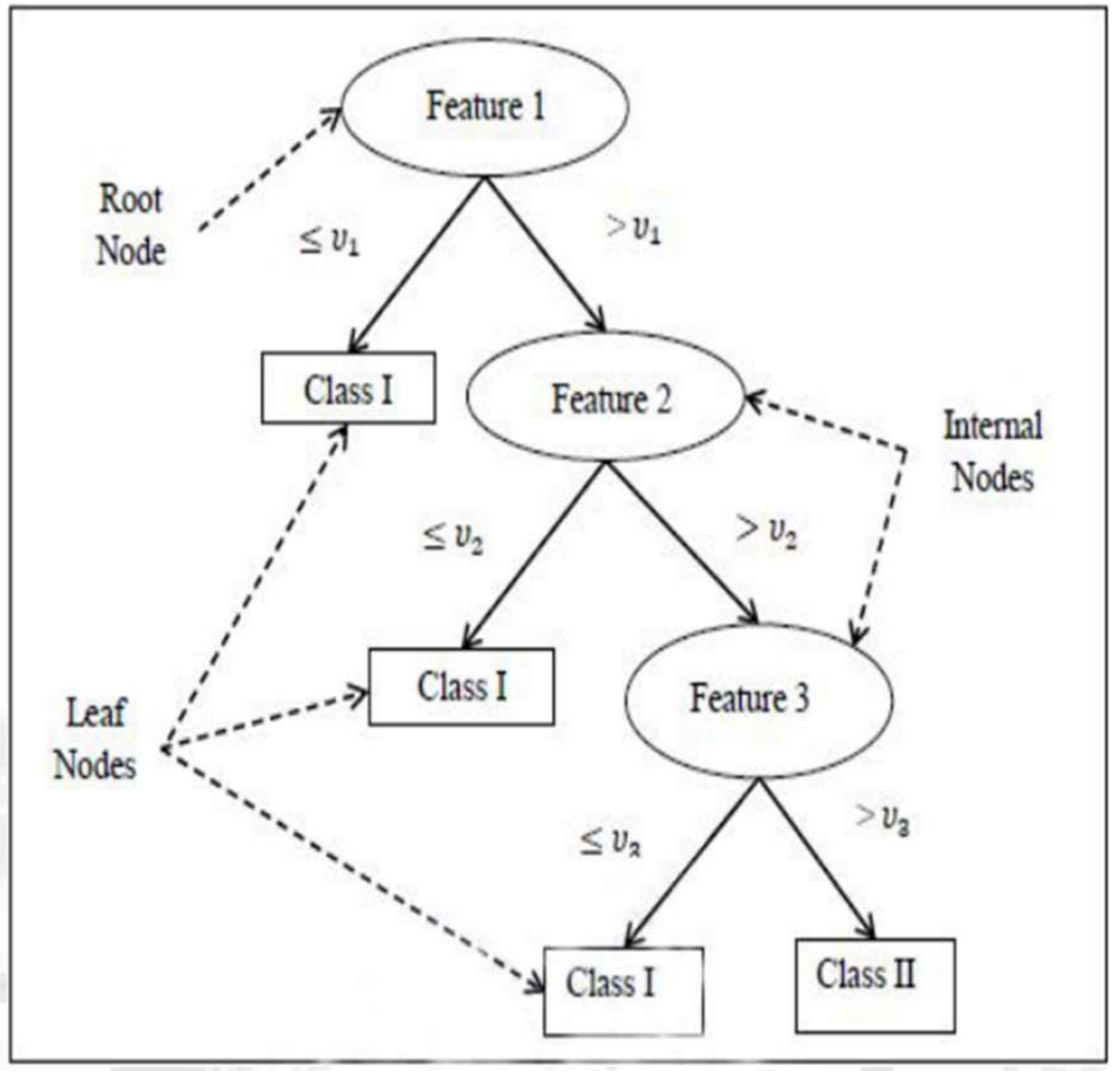

Fig. 2.3 Decision Tree for Classification Problem

Once the decision tree is constructed, classification of test records is very easy task. Starting from root node, an attribute test condition is applied to test record and follow the appropriate branch based on the outcome of the test. The output of test condition leads either leaf node or internal node for which a new test condition is applied. The class labels associated with the leaf node is then assigning to the records. The classification of unlabeled record is depicted in Fig 2.4.

Algorithm of Decision Tree Induction (C 4.5)

The C4.5 algorithm is used to build the decision. It builds decision tree from training data set by using the information gain as the attribute test condition at non-terminal nodes. At each node the algorithm choose the one feature/attribute of training data that splits the data into subsets. The feature with highest information gain is selected to take decision. When any subset has the data belonging to same class after splitting, algorithm creates the leaf node and assigns it to the corresponding class.

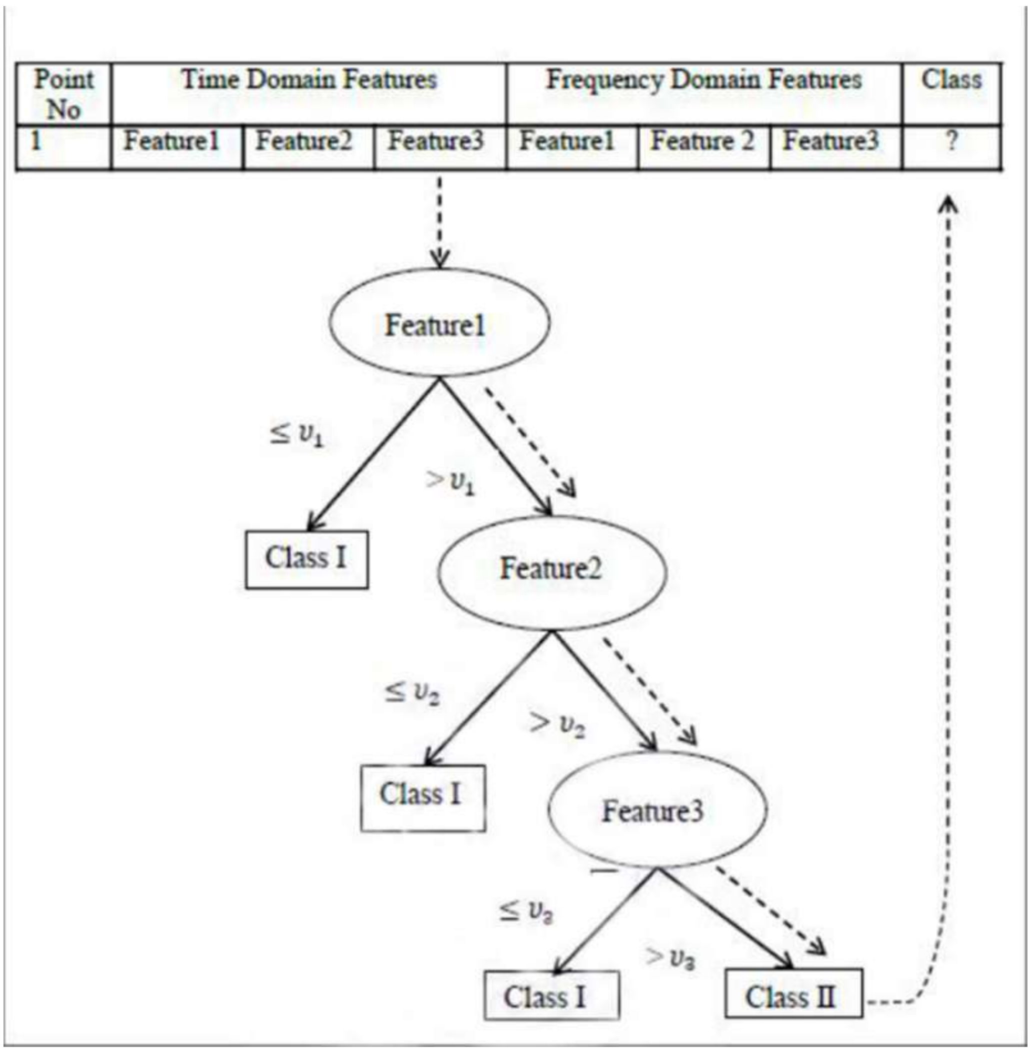

Fig. 2.4 Deduction of Decision Tree for Classification Problem

III. EXPERIMENTATION AND DATA ACQUISITION

Description of Composite Plates

In this project, Glass epoxy composite plates with dimension 220mm x 190mm are used. Six plates have been made in the configuration of [0/90/0/90] and are used in this project. One plate is healthy and seven plates are damaged by introducing delamination. Delamination is in form of Teflon cloth at various locations. In all plates, delamination lies between second and third ply.

Various delamination positions and their designation are mentioned in Figure 3.2. Plate no P1 is healthy without any delamination whereas plate no P2, P3 and P4 have delamination at center of size 44mm x 44mm, 55mm x 55mm, 33mm x 33mm respectively. The plate no P6, P7 have delamination of size 44mm x 44mm at various locations mentioned in Figure 3.1. Composite beam used in cantilever mode.

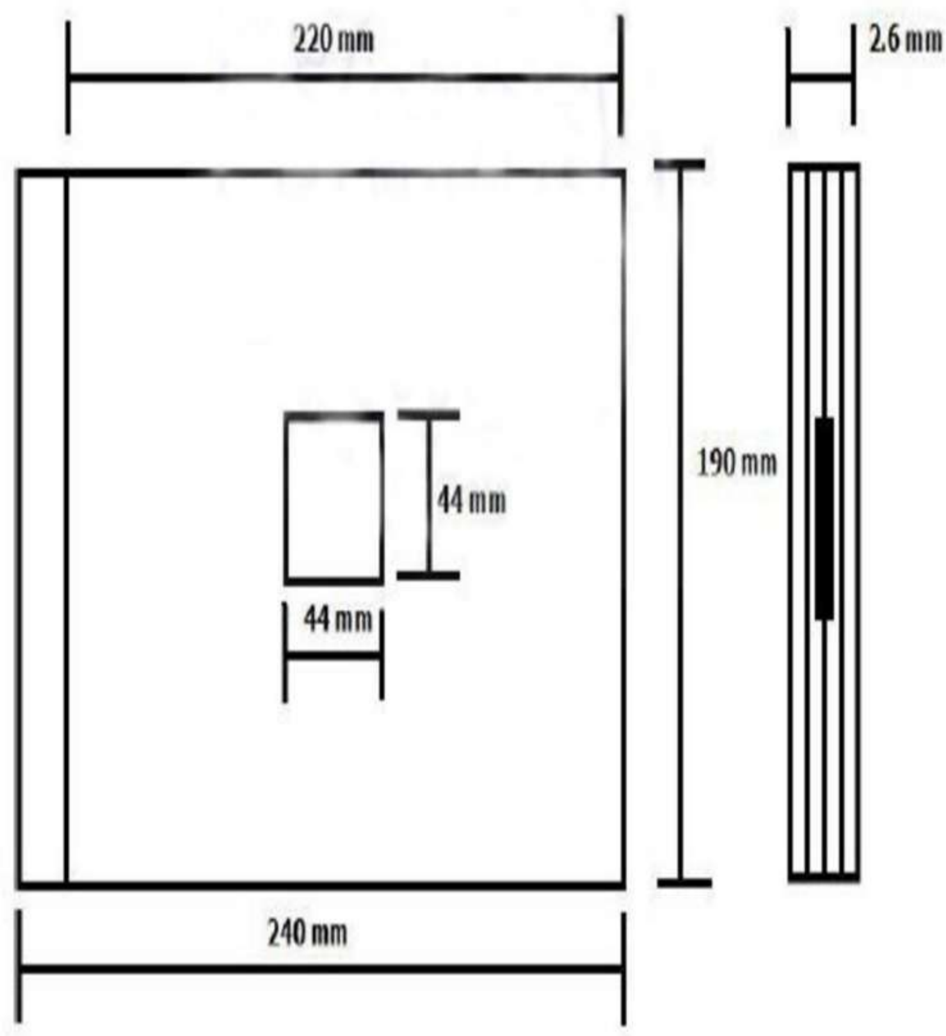

Fig. 3.1 Dimensions and Delamination in Composite Plate

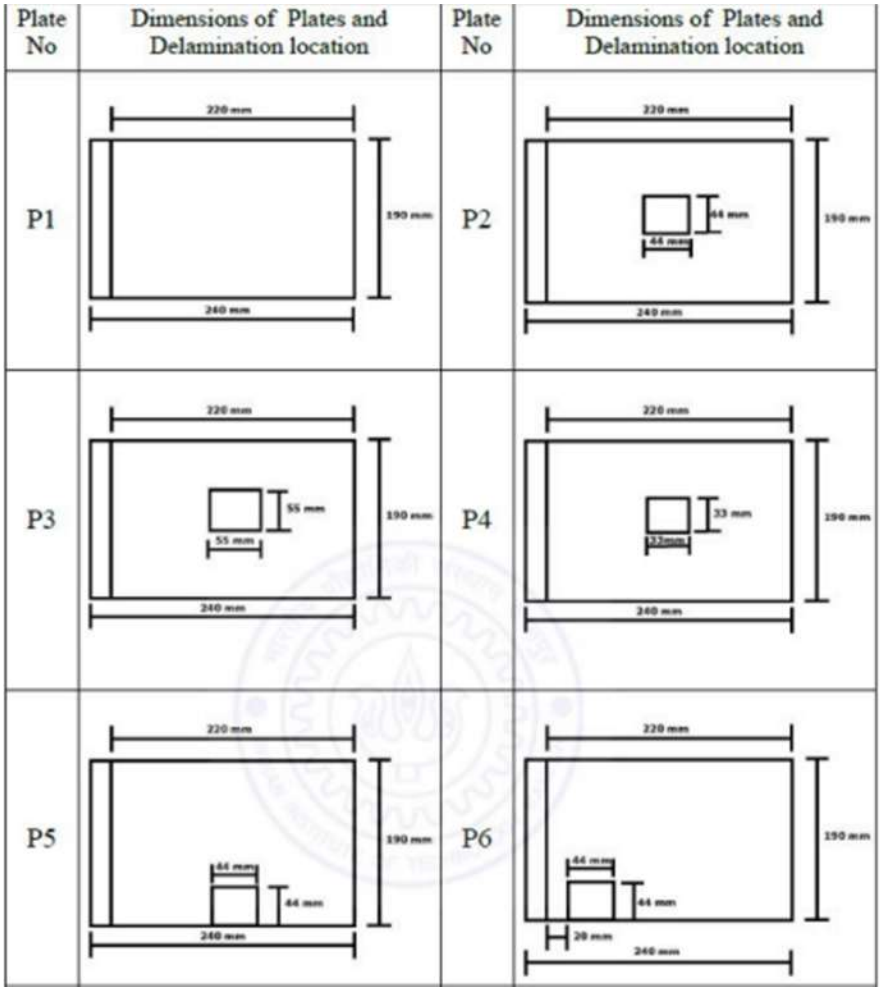

Fig. 3.2 Dimensions of Composite Plate's and Delamination Position

IV. RESULT OF THE PROJECT

5.1 Results

The results obtained from the WEKA workbench are explained for two cases. The decision regarding the presence of damage in composite is taken on the basis of maximum number of data points classified as healthy and unhealthy class.

CASE I

(a) Acceleration 40 point data (frequency domain features) (b) Velocity 40 point data (frequency domain features)

CASE II

(a) Acceleration 20 point data (frequency domain features) (b) Velocity 20 point data (frequency domain features)

CASE I - 40 point Data

(a) Acceleration 12 point data (Frequency domain features)

In training phase, we obtained the classification accuracy of the rotation forest as well as bagging and it was observed to be higher, as compared to the C 4.5 classifier. The decision tree for this case is depicted in Figure 5.1 and shows that the Root Mean Square Frequency (RMSF) is the first feature to split the data points, and for remaining data points, standard deviation frequency and maximum frequency value is selected.

We concur that all the classification algorithms have performed well on the given dataset and have correctly predicted the unhealthy state of the plate. We will extend this study by increasing the number of data points for identification of the damage condition and will check the accuracy of the algorithms comparatively.

Training Phase						
Sr.no	Ensemble Method	confusion Matrix			Classification Accuracy	Classification Error
		healthy	unhealthy	Predicted		
1.	Decision Tree C4.5	14	06	healthy	70%	30%
		06	14	Unhealthy		
2.	Rotation Forest	14	06	healthy	72.5%	27.5%
		5	15	Unhealthy		
3.	Bagging	15	05	Healthy	80%	20%
		03	17	Unhealthy		

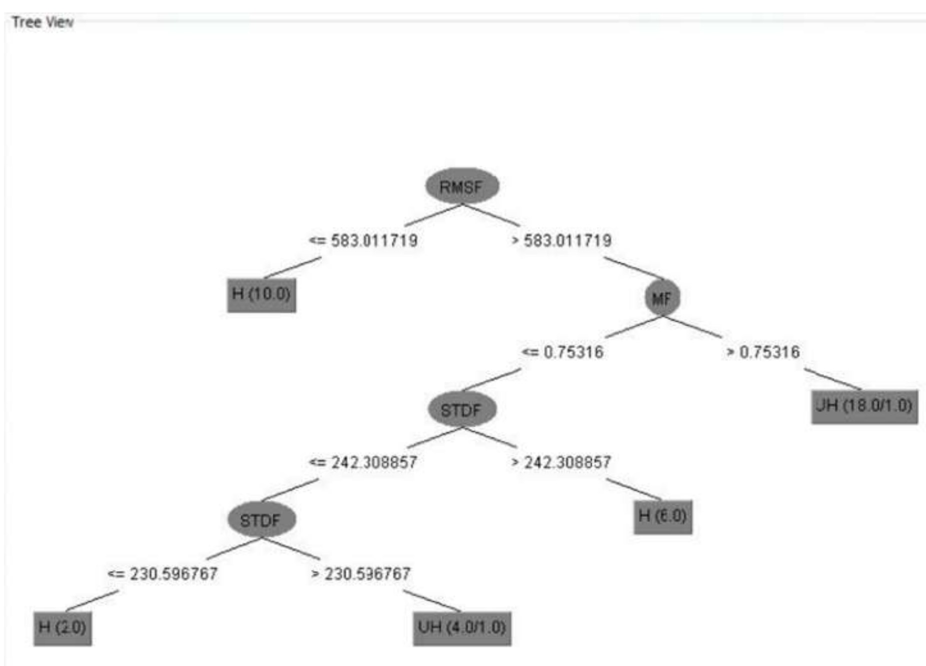

Fig.5.1 Decision Tree for 40 point acceleration data using the frequency domain features

Table 5.2 Classification Phase for 40 Point Acceleration Data using Frequency DomainFeature

Classification Phase (Testing phase)						
Sr.no	**Ensemble method**		**Damage Condition**			
			P3	**P4**	**P6**	**P7**
1.	Decision Tree C4.5	H	1	05	0	04
		UH	19	15	20	15
		Decision	UH	UH	UH	UH
2.	Rotation	H	4	08	1	04
		UH	16	12	19	15
		Decision	UH	UH	UH	UH
3.	Bagging	H	2	5	1	04
		UH	18	15	19	16
		Decision	UH	UH	UH	UH

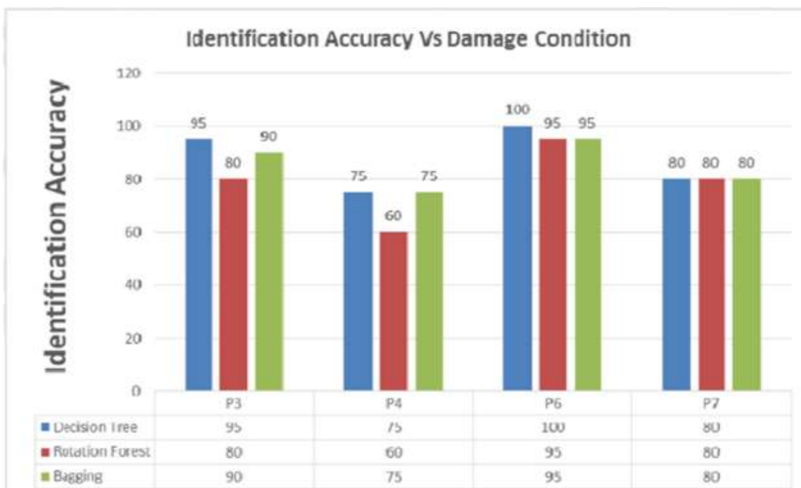

Fig.5.2 Identification Accuracy vs Damage condition for 40 point Acceleration data using the Freq

(b) Velocity 40 point data (Frequency Domain features)

For this case we achieved improvement in classification accuracy compared to the acceleration 40 point data using frequency domain features. The decision tree built by using only maximum value, mean frequency and standard deviation frequency depicted in fig 5.3

Training Phase						
Sr.no	Ensemble Method	confusion Matrix			Classification Accuracy	Classification Error
		healthy	unhealthy	Predicted		

1.	Decision Tree C4.5	17	03	healthy	80%	20%
		05	15	Unhealthy		
2.	Rotation Forest	17	03	healthy	87.5%	12.5%
		2	18	Unhealthy		
3.	Bagging	16	04	Healthy	80%	20%
		04	16	Unhealthy		

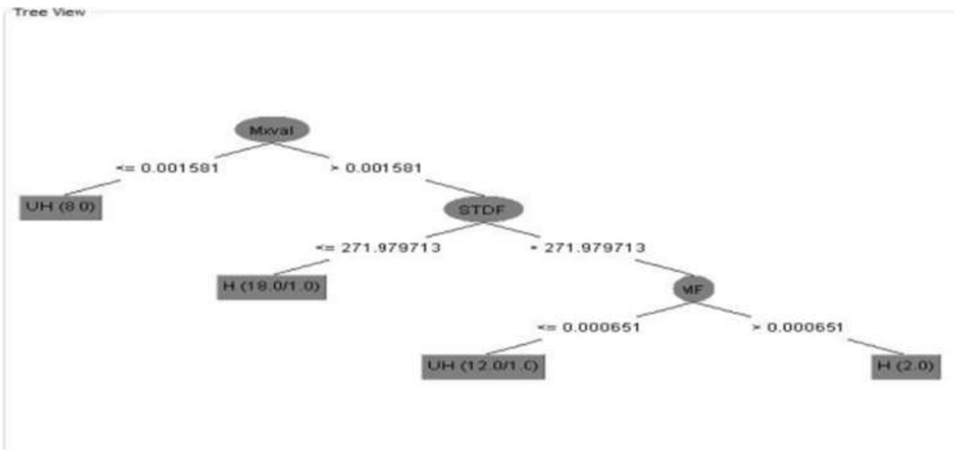

Fig. 5.3 Decision Tree for 40 Point Velocity Data using the Frequency Domain Features

Table 5.4 Classification Phase for 40 Point Velocity Data using Frequency Domain Features

Classification Phase (Testing phase)						
Sr.no	**Ensemble method**		**Damage Condition**			
			P3	**P4**	**P6**	**P7**
1.	Decision Tree C4.5	H	6	04	02	08
		UH	14	16	18	12
		Decision	UH	UH	UH	UH
2.	Rotation	H	5	18	03	08
		UH	15	2	17	12
		Decision	UH	H	UH	UH
3.	Bagging	H	6	15	2	08
		UH	14	5	18	12
		Decision	UH	H	UH	UH

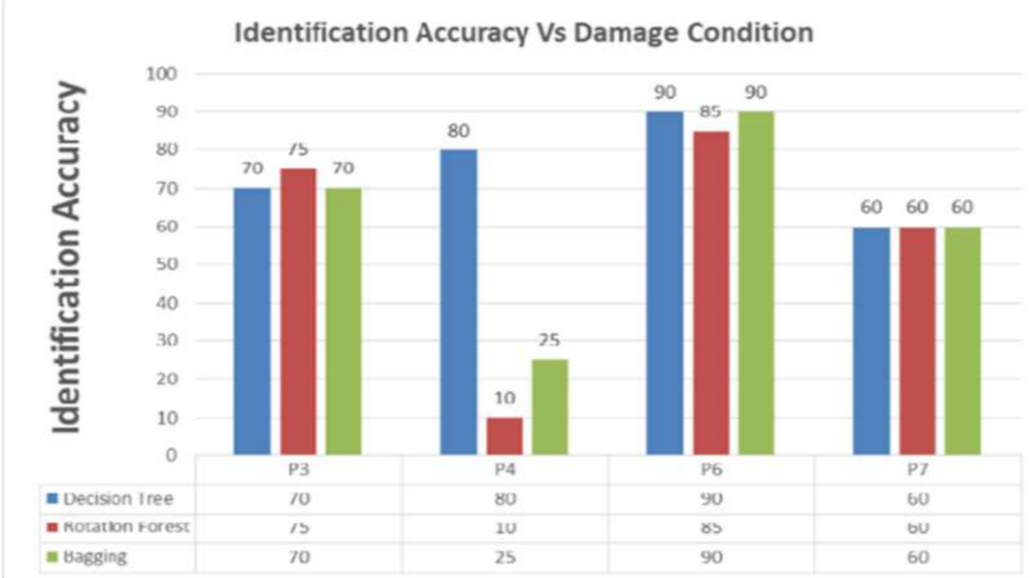

Fig 5.4 identification accuracy Vs Damage condition for 40 point velocity Data using the freq Domain Features

CASE II - 50 Point data

(a) Acceleration 50 point Data(Freq domain features)

We obtained the maximum 75% classification accuracy for rotation forest and decision tree using these data point. In identification phase, we identified the damage condition P6 and P7 correctly using rotation forest

Table5.5 ClassificationPhasefor50pointAccelerationDatausingFrequencyDomainFeatures

Training Phase						
Sr.no	Ensemble Method	confusion Matrix			Classification Accuracy	Classification Error
		healthy	unhealthy	Predicted		
1.	Decision Tree C4.5	17	08	healthy	74%	26%
		05	20	Unhealthy		
2.	Rotation Forest	22	03	healthy	86%	14%
		4	21	Unhealthy		
3.	Bagging	22	03	Healthy	82%	18%
		06	19	Unhealthy		

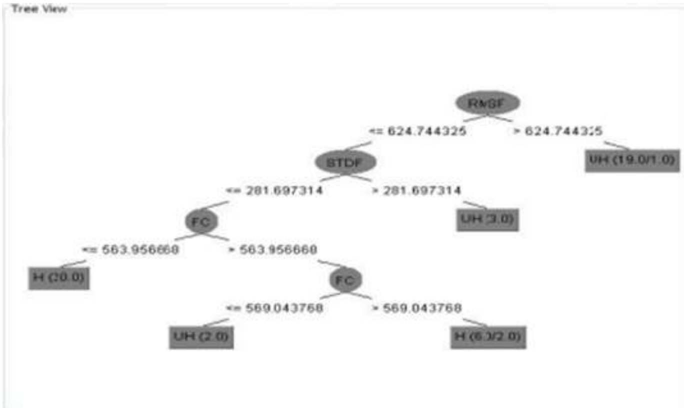

Fig.5.5 DecisionTreefor50PointAccelerationDatausingtheFrequencyDomainFeatures

Table5.6 ClassificationPhasefor50pointAccelerationDatausingFrequencyDomainfeature

Classification Phase (Testing phase)						
Sr.no	**Ensemble method**		**Damage Condition**			
			P3	**P4**	**P6**	**P7**
1.	Decision Tree C4.5	H	12	10	05	05
		UH	8	10	15	15
		Decision	H	?	UH	UH
2.	Rotation	H	15	14	09	08
		UH	5	6	11	12
		Decision	H	H	UH	UH
3.	Bagging	H	11	9	6	05
		UH	9	11	14	15
		Decision	H	UH	UH	UH

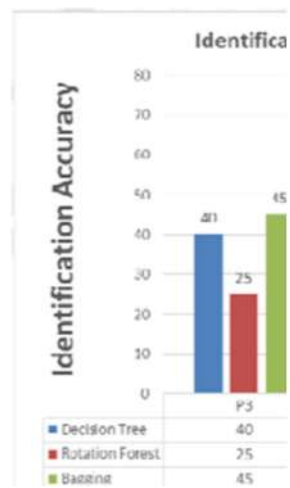

Fig5.6 IdentificationaccuracyVs.Damageconditionfor50pointaccelerationdatausingthefrequency domain features

(b) Velocity 50 point data (Frequency domain features)

Table5.7 Training phase for 50 point velocity data using frequency domain features

Training Phase						
Sr.no	Ensemble Method	confusion Matrix			Classification Accuracy	Classification Error
		healthy	unhealthy	Predicted		

1.	Decision Tree C4.5	13	13	healthy	70%	30%
		02	22	Unhealthy		
2.	Rotation Forest	22	04	healthy	90%	10%
		1	23	Unhealthy		
3.	Bagging	21	05	Healthy	84%	16%
		03	21	Unhealthy		

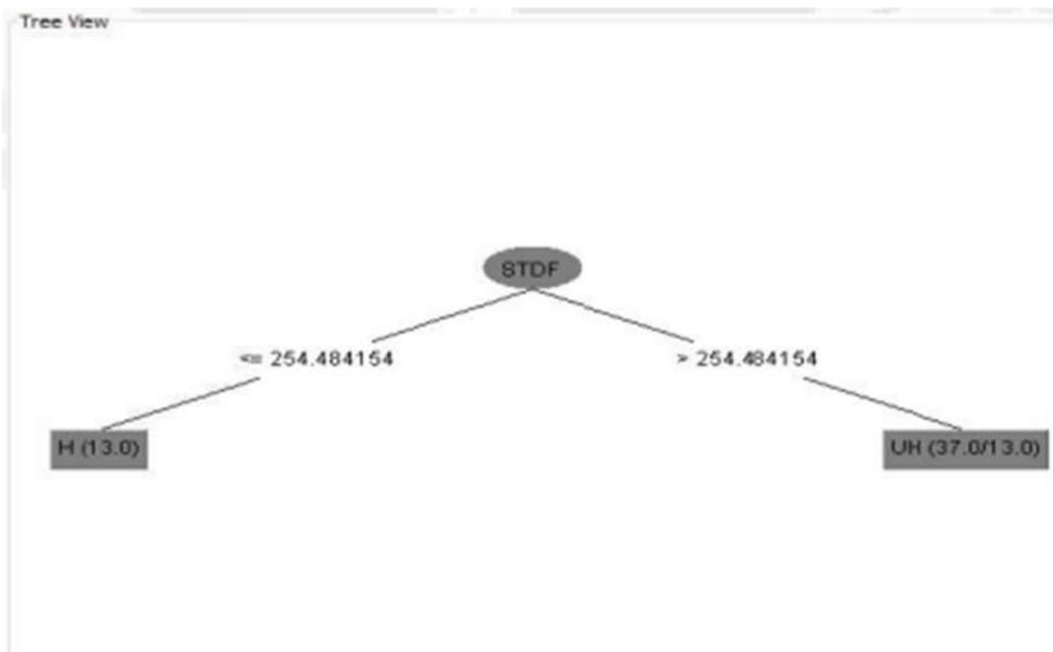

Fig 5.7 Decision Tree for 50 point velocity data using the frequency domain features

Classification Phase (Testing phase)						
Sr.no	**Ensemble method**		**Damage Condition**			
			P3	**P4**	**P6**	**P7**
1.	Decision Tree C4.5	H	03	17	03	03
		UH	17	3	17	17
		Decision	H	UH	UH	UH
2.	Rotation	H	9	19	03	10
		UH	11	1	17	10
		Decision	H	UH	UH	?

3.	Bagging	H	10	17	4	09
		UH	10	3	16	11
		Decision	?	UH	UH	UH

Table5.8 Classification phase for 50 point velocity data using frequency domain features

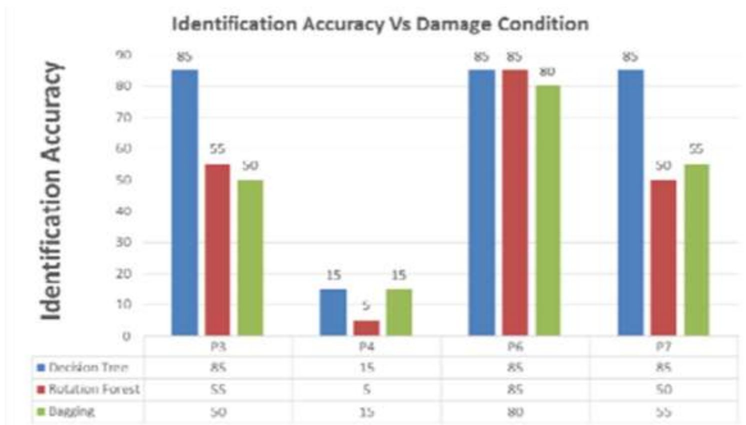

Fig5.8 IdentificationaccuracyVs.Damageconditionfor50pointVelocityDatausingtheFrequency Domain Features

V. CONCLUSION AND FUTURE SCOPE

For damage identification in composite plates, three methods are presented in this thesis, decision tree and two ensemble methods namely rotation forest and bagging. The dynamic response is measured using the LDV for 8 composite plates: one is healthy and seven are damaged in the form of delamination of various sizes and at various locations. The time domain features from velocity time data and FFT domain features from acceleration frequency domain data and velocity frequency domain data are extracted and used as input for WEKA workbench. The following are the inferences are made from the results obtained from WEKA workbench for three methods.

1. The classification accuracy of ensemble method is much higher than the accuracy of decision tree which is the base classifier used for these ensemble methods in most of the damaged conditions.

2. The damage identification accuracy of ensemble methods is also higher than the decision tree and among ensemble methods; the rotation forest gives much better results than the Bagging for the 20 point data features.

3. In Case I, (a) Rotation forest (RF) failed to predict damage condition P4, while the bagging and decision tree predicted the same and we cannot take the decision for P7 damaged condition using the rotation forest. But for CASE II (a), RF predicted the damaged condition P4 as well as P7.

4. In CASE II (c) only frequency domain features are sufficient to build the decision tree but for CASE I (c) both time domain and frequency domain features are required.

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