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# A REVIEW ON ROLE OF AI IN DAMAGE ASSESSMENT INLAMINATED COMPOSITE STRUCTURES

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*Abstract:* **Composite structures are susceptible to various forms of non-linear failures, such as delamination, voids, and matrix cracks, during their operational life. Detecting such damages early is crucial to ensuring the structural integrity and reliability of these materials. As a result, researchers are continuously exploring more accurate and efficient methods for structural health monitoring of composite plates. In recent years, Artificial Intelligence (AI) techniques have shown immense potential as versatile tools for assessing damages in these materials. The present work provides a comprehensive review of the feasible methodologies utilized for delamination and crack observations in laminated composites, with a particular emphasis on machine learning techniques. The objective ofthe present article is to demonstrate a comprehensive perspective on the present state-of-the-art of health monitoring of laminated composite structures. Such insights are invaluable, given the escalating usage of laminated composites in various product engineering industries like automotive, aviation and aerospace, where critical quality, presence and location of damages/cracks is critical for improving their structural integrity. Furthermore, this review provides a critical analysis of thestrengths and limitations of wide damage detection techniques and offers insights into potential future research directions.**

*Keywords*: **laminates ,Machine learning, ANN, KNN.**

## I. INTRODUCTION

Laminated composite materials are the unique materials synthesized with the combination of fiber and matrix materials. The elastic and structural behavior of the laminated composite structures can be enhanced by reinforcing certain nanosized particles or flakes such as carbon nanotubes[1], graphite[2], graphene[3] and MXene[4] nanoflakes. The exceptional properties of laminated composites like enhanced range of stiffness, feasible elastic properties and long fatigue life, laminated composites have been increasingly replaces the traditional metallic materials in the industrial sectors like aviation, automobile, wind energy systems and aerospace sectors[5,6]. Despite their advantageous features, the heterogeneous nature of the composite laminates leads to the complex modes of failures. For instance, presence of voids in matrix phase, delamination, fiber breakage, matrix cracking and core de-bonding are some of the common types of failures/damage that may occur during the manufacturing process or operational life of laminated composites, leading to catastrophic failure in these structures [7,8]. The development and presence of damage/breakage in composite laminates was a complex process that cannot be easily inspected through visual testing or generalized methods. The damages, such as matrix cracks or delamination, are often hidden and require sophisticated techniques to detect, locate, and quantify. Therefore, the accurate assessment of laminated composites for presence of delamination, presence of interlaminar cracks, localization and quantification is of essentially needed for the safe and effective use of laminated composites in onboard applications.

Traditional visual inspections can be expensive, time-consuming, and often require easy accessibility to components. Additionally, conventional methods of detecting damage, such as ultrasonic testing, thermography, and X-rays, can be pricy and rely heavily on machinist experience and skill. Structural Health Monitoring (SHM) technologies offer a feasible alternate to traditional inspection methods. SHM uses non-destructive testing through integrated sensors to continuously monitor the structure. Acoustic emission is a form of SHM technique but still requires operator expertise. Vibration-based SHM inspections were relies upon the theory that structural

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damage changes the vibrative characteristics like free vibration behavior, damping characteristics and its vibratory modes. By analyzing these parameters, analytical/numerical model and computerized intelligence can identify and characterize damage[9]. SHM methodology focuses to provide the enhanced model for periodic and permanent monitoring of the critical variables, allowing for thedetection of potential failures before they become catastrophic. SHM has applications in various engineering fields such as aerospace, mechanics, and civil engineering. SHM systems provide structures with detection and analysis capabilities, enabling periodic or continuous monitoring and evaluation autonomously. The incorporation of SHM can lead to proactive corrective actions, preventing catastrophic failures by detecting damage early[10].

Two main approaches to structural health monitoring (SHM) are currently employed: passive and active SHM [11]. Passive SHM utilizes operating parameters to determine the overall remaining useful life of the structure. However, it fails to directly detect and measure the extent of structural damage, which is crucial for fault diagnosis. In contrast, active SHM involves embedding the damage sensory networks within the laminate structure and monitors the real-time operation of the structure which provides the precised magnitude and presence of the damage in a composite laminate. Active SHM is similar to non-destructive testing (NDT) methodologies, but takes into consideration critical factors, such as stress, temperature, and vibration levels. This approach can effectively detect andquantify the extent of damage in a structure, making it a morereliable method for assessing structural health. Various active SHM methods have been researched and developed over the years, such as wave-guided, wave-based, and per dynamics- based strategies, among others[12]. These methods utilize advanced technologies, such as sensors, actuators, and signal processing techniques, to provide accurate and reliable data on the condition of the structure. The present paper will focus on the active SHM approach, which is essential for detecting and monitoring structural damage. By utilizing advanced technologies and methods, active SHM provides a more comprehensive and accurate assessment of the health status of structures. This approach is vital for ensuring the safety and reliability of laminated composite structures.

In recent years, the field of machine learning has grown to become a powerful tool for separating and combining complex data to help us make sense of the world around us[13,14]. This technology has even made its way into the field of damage detection and structural health monitoring for composite materials, where it can be used to identify and track damage inreal-time[15]. However, the challenge lies in defining a comprehensive set of discriminatory factors that can accurately differentiate between all types of damages/injuries and their respective severity levels. Furthermore, each machine learning strategy may have varying levels of effectiveness depending on the specific damage mechanism being analyzed. The machine learning can also be used to predict the remaining useful life (RUL) of a damaged component or structure[16]. By analyzing data on past damage and failure events, machine learning algorithms can develop models that can predict when a component is likely to fail andprovide recommendations for maintenance or replacement. Inaddition to damage detection and prediction, machine learning can also be used to optimize structural design and materials selection. By analyzing data on material properties, design parameters, and performance criteria, machine learning algorithms can generate optimized designs that meet specific requirements and constraints. Overall, implementation of machine learning in damage/failure detection and structural health monitoring has tremendous potential to improve safe operable range, reliability, and performance of laminated composites [17-19,70,71].

The article discusses various aspects of damage associated with integrated structures and the smart algorithms related to them. While these algorithms are certainly useful, it is important to contemplate the role of machine learning algorithms in this context. Machine learning is a discipline which necessitates the analysis of statistical algorithms as wellas mathematical tools that can be used to establish and to determine the correlation between the independent and dependent variables based on trained set of rules and knowledges. Machine learning has been broadly classified as[20],

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

Supervised learning requires a supervisor or teacher who teaches the machine. If the dependent datasets were well labeled, supervised learning algorithm can be used to train the machine. In other words, we already have set of data associated with the precised output, which has been used to train the machine learning framework to identify the possible relationship between the input and output variables. Thus, supervised machine learning framework involves developing an optimal mathematical framework that applies the dataset that contains the required output and input variables. For example, if a dataset contains the numerous images of cats anddogs, the machine can be trained one by one with the featurespresented in the each image like shapes, color and texture. For instance, if the image is having the feature of more muscular and its proportionate body parts with the circular face structure, it is labeled as a dog. If the image file is having the feature of angular face, smoother and fine fur and slender body, it is labeled as a cat. When the computational frameworkis employed to identify a cat from the stored dataset, it utilizesthe data points learned from the past training and classifies the specific images. Therefore,

the supervised machine learning algorithm utilizes the datasets to train its framework and then uses the new data for testing[21].
Additionally, the machine learning frameworks can be appliedto address the following types of problems[22],

- Classification
- Regression
- Density Estimation

Classification involves the development of creating a computerized framework by coupling the estimate vectors with the significant labels. If a machine learning model is created using pre-existing data (known as training data), it canbe utilized to make predictions on new data points and assign them corresponding labels on a similar scale. Regression is a kind of a machine learning in which a computerized framework is built by utilizing training data to establish a relationship between continuous target values and one or moreindependent variables. This allows the model to predict or estimate the values of a dependent variable based on the input of new independent variables. Density estimation refers to theprocess of estimating the probability density function of a arbitrarily variable from the quantified samples, without making any assumptions about the underlying distribution. Unsupervised learning, is a type of machine learning where the framework trains on unlabeled data without any predetermined outcomes. This allows the algorithm to identifypatterns, trends, and relationships in the data without any guidance or direction. In mathematical terms, unsupervised learning involves the creation of an algorithm without a predetermined output and only inputs. This type of machine learning is used to identify patterns or relationships in data thatare not labeled or classified[23]. For example, an analytics company may use unsupervised learning to segment patients into smaller groups based on similar diseases. This can help medical companies more easily target these groups for specific treatments or interventions.
Unsupervised Machine learning can be classified as follows [24],

- Clustering is a technique used to group data points that share similarities or patterns, allowing for meaningful insights to be derived from the data.
- Dimensionality reduction is a method used to compress large and complex data sets by reducingthe number of variables or features while retaining as much relevant information as possible.
- Association analysis is a statistical method used to identify the relationships or associations between variables in high quantified datasets, where the occurrence of one variable (x) is often linked to the occurrence of another variable (y). This can be expressed as “if x, then y” to indicate the presence ofa strong association between the two variables

Reinforcement learning, as the name suggests, involves making decisions sequentially without any feasible or accurate outputs. The required task can be performed with the help of reinforcement parameters. Since, the reinforcement framework can able to learn from the experience even without training dataset. The dependent output computed with the current independent variable, and the next independent variable depends on the dependent variable of the past independent variable[25]. Machine learning is an important aspect of intelligent algorithms in the context of damage associated with integrated structures. It can be used to address various problems, including classification, regression, and density estimation. With its ability to train itself without explicit direction, unsupervised learning is particularly usefulfor grouping and compressing data. Meanwhile, reinforcementlearning is useful when there is no training data set and decisions need to be made sequentially. Overall, machine learning provides a powerful tool for predicting and analyzing damage to integrated structures.

## II. DAMAGE DETECTION USING ARTIFICIAL INTELLIGENCE

The machine learning to detect the damage in laminated composite plates can effectively implemented with the elimination of crucial aspects of damage. However, it is not feasible to identify the comprehensive sets contains the criticalrisk factors that can be utilized to detect the damage in laminated composite structures, such as those found in aerospace, public infrastructure, oil and gas, etc. Therefore, itis crucial to provide a comprehensive guide that explains the types of discriminative objects and algorithms used for featureclassification. In this review, we examine a variety of machinelearning tools, including Artificial Neural Network (ANN), K Methods, K Nearest Neighbors (KNN), Auto-Regress Models and Support Vector Machine (SVM) for analyzing censorious aspects of destruction under both uncontrolled and controlled conditions.

### 2.1 Artificial Neural Network (ANN)

The history of Artificial Neural Networks (ANN) can be datedback to 1800s when scientists started to explore ways to clone the functions neurons presented in the cerebellum[26]. ANN isa computing system that is inspired by biological neurons. These networks can be either organic or artificial in nature. One of the significant benefits of utilizing ANN is that not necessary redesign the dependent variable since the neural framework computes the best possible result. In fault diagnosisprediction, the importance of neural networks is increasing significantly. ANN can be classified into several types, and themost common ones are discussed below. In 1958, Frank Rosenblatt modelled the

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perceptron based network, is the oldest neural network that possess a neural node[27].

Feed forward Neural Networks, also known as Multilayer Perceptron (MLP), are the framework consists of an layer of input nodes, one or more hidden layers, and an layer of output nodes[28,29]. These neural networks have become increasingly popular numerous fields consists of Natural Language processing (NLP), Neural Networks (NN) and Computer Vision, because of their capability to handle nonlinear data effectively[30]. MLPs can be trained using a supervised learning algorithm, where the neural framework learn from labeled data, or an unsupervised algorithm, where the framework identifies patterns in the datasets without any pre-existing labels. Overall, the versatility and power of MLPs make them an important tool in many machine learning applications.

Convolutional Neural Networks (CNNs) and Multilayer Perceptron (MLP) are both types of neural networks used in machine learning. However, CNNs are specifically designed for image and pattern recognition tasks[31], while MLPs are more versatile and can be used in a wide range of applications. CNNs use matrix multiplication and linear algebra principles to detect patterns in images. CNN networks were composed of several layers known as convolutional layers, fully connected layers and pooling layers, which allow them to extract and learn complex features from the input data. By nature these networks are highly capable for complex tasks like object recognition, computer vision and image segmentation[32]. Recurrent Neural Networks (RNNs), on the other hand, are designed for processing timely varying datasets like language processing and speech recognition[33]. Unlike MLPs and CNNs, RNNs have feedback loops that allow them to learn from previous inputs and produce outputs based on the current input and the previous state[34,35]. This makes them highly effective for predicting future possibilities based on historical data. RNNs have been used in a variety of applications, such as predicting stock prices and weather forecasting.

Artificial Neural Networks (ANNs) has been proven as an effective framework in Structural Health Monitoring (SHM) of composite materials[36-39]. The ability of ANNs to learn and recognize patterns in large datasets makes them particularly useful in identifying damage and predicting the remaining useful life of composite structures. One area where ANNs have been particularly effective is its ability to detect and estimate the location of in laminated composites. Several studies have utilized back propagation neural networks to accurately detect and measure the size of delamination in composite materials [40-42]. For instance, Oka for et al. [43] utilized the back propagation based artificial neural network to identify the size of delamination in a smart material, achieving good prediction accuracy for delamination sizes ranging from
0.22 to 0.82, but struggled to predict delamination sizes less than 0.08. Another area where ANNs have been applied is in the identification and classification of different failure modes in composite materials. Figure 1 illustrates the typical neural architecture can be implemented on failure analysis of laminated composite plates.

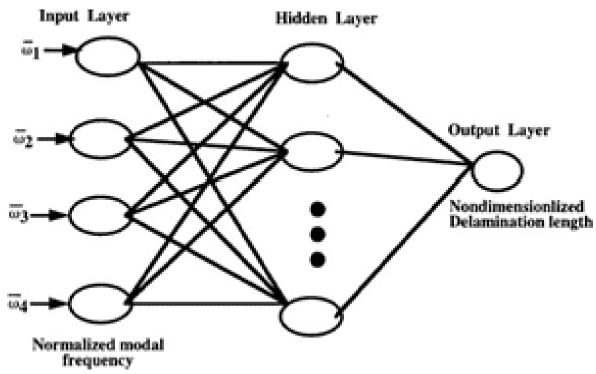


Figure 1. Graphical Illustration of Neural Architecture for Delamination Analysis [43]

Furthermore, Bar et al. [44] identified the ineffective pathways presented in reinforced plastic compounds by using the artificial neural networks aided with acoustic emission markets. The failure features such as, delamination, matrix cracks and fiber failure, were mapped with the aid of Kohonen self-organizing feature map (KSOM). It was reported that the KSOM deployed MLP framework segregates the failure features of the reinforced materials with help of the variance in acoustic emissive pulses. ANNs have also been used for damage detection and localization in composite structures. The damages in the carbon reinforced laminated panels were monitored by Chetwynd et al. [45] with the help of surface transducers assisted with the MLP framework. The retrospective transducer network was framed with twenty eight sensory buses of the 8 face lift transducers. The MLP based network segregates the non-damaged and damaged segments of the composite panel and later the trained networkwas utilized to estimate the location of damages in the plate geometry. In summary, ANNs have proven to be a powerful tool in SHM of composite materials, especially in the areas of delamination detection, failure mode identification and classification, and damage detection and localization. With the continued advancements in ANN architectures and training algorithms, they are likely to play an even more significant role in SHM in the future.

**2.2 K-Nearest Neighbors (KNN) and K-Means Algorithm** K-means is a cutting-edge unsupervised learning method that has been employed to detect K-groups or clusters in unlabelleddata[46]. This algorithm has shown great promise in identifying patterns in acoustic emission (AE) signals that correspond to different types of damage, such as matrix fragmentation and interfacial decohesion. God in et al. [47] successfully used K- means to cluster AE signals based on characteristics such as duration, calculation value, count, magnitude and life expectancy. The resulting clusters were then labelled using the K-nearest neighbours (KNN) algorithm, which is a supervised learning framework commonly used for segmentation tasks. The trained K-nearest neighbors classifier was then used to classify new AE signals, demonstrating the effectiveness of this approach. In a recent study, researchers have proposed a novel approach that combines the K-means learning methodology with a evolutionary algorithm such as genetic algorithm for classification and clustering multiple failure modes in experimental mode I delamination in a laminated sandwich composite plate [48-50]. This unsupervised damageclustering approach offers a promising solution for identifying and classifying different types of damage in laminated composites. Overall, the use of K-means in SHM of laminatedcomposites provides a powerful tool for identifying and classifying different types of damage, ultimately leading to better maintenance and longevity of these materials. The proposed approach combining K-means and genetic algorithmoffers a novel and effective solution for unsupervised damage clustering. Figure 2 represents the application of KNN framework to classify the damage modes by utilizing theacoustic emissive signals.

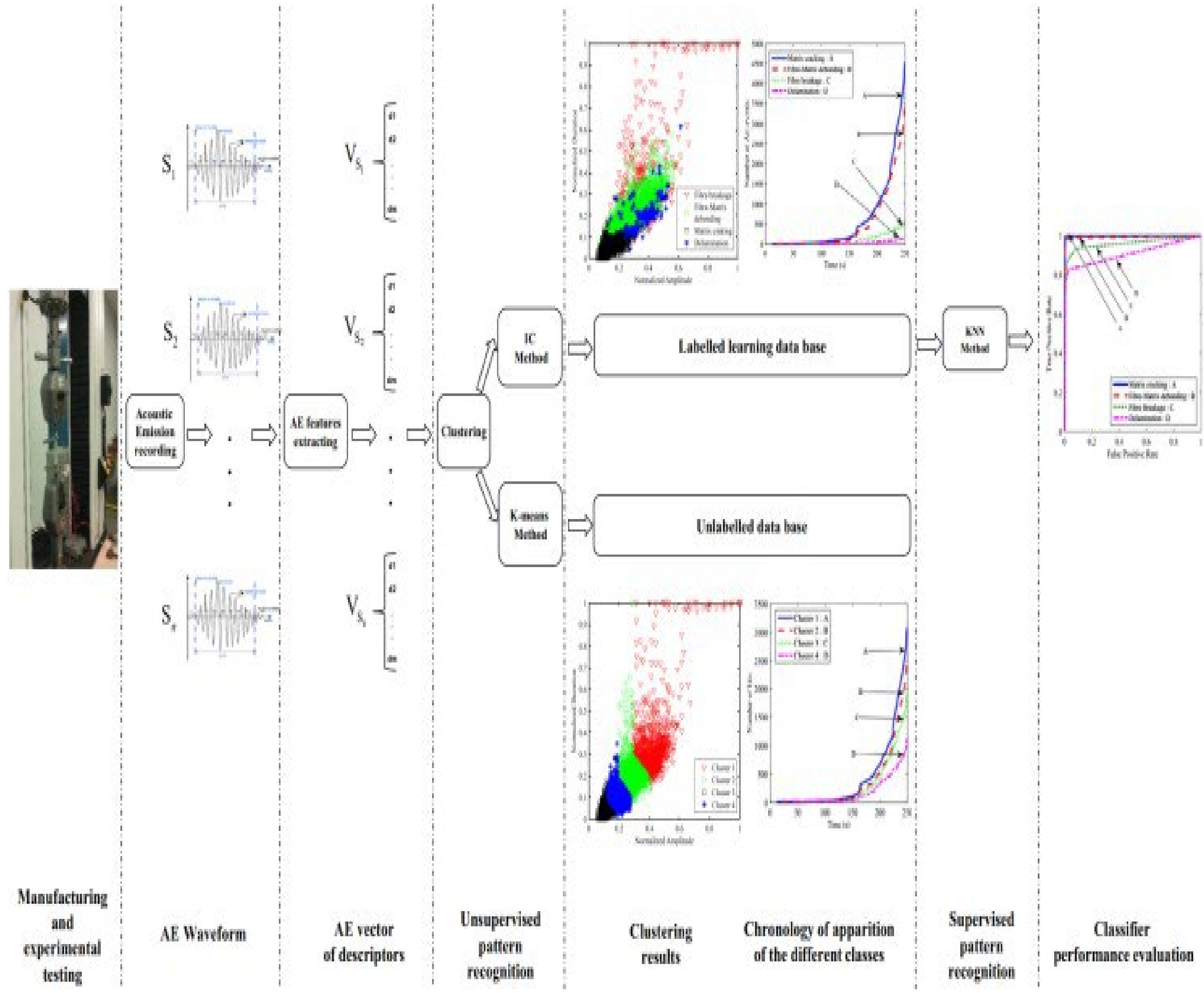


Figure 2. Graphical representation of KNN framework based damage classification [50]

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### 2.3 Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) is a powerful technique that has been widely used to analyze structural responses and identify critical risk factors in various applications. PCA has been applied in sensor validation, environmental monitoring, and structural damage assessment, to name a few[51,52]. Recently, researchers have proposed a novel approach to discriminate between different types of damage in composite materials using acoustic emission (AE) signals. The proposed method involves integrating Fuzzy C Means (FCM) clustering with AE data analysis to identify different clusters of acoustic signatures associated with debonding between the matrix and fiber material, fiber breakage and matrix cracks [53-55]. The study considers various characteristics of AE signals, such as frequency, magnitude, strength, calculation value and awakening time. By reducing the feature space using PCA, the approach identifies critical risk factors and clusters them together to detect and categorize damage accurately. The proposed method has the potential to improve the maintenance and extend the longevity of composite structures in various industries such as aerospace, automotive, and marine. This innovative approach provides a powerful tool for accurately identifying different types of damage in composite materials based on their acoustic signatures[55-58]. The results are promising and offer a new avenue for damage assessment that could lead to more efficient maintenance and improved safety in composite structures.

### 2.4 Auto-Regressive Model

The Auto-regression (AR) framework is one of a powerful analytical model that has been widely utilized for dynamic (Time-dependent) processes in various fields, including finance, physics, and engineering. In the field of damage detection, the AR model has been applied in several interesting ways, such as compression monitoring and error detection [59], fault detection in structural frames[60], health monitoring in generic in fractures[61,62], fault detection in wind turbine[63]. In recent research, Liu et al. [64] proposed a novel approach that integrates the AR model with the deep machine learning technique known as convolutional neural networks (CNN) for fault diagnosis in laminated composite structures. The proposed method is capable of detecting both the severity of damage and its location by analyzing the changes in the acoustic emission (AE) signals generated by the damaged structure. The AE signals are first decomposed using the wavelet transform, and then the AR model is used to extract the features of the decomposed signals. Finally, the CNN classifier is trained on these features to analyze the potential and location of damage. This novel approach has shown promising results in detecting damage in composite structures, and it has the potential to be extended to other types of structures as well. The integration of the AR model with deep learning techniques opens up new avenues for more accurate and efficient damage detection in various fields of engineering.

### 2.5 Support Vector Machine (SVM)

Support Vector Machines (SVM) are machine learning algorithms that use a kernel function to transform the input feature space into enhanced dimensional space having a hyper plane has been used to segregate datasets[65]. SVMs has been utilized in various mechanical diagnostic applications like gear error diagnosis under dynamic conditions, acoustic emission source localization, and turbine engine fault diagnosis. However, SVMs have also been utilized in novel ways for damage detection. Das et al. [66] proposed a unit- phase SVM classifier to identify four categories of damage (hollow holes, saw cut, delamination and saw) in smart materials integrated composite laminates. A dynamic frequency based approach has been utilized to extract the was used to extract censorious features from piezoelectric responsive pulses. Prashant and Sung [67] created an support vector machine-based approach for onboard damage detection in chopper blades, by utilizing vibrational loads as a feature of delamination and matrix cracking. Farooq et al.
[68] compared the efficacy of artificial neural network and support vector machine for damage detection in a fiber-reinforced panel, and found that SVM was more effective than ANN for detecting and magnifying fracture damage. Figure 3 represents the classification in SVM framework. Dib et al. [69] proposed a novel framework contains a unit support vector machine for detecting failure/damage in glass fiber composite plates. Discriminatory features were identified by L-bins spitted by using lamb waves which was utilized for calculating FT (Fourier transform) at each bin time. Overall, SVMs have proved to be a versatile and effective tool for detecting and categorizing various types of damage in mechanical systems, and novel applications of SVMs are continuously being explored.

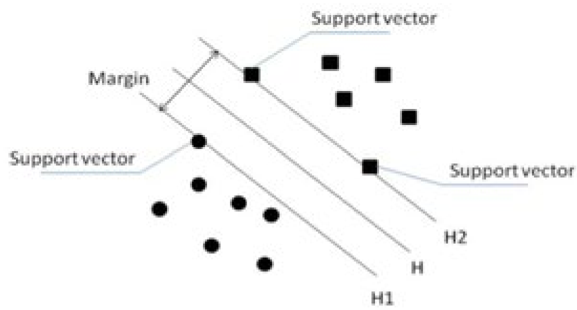


Figure 3. Illustration of Binary classification using Support Vector Machine [68]

## III. CONCLUSION

The growing application of laminated composite structures in different industries has increased the demand for timely detection of defects. This article reviews the implementation of machine learning frameworks on critical failure detection and assessment on laminated composite plates. Both unsupervised and supervised machine learning frameworks are discussed and found to be effective in estimation of locations and presence of delamination and its propagation through vibration signature analysis. Machine learning has found applications in various fields, including industrial safety, economics and resource management. The articles reviewed suggest that unsupervised machine learning frameworks can be implemented with categorized data to obtain segregate knowledge for different class of failure and build predictive models. The frequency of the acoustic emission signals provides information about fiber breakage and matrix cracking, with low and high frequency information representing fiber breakage and matrix cracking, respectively, and frequencies in between indicating debonding. An inverse diagnostic tool has also been created using GA that can detect faults within milliseconds. Supervised machine learning frameworks are much lower computationally extortionate and work well with least amount of learning data by requiring characteristics from data sources. On the other hand, unsupervised learning is costlier and needs high computing performance machines like Graphical Processing Units with a huge amount of training datasets to identify the significant characteristics based on the onboard datasets.

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