Machine learning process evaluating damage classification of composites

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ABSTRACT
Composite materials have tremendous and ever-increasing applications in complex engineering systems; thus, it is important to develop non-destructive and efficient condition monitoring methods to improve damage prediction, thereby avoiding catastrophic failures and reducing standby time. Non-destructive condition monitoring techniques when combined with machine learning applications can contribute towards the stated improvements. Thus, the research question taken into consideration for this paper is "Can machine learning techniques provide efficient damage classification of composite materials to improve condition monitoring using features extracted from acousto-ultrasonic measurements?" In order to answer this question, acoustic-ultrasonic signals in Carbon Fiber Reinforced Polymer (CFRP) composites for distinct damage levels were taken from NASA Ames prognostics data repository. Statistical condition indicators of the signals were used as features to train and test four traditional machine learning algorithms such as K-nearest neighbors, support vector machine, Decision Tree and Random Forest, and their performance was compared and discussed. Results showed higher accuracy for Random Forest with a strong dependency on the feature extraction/selection techniques employed. By combining data analysis from acoustic-ultrasonic measurements in composite materials with machine learning tools, this work contributes to the development of intelligent damage classification algorithms that can be applied to advanced online diagnostics and health management strategies of composite materials, operating under more complex working conditions.

KEYWORDS: additive manufacturing, machine learning, health management

1.0 INTRODUCTION
With an increasing demand for new materials that combine low weight and high strength properties for several engineering applications, the interest of industries is increasing at the same proportion in composite materials. However, this class of materials presents a complex internal structure, which makes their damage initiation and propagation mechanism more difficult to predict as compared to metallic materials. Since composite materials have been increasingly used in critical applications such as aircraft structural components, understanding their failure properties is crucial for the reliability of these structures. Damage induced by fatigue in composite structures, due to complex in-service loading regimes throughout a high number of cycles, typically occurs in rotating machinery such as wind turbines and helicopter rotors. These failure mechanisms are known to initiate at the level of the constituents (e.g., matrix microcracks, delamination, fiber breakage) and should be understood on multiple scales [1-6]. In order to reduce maintenance costs and prevent catastrophic failure of composite structures, efficient structural health monitoring (SHM) and prognostics strategies need to be employed and it has been one of the major research focus during the past decade. SHM methods usually utilize the data measured by a network of sensors attached to the structure to determine its current damage state and, then prognostics strategies can predict the remaining useful life (RUL) of the structure. Therefore, damage detection in composite materials through SHM strategies is a very important step in order to perform prognostics and prediction of RUL [7-13]. Amongst several existing SHM strategies of composite materials, non-destructive techniques based on acousto- ultrasonic measurements have proven to be effective in numerous applications. Guo and Cawley investigated the Lamb wave propagation in composite laminates both with and without defects and determined acousto-ultrasonic parameters based on predicted and measured responses. Saxena et al. described a fatigue loading cycle experiment of Carbon Fiber Reinforced Polymer (CFRP) composite coupons with various layups in which Lamb wave propagation signals were collected from piezoelectric sensors to capture the effects of damage growth [14-19]. Rheinfurth et al. conducted an experimental investigation of the applicability of air-coupled Lamb waves to monitor induced fatigue damage in

composites. Cot et al. proposed a methodology based on the combination of an ultrasonic sensing technique and a state-parameter estimator to predict the fatigue damage in a composite structure component. Eleftheroglou et al. proposed a fused SHM approach based on acoustic emission measurements and digital image correlation followed by Non-Homogeneous Hidden Semi Markov model to estimate the RUL of carbon/epoxy specimens. Liu et al. also proposed a prognostic method based on machine learning where the linear regression model, Support Vector Machine (SVM), and Random Forest (RF) were investigated using Lamb wave propagation data in CFRP composite coupons. Despite the promising results shown in these attempts, the concern about sensitivity of learning algorithms to the processing of data and feature extraction methods remains and a systematic investigation is needed to improve the SHM strategies of composite materials [20-27]. In order to account for the stated gap, present work investigated different machine learning and feature extraction techniques to classify damage in CFRP composite coupons using acousto-ultrasonic measurements. For this work, acoustic- ultrasonic measurements in carbon fiber reinforced polymer specimens were obtained from NASA prognostics data repository. Then, several time-domain and frequency-domain techniques were used to extract features from the data that indicated the presence of damage in coupons. Finally, the extracted features were used to train K-nearest neighbors (KNN), SVM, Decision Tree (DT) and Random Forest (RF) algorithms and their performances were compared. Results showed the superior performance of DT with time-domain feature extraction and RF with frequency-domain feature extraction [28-36].

2.0 METHODOLOGY

The dataset, for fatigue loading of CFRP composite materials, was taken from NASA Ames Prognostics Data Repository. The data was available for three different types of layup of CFRP composite materials with multiple data files for multiple coupons at different damage states, out of which one element of one layup was taken into consideration for this analysis [37-42]. The coupons were subjected to fatigue loading and with the help of actuator-sensor combinations, the damage was detected. The placement of Piezoelectric (PZT) sensors and actuators on the coupon is as shown in FIGURE 1.

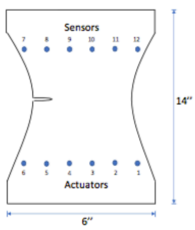

FIGURE 1: THE PLACEMENT OF ACTUATORS AND SENSORS ON THE CFRP COMPOSITE MATERIAL (AS SHOWN FROM THE INFORMATION FILE FROM DATASET) [11]

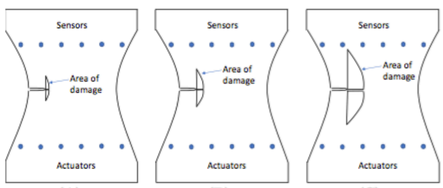

FIGURE 2: SCHEMATIC OF COUPONS AT THE THREE DAMAGE LEVELS TAKEN FROM THE X-RAY FILES (A) 4 CRACKS, (B) 34 CRACKS, AND (C) 60 CRACKS [11]

The actuators induced a Lamb-wave pulse which was being propagated and monitored by the sensors on the other side. The readings of these PZT signals were taken for all the combinations of actuator-sensor pairs with 7 different frequencies making it a 252-path data. Furthermore, X-ray images of the selected specimens were taken into consideration to draw the schematic diagrams in order to visualize the damage states and are shown in FIGURE 2. Composite materials undergo multiple modes of failure under fatigue loading, but fiber cracking and delamination are the most important modes of failure that greatly affect the health of the structure [43-56]. It also should be noted that even if the classification considers a number of cracks to be the damage level, it is associated with delamination as these two modes of failure are interdependent. The data was available in the form of piezoelectric signals for all the intermediate states, and because of the interdependency, the signals collected from sensors at specific intervals contain information of both the failure modes [57-64].

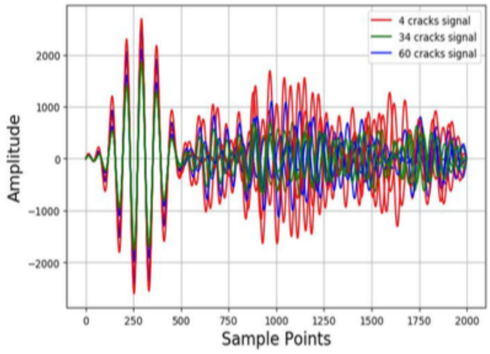

FIGURE 3: PZT SIGNAL FOR THE CLASSES UNDER CONSIDERATION [11]

The association of type of failure with the signal characteristics is a critical factor in order to effectively classify the damage state. However, for this analysis, the pre-processing was not conducted to differentiate the damage types but to classify the overall damaged states using the whole signal. The analysis was divided into three steps. In step 1, the three damage states in the coupon were considered (with 4 cracks, 34 cracks, and 60 cracks) with path data of actuators 1 and 2 (with all sensors) only. In step 2, the same damage levels as step 1 were considered, but with the total dataset of 252 paths measured with actuators 1-6 (with all sensors). In step 3, the two extreme damage levels (with 4 cracks and 60 cracks) were considered with 252 path data. The analysis was conducted for one coupon of one layup to detect the damage state of the specimen by the PZT sensor signal readings using basic supervised machine learning algorithms. The data was available for many intermediate crack levels, but the algorithms used in this analysis were basic machine learning algorithms and are not compatible to handle complexities of the dataset thus, only three damage levels were selected which were significantly far from each other. The statistical features of other damage levels were numerically close to each other, hence could not be separated as a class. Thus, to test the classification algorithms at significantly distinct levels, the said damage states were selected. The difference is clearly visible in FIGURE 3, where the signals for three distinct damage levels under consideration are plotted and it can be noted that the damage level with 34 and 60 cracks are very close to each other unlike the signal for damage level with 4 cracks [65-69].

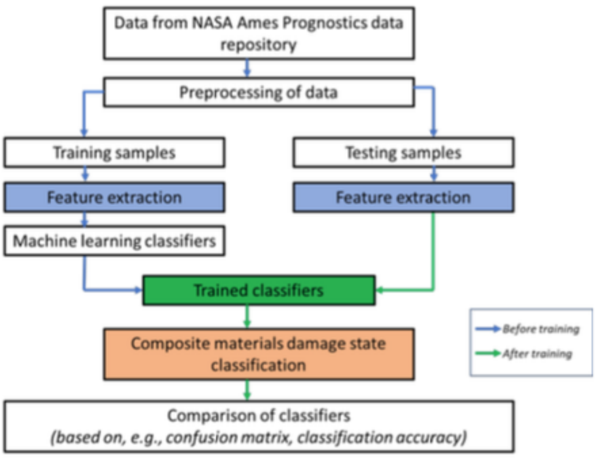

FIGURE 4: FRAMEWORK FOR CLASSIFICATION OF DAMAGE LEVELS

The framework for the classification of damage state of composites is as shown in FIGURE 4. According to the flowchart, the collected data was pre-processed which included a selection of coupons, determining damage states, conversion into the frequency domain and feature extraction. Selection of coupon and determination of damage states is already discussed in this section. Fast Fourier Transform was used to convert the data into the frequency domain using MATLAB. Statistical condition indicators were extracted from each signal in both time and frequency domain and were used as features, which are enlisted in TABLE 1. Those features were extracted manually to feed the algorithms for further classification. The remaining machine learning analysis as shown in the flowchart, was performed using Python and sklearn packages. The dataset of features was then divided randomly by the algorithms as 80% of the data for training the classifiers and 20% for testing. The performance was compared based on accuracy score, confusion matrix and other performance indicators as discussed in further sections [70-78].

TABLE 1: STATISTICAL FEATURES EXTRACTED FROM THE DATA

Feature	Feature
Mean	Skewness
Standard Deviation	RMS
Variance	Peak to Peak
Minimum Value	Crest Factor
Maximum Value	Peak2RMS
Kurtosis	

Four machine learning classification algorithms were taken into consideration, namely, K-nearest neighbors (KNN), Support Vector Machine (SVM), Decision tree (DT), and Random Forest (RF). The purpose of this analysis was to test the concept of classification of composite materials based on their damage states thus, supervised algorithms were taken into consideration and KNN, SVM and, DT being the most popular algorithms working on three different concepts of classifications, were selected and tested. RF is an ensembled approach of DT based on bagging [1-11]. For this analysis, RF was used for depth of 3 and compared with the rest of the algorithms. KNN is based on the Euclidean distance measurements from the nearest 5 data points (the number of points can be varied). It classifies the data point in question into the class to which the highest number of nearest neighbors belong. In the case of SVM, it draws a hyperplane between the classes and classifies based on the distance and direction of datapoint in question and the hyperplane (also known as support vectors). KNN and SVM are not learning algorithms, unlike DT which is based on the flowchart of the condition and a tree-like structure that tests each condition and then classifies the data points in question. It learns the features provided and thus known as the learning algorithm. RF, on the other hand, is based on bagging of multiple algorithms and hence believed to be faster learning and better responding algorithm as it combines the weak learning algorithm like DT and becomes a strong learning algorithm [12-19].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}, \qquad (1)$$

where, TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives.

The four classification algorithms considered in this analysis are supervised algorithms and some of these algorithms are better suited for one type of classification problem than the other. Also, there is a trade-off between the computation time, size and complexity of data according to which the algorithms need to be selected. For this analysis, the data size was reduced to one element and three damage levels in order to test the classification, thus these algorithms were selected. Each algorithm was trained and tested with the same features [20-26]. Every time the algorithms were executed, the division of training and testing samples were selected randomly for each run, thereby generating different results. In order to account for this variability, each algorithm was executed 100 times for every case. The results of the analysis are discussed in the Results and Discussion section [27-34]. Performance of these classification algorithms was compared based on accuracy, precision, recall, F1-score and confusion matrix [12]. The accuracy score was calculated as shown below:

$$\text{Precision} = \frac{TP}{TP+FP}. \quad (2)$$

TP and TN indicate the actual number of data points of positive class and negative class respectively that the machine also labeled as True. Whereas, FP indicate the number of negatives that the machine classified as positives and FN represents the number of positives that the machine classified as negatives [35-40]. This is further explained in the Results and Discussions section. The precision score is calculated for each class of classification problem, thus for each class, the precision is calculated as below. Similarly, Recall and F1-scores are also calculated for each class and are as shown in Eqs. (3) and (4). These values indicate the level of performance of classification algorithms in the classification of each class. Accuracy score is the only parameter that indicates the overall accuracy of classification. Confusion matrix indicates the number of TP, FP, TN, and FN which basically indicates that how confused the algorithm is in the classification problem. Using confusion matrix and Eqs. (1)-(4), performance indicators can be calculated [41-48].

$$\text{Recall} = \frac{TP}{TP+FN}, \quad (3)$$

$$F1 - \text{Score} = \frac{2 \times Recall \times Precision}{Recall + Precision}. \quad (4)$$

3.0 RESULT

The mean and coefficient of variation (COV) of accuracies for all the four classifiers, over 100 runs, for both time and frequency domain are as shown in TABLE 2 [12]. The performance was compared based on accuracy, confusion matrix, and other performance parameters. According to the results, the accuracy of SVM was lowest amongst all four classifiers in both the domains, whereas DT and RF were the top two classifiers [49-54]. The overall accuracy of classification was observed to be better in the frequency domain. In both the domains, RF showed the largest accuracy of classification. Comparison of accuracies of both domains for each algorithm with respect to a number of runs is as shown in FIGURE 5. It is evident from FIGURE 5 and TABLE 2, that the accuracy of RF, DT, and KNN in frequency domain was significantly higher with lower COV than that in the time domain [55-61].

TABLE 2: MEAN AND COV OF ACCURACIES OF CLASSIFIERS OVER 100 RUNS

	Time domain		Frequency domain	
	Mean	COV	Mean	COV
KNN	0.443	0.161	0.808	0.068
SVM	0.270	0.117	0.267	0.135
Decision Tree	0.515	0.139	0.804	0.074
Random Forest	0.531	0.145	0.822	0.063

FIGURE 6 shows the comparison of all the classification algorithms in both domains and as mentioned earlier, it is clearly evident that the frequency domain resulted in better classification and SVM had the lowest accuracy in both domains. The time is taken for the training of KNN, SVM, and DT classifiers was almost the same whereas, RF took slightly more time for training in both the domains. For further comparison, the average confusion matrix for 100 runs is shown in FIGURE 7 and FIGURE 8. The confusion matrices shown in FIGURE 7 and FIGURE 8 represent the percentage of correct and incorrect classification of each class. Note that the confusion matrix shown in this paper are normalized and are shown for the validation/test dataset (i.e. 20% of the total dataset).

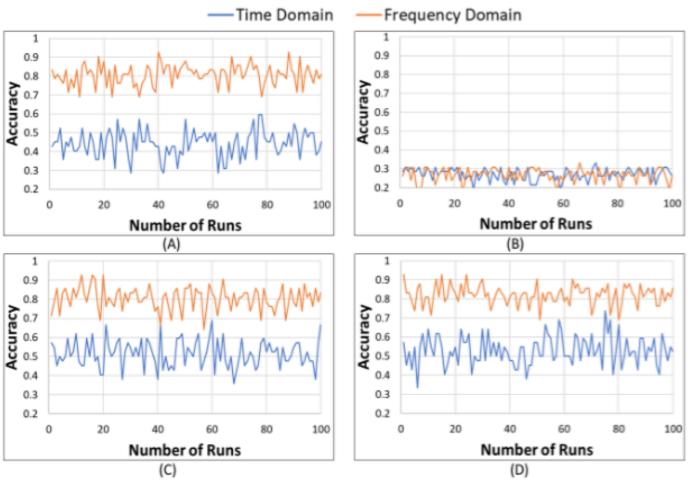

FIGURE 5: VARIATION OF ACCURACIES WITH RESPECT TO NUMBER OF RUNS FOR DATA IN TIME DOMAIN AND FREQUENCY DOMAIN (A) KNN (B) SVM (C) DECISION TREE (D) RANDOM FOREST

Considering FIGURE 7(A), the rows represent True label (i.e. the real data) and the columns represent Predicted label (i.e. the classification by algorithm). The rows represent the total dataset of damage level with 4 cracks in validation dataset (i.e. the sum of the row is approximately 1 as the fractions are approximated to two decimal points).

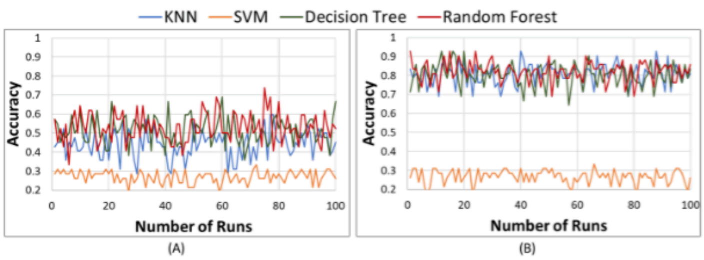

FIGURE 6: COMPARISON OF ALL THE MACHINE LEARNING ALGORITHMS BASED ON ACCURACY WITH RESPECT TO NUMBER OF RUNS. (A) DATA IN TIME DOMAIN (B) DATA IN FREQUENCY DOMAIN

Considering FIGURE 8, we can see that the classification of damage level with 34 cracks was better for all the classifiers except SVM. The performance indicators were calculated using the confusion matrix and the equations (1)-(4) and are shown in TABLE 3 and TABLE 4. It can be observed that the overall accuracies of all the classifiers were decreased when the dataset was increased. In this case, also, the same features were extracted as the earlier case. Considering the confusion matrix shown in FIGURE 10, it is evident that the classifiers mostly misclassified damage level with 34 cracks and damage level with 60 cracks even when the number of cracks in two damage level are equally apart as 4 cracks level and 34 cracks level. However, the classifiers could identify damage level with 4 cracks better than the other two. The same can be confirmed with performance parameters shown in TABLE 4. As mentioned earlier, the sample column in this table also indicates the number of testing samples under consideration for each class [61-68]. Unlike in section 3.1, where the data associated with a notch was not taken into consideration for checking the travel of damage across the cross-section, this case considered the whole dataset. TABLE 3 shows that the maximum efficiency was achieved in classifying damage level with 4 cracks for all the classifiers and RF had better recall and F1-score than the other two, but DT has better precision for the same class. Rheinfurth et al. conducted an experimental investigation of the applicability of air-coupled Lamb waves to monitor induced fatigue damage in composites. Cot et al. proposed a methodology based on the combination of an ultrasonic sensing technique and a state-parameter estimator to predict the fatigue damage in a composite structure component.

TABLE 3: PERFORMANCE PARAMETERS OF ALL CLASSIFIERS IN TIME DOMAIN

Classifiers	Cracks	Precision	Recall	F1- score	Samples
KNN	4	0.650	0.880	0.750	17
	34	0.230	0.210	0.220	14
	60	0.170	0.090	0.120	11
SVM	4	0.000	0.000	0.000	15
	34	0.260	1.000	0.420	11
	60	0.000	0.000	0.000	16
DT	4	0.620	0.670	0.640	12
	34	0.640	0.880	0.740	16
	60	0.860	0.430	0.570	14
RF	4	0.570	0.860	0.690	14
	34	0.710	0.330	0.450	15
	60	0.360	0.380	0.370	13

Eleftheroglou et al. proposed a fused SHM approach based on acoustic emission measurements and digital image correlation followed by Non-Homogeneous Hidden Semi Markov model to estimate the RUL of carbon/epoxy specimens. Liu et al. also proposed a prognostic method based on machine learning where the linear regression model, Support Vector Machine (SVM), and Random Forest (RF) were investigated using Lamb wave propagation data in CFRP composite coupons. Despite the promising results shown in these attempts, the concern about sensitivity of learning algorithms to the processing of data and feature extraction methods remains and a systematic investigation is needed to improve the SHM strategies of composite materials [69-78].

TABLE 4: PERFORMANCE PARAMETERS OF ALL CLASSIFIERS IN FREQUENCY DOMAIN

Classifiers	Cracks	Precision	Recall	F1- score	Samples
KNN	4	0.590	0.910	0.710	11
	34	1.000	1.000	1.000	18
	60	0.860	0.460	0.600	13
SVM	4	0.000	0.000	0.000	14
	34	0.000	0.000	0.000	17
	60	0.260	1.000	0.420	11
DT	4	0.850	0.690	0.760	16
	34	1.000	1.000	1.000	12
	60	0.710	0.860	0.770	14
RF	4	0.670	1.000	0.800	12
	34	1.000	1.000	1.000	15
	60	1.000	0.600	0.750	15

In order to account for the stated gap, present work investigated different machine learning and feature extraction techniques to classify damage in CFRP composite coupons using acousto-ultrasonic measurements. For this work, acoustic- ultrasonic measurements in carbon fiber reinforced polymer specimens were obtained from NASA prognostics data repository. Then, several time-domain and frequency-domain techniques were used to extract features from the data that indicated the presence of damage in coupons. Finally, the extracted features were used to train K-nearest neighbors (KNN), SVM, Decision Tree (DT) and Random Forest (RF) algorithms and their performances were compared. Results showed the superior performance of DT with time-domain feature extraction and RF with frequency-domain feature extraction [1-17]. Four machine learning classification algorithms were taken into consideration, namely, K-nearest neighbors (KNN), Support Vector Machine (SVM), Decision tree (DT), and Random Forest (RF). The purpose of this analysis was to test the concept of classification of composite materials based on their damage states thus, supervised algorithms were taken into consideration and KNN, SVM and, DT being the most popular algorithms working on three different concepts of classifications, were selected and tested [26-34].

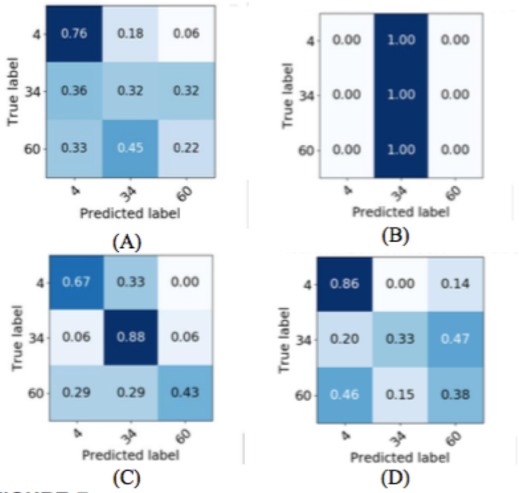

FIGURE 7: CONFUSION MATRIX FOR EACH CLASSIFIER IN TIME DOMAIN. (A) KNN (B) SVM (C) DECISION TREE (D) RANDOM FOREST

RF is an ensembled approach of DT based on bagging. For this analysis, RF was used for depth of 3 and compared with the rest of the algorithms. KNN is based on the Euclidean distance measurements from the nearest 5 data points (the number of points can be varied). It classifies the data point in question into the class to which the highest number of nearest neighbors belong. In the case of SVM, it draws a hyperplane between the classes and classifies based on the distance and direction of datapoint in question and the hyperplane (also known as support vectors) [42-51]. KNN and SVM are not learning algorithms, unlike DT which is based on the flowchart of the condition and a tree-like structure that tests each condition and then classifies the data points in question. It learns the features provided and thus known as the learning algorithm. RF, on the other hand, is based on bagging of multiple algorithms.

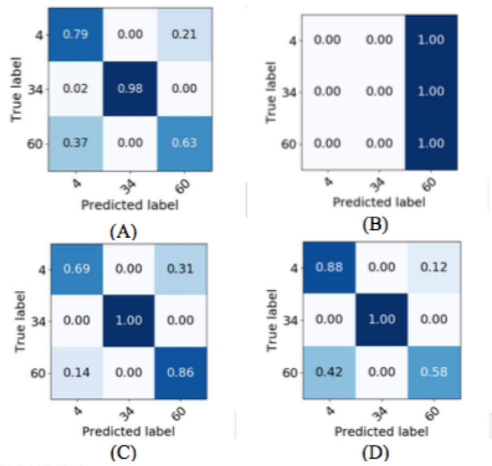

FIGURE 8: CONFUSION MATRIX FOR EACH CLASSIFIER IN FREQUENCY DOMAIN. (A) KNN (B) SVM (C) DECISION TREE (D) RANDOM FOREST

4. CONCLUSION

In this paper, the framework for classification of damage levels in CFRP composite materials was proposed based on machine learning algorithms using statistical feature extraction of piezoelectric signals at different damage levels. It can be concluded from the analysis that the average classification accuracies were better in the frequency domain with lower COV than that in the time domain. The algorithms that performed better were KNN, DT, and RF in different cases.

In the first step of analysis where the paths away from the actual damage were considered, the performance of all the classifiers was better as the signal contained information of only the damage that traveled farther in the cross-section. Unlike in the first step, the second step considered the whole dataset including the actual damage location which contained information of both cracks and delamination. The features extracted were not sufficient to differentiate the two different types of damages for the algorithms to classify them accurately. Also, this large real-time data introduced noise and uncertainties which were not taken care of by the preprocessing of signals. For this analysis, the whole signal was taken into consideration. All these factors contributed in increasing the complexity of the problem and thus resulting in an overall reduction in performance metrics in the second step. However, in the third step, where the complexity was decreased considering two extreme damage level, the performance of classification improved. Hence it can be concluded that the performance of the machine learning classifiers greatly depends on the preprocessing and features extraction of the dataset. It was shown that by using the correct combination of features, greater accuracy can be achieved and the features resulting in lowering the accuracy can be avoided. This also results in reducing computation time. Additionally, the complexity of the problem can be handled by decomposing the signals and by isolating the part of the signal containing delamination and cracks, thereby, processing them separately. Also, this will help to reduce the noise in the signal associated with the real-time experimental uncertainties as the useful information will be isolated. The features can then be extracted focusing these two damage levels separately. This analysis is still in progress and it is expected that this type of pre-processing will help to improve the performance and hence result in better classification.

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