Use of Artificial Intelligence in Design, Development, Additive Manufacturing, and Certification of Multifunctional Composites for Aircraft, Drones, and Spacecraft

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Abstract: Multifunctional composites provide more than one function from the same part. The anisotropy, material, and process characterization challenges and the lack of standardization on the 3D-printed multifunctional carbon composites make it difficult for application into aerospace. The current solutions for additive manufacturing (AM) technologies and additively manufactured monofunctional and multifunctional composites are not mature enough for safety-critical applications. A new approach is proposed to explore the use of machine learning (ML) in the design, development, AM, testing, and certification of multifunctional composites for aircraft, unmanned aircraft systems (UAS), and spacecraft. In this work, an artificial neural network (ANN) architecture is proposed. An AM-embedded building block approach integrates the complete lifecycle of aircraft, UAS, and spacecraft using ANN to support the continued operational safety (COS) of aircraft, spacecraft, and UAS. The proposed method exploits the power of ANN on the metadata for the characterization of multifunctional material properties and processes and the mapping of the failure modes compared with the predicted models and history. This paper provides an in-depth analysis and explanation of the new methods needed to overcome the existing barriers, problems, and situations.

Keywords: certification; artificial intelligence (AI); machine learning (ML); artificial neural network (ANN); multifunctional additive manufacturing

1. Introduction

Artificial Intelligence (AI) is defined as the computations that are used for perceiving, reasoning, and acting [1]. In general, AI is also defined as the technology for enabling machines to imitate complex human skills [2]. The scientific goal of AI determines the ideas about knowledge representation, knowledge usage, and systems assembly for explaining various types of intelligence [1]. Machine learning (ML) is known as programming computers for the optimization of a performance criterion using example data or previous experience (historical information) [3]. Anisotropy, material, and process characterization challenges, and the lack of standardization, certification rules, and policies on the additively manufactured multifunctional carbon composites, make it difficult for applications into aerospace. Other challenges are the presence of a large number of process parameters and variability; size and amount of data; control of voids and porosity; the influence of AI on AM; among others. The current trend in AM for monofunctional polymer composites is the use of the traditional Building Block Approach [4]. There is also an increasing interest in conducting further research regarding the use of multifunctional carbon fiber composites manufactured via AM for aircraft. The AI-enabled AM multifunctional carbon composites will aid in achieving repeatability in manufacturing and processes, thus making the AM technology suitable for safety-critical applications. The ability to control fiber placement by using AI-enabled AM technology can enhance the properties of the AM part since the AM technology allows for selective material deposition, improving repeatability.
and consistency [5]. Additively manufactured monofunctional composites parts are not matured for safety-critical and structural load-bearing applications. Increased levels of automation and the use of robotics in composites manufacturing introduce other issues like quality control and quality assurance that are predominantly influenced by the use of AI on AM. The laborious manual inspection of composites during development does not seem promising due to the increased level of automation and use of data-driven technologies like blockchain and MLs. One of the most common ML algorithms is the artificial neural network (ANN), which is inspired by the structure and function of the human brain and can perform complex computations on the input data to extract meaningful features and patterns through a large number of neurons, organized into layers, with each layer performing a specific set of calculations on the input data [6].

**Current Technologies and Methodologies**

An automated inspection system based on convolutional neural networks (CNN) and image segmentation tasks was proposed to enable rapid part inspection and analysis [7]. An ML approach for the planning, optimizing, and inspection of AFP processes was proposed to automate data capturing, data storing, modeling, and optimizing [8]. Deep learning is quite popular and seeks to extract the representative features of inputs in order to identify unique patterns in the data [9]. CNNs are deep learning algorithms that can train large datasets with millions of parameters in the form of 2D images as input and convolve them with needed filters to produce the desired outputs by using convolution [10]. The CNN models were created to assess their performance in image detection and recognition from the assigned datasets [10]. Recurrent neural networks (RNNs) are defined as a class of neural networks in which the previous outputs are used as inputs while having hidden states [11]. Despite the various benefits of using RNNs (processing input of any length; model size not increasing with the size of input; computation considers historical information; weights are shared across time), the computation is slow, which makes it difficult for gathering information from a distant historical event, and it cannot consider any future input for the current state [11]. RNNs are used for applications that contain data in a sequence and time series for classification purposes [12]. While tailoring the electrical and structural properties of 3D-printed composites and the quasi-static multifunctional characterization of 3D-printed carbon fiber composites is the critical step for their compressive-electrical properties, this paper did not address the use of ANN in design, development, additive manufacturing, and certification of the multifunctional carbon fiber composites for aircraft, drones, and spacecraft [13]. The reported quasi-static multifunctional properties and the failure modes and locations, coupled with machine learning (ML), could help inform future iterations of the design, development, and advanced manufacturing with the hope of offering significant weight reductions and potentially replacing the bulky electrical wires in aerospace applications [13]. A novel automated quantification methodology was developed to evaluate the health and performance of the wind turbine blade leading edge erosion using the data from the 140 field images covering the varying blade orientation, resolution, aspect ratio, and lighting [14]. Supervised ML and unsupervised ML models were created for evaluating the automated quantification of the damage states obtained from the field images of the wind turbine leading edges. While the supervised ML model applied convolutional neural networks (CNN) and learnt damage details/types as features that are found in the typical datasets of training of the 140 field images, the unsupervised ML model conducted a consolidation of pixel intensity thresholding with the calculation of a pixel-by-pixel shadow ratio to independently identify features within the 140 field images of the wind turbine leading edges [14]. It was found that the CNN model was better in the identification of shallow damage and yielded higher performance when used with the 140 field images after their preprocessing to common blade orientation [14]. While there have been various damage classification techniques using the supervised ML models for self-organizing maps in the structural health monitoring (SHM) systems, this study did not address the use of ML in the design, development, manufacturing, testing, and certification.
of the aircraft, UAS, and spacecraft using the digital data from across different entities such as accidents/incidents databases, service difficulty reporting, airlines, maintenance, repair and alteration, design–manufacturing–testing data, etc.\cite{15}. The electro-tensile properties of the additively manufactured continuous carbon fiber multifunctional composites\cite{16} and the coupled electro-flexural evaluation of 3D-printed multifunctional composites, along with their failure modes and locations, provide significant data and engineering information for aerospace applications, airworthiness, and sustainment\cite{17}. While an automated impact damage detection methodology for the advanced solid laminate composite structures was developed based on ML classification and thermographic image processing, this paper did not adequately address the effectiveness of this methodology and the effects of the test data from the geometric variation of the tested specimens, for classification percentages and suitability in the use of ML in the design, development, manufacturing, testing and certification of aerospace vehicles\cite{18}. The test coupons were induced to an impact damage caused by varying energy levels (4 to 12 J)\cite{18}. A statistical analysis and ML technique were used in this study to evaluate the prediction accuracy of the proposed classification technique as ranging from 78.7\% to 93.5\%\cite{18}. While the novel damage detection of advanced composites using deep neural networks (DNN), known as CNN and data fusion, yielded the gramian angular field as the best and most efficient method, this research work did not address the use of the ML in the design, development, manufacturing, testing, and certification of the aerospace vehicles\cite{19}. Despite the advantages of the use of CNN coupled with the data fusion technique to handle the rigor and complexity of the damage states classification of the advanced composites with multi-modes of failure and mechanisms, this methodology did not address the use of the ML in the design, development, manufacturing, testing, and certification aspects of aircraft, UAS and spacecraft, utilizing the datasets from the existing databases like AGATE, NCAMP, service difficulties reporting, accidents-incidents data, design data, etc.\cite{19}. Two ML algorithms (linear regression and random forest) were used for the prediction of the impact damaged locations on the thermoplastic aircraft control surfaces—elevators, based on the acoustic emission (AE) signals to develop a novel structural health monitoring (SHM) system for autonomous detection and localization of impact damages\cite{20}. While the test results showed high accuracies for the random forest models and linear regression in the prediction of the impact damage locations, this study did not address the use of ML in the design, development, manufacturing, testing, certification and sustainment of aerospace vehicles\cite{20}. A type of supervised learning algorithm known as a support vector machine was used in ML to conduct binary classification problems of the image by categorizing digital data into two groups\cite{21}. While TensorFlow was used for target identification and movement classification, this paper did not address the use of ANN in the design, development, testing and certification of multifunctional composites for drones, spacecraft and aircraft\cite{21}. Twelve ML techniques were used in data-driven predictions of the compressive strength of the fiber-reinforced polymer-confined concrete test coupons\cite{22}. The experimental test results were fed into an ML model after they were processed with the new data science techniques\cite{22}. While the tree-based methods resulted in the highest accuracy, and it was depicted that an accurate and fast computation was developed by adjusting the experimental test data and the ML models, this study did not address the use of ML in the design, development, testing, manufacturing, certification and sustainment of aerospace vehicles\cite{22}. While the use of ML techniques in the prediction of the absorption properties of the thermoplastic composites comprised of matrix recycled polyvinyl butyral was thoroughly explored, this study did not address the use of ANN in the design, development, testing, manufacturing and certification of aircraft, UAS and spacecraft\cite{23}. Despite the use of the ML technique for evaluating the predictive models for the characterization of internal defects in the 3D-printed materials from active thermography sequences, this paper did not address the use of ANN in the design, development, testing, manufacturing and certification of aerospace vehicles based on existing datasets\cite{24}. While the use of ML techniques for the density prediction in powder bed fusion 3D-printing techniques was used, this
investigation did not address the use of ANN in the design, development, manufacturing, testing and certification of advanced composites for aerospace applications [25]. While a detailed review was conducted on the use of unsupervised ML models for vibration-based structural health monitoring (SHM) systems, limitations of the SHM methods were also presented; this study did not address the use of ANN in the design, development, manufacturing, testing and certification of aerospace vehicles [26]. A new convolutional-deep neural network (C-DNN) method was developed for evaluating the probabilistic low cycle fatigue (LCF) life prediction of metallic turbine blisk [27]. The convolutional neural network (CNN) method was utilized for extracting the useful features of LCF life data by using two convolutional layers to ascertain the precision of the C-DNN modeling [27]. The regression modeling of the aeroengine turbine blisk LCF life was obtained by using the two layers in DNN for the accuracy of the LCF life prediction [27]. While the proposed C-DNN method was found to be an effective method for the metallic turbine blisk LCF life prediction for complex structures, this study did not address the use of artificial intelligence in design, development, additive manufacturing and certification of multifunctional carbon fiber composites for aircraft, drones and spacecraft [27]. A novel method of clustering called Intelligent Clustering Routing Approach (ICRA) for UAV Ad Hoc Networks (UANETs) was proposed that is comprised of three components: the clustering module, clustering strategy adjustment module and routing module [28]. While the ICRA’s robustness and superiority over the existing methods was validated, and the results showed that ICRA could obtain better clustering efficiency compared to the existing schemes, this research did not address the use of ANN in the design, development, additive manufacturing, and certification of multifunctional composites for aircraft, drones, and spacecraft with respect to aerospace structures and the application of advanced composites [28]. Reinforcement Learning was used for Context-Awareness Trust Model for vehicular ad hoc networks (VANETs) that involved the adjustment of the evaluation strategy for maintaining accuracy in different scenarios, and verification of the effectiveness of the proposed model [29]. While the results demonstrated that the proposed model can be adaptive with negligible time overhead and can obtain a higher evaluation precision rate, this research does not address the use of ANN in design, development, additive manufacturing, testing and certification of multifunctional composites for spacecraft, aircraft and drones [29]. While a novel method called Lightweight Trustworthy Message Exchange (LTME) in Unmanned Aerial Vehicle Networks was proposed to potentially offer improved functionality and better robustness with a low computation overhead, this research does not address the use of ANN in design, development, additive manufacturing and certification of multifunctional composites for drones, aircraft and spacecraft with respect to how the aerospace structures and airframes are designed, developed, additively manufactured, tested and certified [30]. The latest journal article about the use of artificial intelligence in aviation does not address the use of ANN in design, development, additive manufacturing, testing and certification of multifunctional composites for aerospace vehicles [31]. A new taxonomy atlas of composite materials’ damage patterns, automated damage diagnostics, analysis methods and measuring signals was developed [32]. While the supervised and unsupervised ML algorithms like self-organizing maps, CNN, autoencoders and a novel z-profiling methodology were used for an assessment, this investigation did not address the use of ANN in the design, development, manufacturing, testing and certification of aircraft, UAS and spacecraft utilizing the common database(s) such as AGATE, NCAMP, etc. [32]. The failure modes, failure locations and failure orientations of the tested specimens play significant roles in the aerospace application and airworthiness state, and are also vital for maintaining the continuous operational safety (COS) known as sustainment. The lack of existing standards and the maturation of technologies make it difficult to certify AI-enabled and additively manufactured multifunctional carbon fiber composites for aircraft. This research’s main objective is to explore the use of ANN in the design, development, additive manufacturing and certification of multifunctional composites for aircraft, UAS and spacecraft. The current state of technologies does not address the use
of ANN in the design, development, additive manufacturing, testing and certification of multifunctional composites for aircraft. Rapidly increasing computing technologies like ANN in advanced manufacturing have explored multifunctional composites. Accuracy, precision, refinement, etc., play vital roles in maintaining the repeatability, quality and variability of the AI-enabled AM multifunctional composites. The Advanced General Aviation Transport Experiments (AGATE) and National Center for Advanced Materials Performance (NCAMP) programs that were built for sharing databases furnished by material suppliers and reducing costs in airworthiness certification need to implement the use of ANN for addressing the shortcomings of the existing procedures and processes. The materials and processes are built and accepted with respect to specific aircraft models and could not be used for other aircraft models per the existing framework and procedures. This allowed using the material and processes’ information from this shared database when the same material and processes are used in similar aircraft applications with proper substantiation. The data from the current reporting systems, such as the Service Difficulty Reporting System (SDRS), U.S. National Transportation Safety Board (NSTB), National Aeronautics and Space Administration (NASA), U.S. Department of Defense (DOD), Airlines, etc., is not fully utilized to the maximum potential in order to build ANN architecture and predict failure loads and failure modes.

In this paper, Section 2 covers the proposed methodology highlighting the shortcomings of the existing procedures and framework and focuses in detail on the great advantages of the proposed solution and methodology. Section 3 addresses the machine learning model for structural characterization, and Section 4 addresses the conclusion and future work opportunities. Section 3 identifies the mathematical approach for machine learning and evaluation metrics for the machine learning validation in Sections 3.1 and 3.2, respectively.

2. Proposed Methodology

An enterprise approach is proposed in which an AM-embedded building block approach closely integrates various process stages, including the concept, testing, design, development, analysis and inspection, in order to address the shortcomings of the existing framework and procedures. This method will aid the certification of AI-enabled and additively manufactured multifunctional carbon fiber composites for aerospace applications such as aircraft, spacecraft and drones. In this proposed method, data and information from databases like from Service Difficulty Reporting System (SDRS), U.S. NSTB, NASA, U.S. DOD, Airlines, etc., are used for ANN algorithms to predict values. This approach will be effective in applying and evaluating the digital twin technology to calculate the total life in terms of the aircraft’s residual strength, durability, damage tolerance and fatigue strength. Parameters such as variabilities, material and process characterization, robustness, boundary conditions, etc., are included in this approach. ANN algorithms can be used in classification tasks, clustering, and even image and signal processing, throughout the lifecycle of the AM, thereby providing real-time feedback for material and process improvements. This method integrates operational data into the concept, design, manufacturing, development and certification phases of the complete lifecycle of the aircraft. This method also supports the repeatability of the processes and parts, and controls the parameters to maintain variability. This method modifies the existing AGATE and NCAMP methods and processes for using ANN to expand the existing common database to enable the in situ and in-AM learning and enhancement of the design, material and parts. This method also exploits the power of the metadata for the characterization of multifunctional composites and the mapping of the failure modes from the predicted models and service history. Metadata or metainformation is defined as a set of data that describes other sets of other data without providing the content of the data, such as the text of the message or the image itself [33]. This method uses ML/NN to compare and compute the certification development data with the previously developed data and delivers the outputs as informed decisions from the NN model. This approach will avoid duplication and streamline the design, development and certification, enhancing data-driven safety improvements. The damage growth
mechanism and final failure mode observed in damaged sandwich specimens are shown in Figure 1. Failure modes of specimens with varying numbers of holes repaired with the resin fill repair method are shown in Figure 2. Similarly, the final failure modes observed in sandwich panels for undamaged, damaged and repaired configurations are shown in Figure 3. Typical tensile test failure modes on solid laminate polymer composites are shown in Figure 4.

Figure 1. Damage growth mechanism and final failure mode observed in damaged sandwich specimens [34].

The existing AGATE and NCAMP methods and processes appear to be labor-intensive, and do not seem to support the application of ANN in the design, development, additive manufacturing and certification of multifunctional composites for aircraft, UAS and spacecraft. The newly proposed method addresses the aforementioned drawbacks of the existing processes, methods and databases to improve digital data-driven decisions.

Figure 5 shows the proposed certification methodology for the use of ANN in the design, development, additive manufacturing and certification of multifunctional composites for spacecraft, UAS and aircraft. As shown in Figure 5, the existing AGATE and NCAMP processes are modified to embed the use of ANN in the design, development, additive manufacturing, testing and certification of multifunctional composites for spacecraft, UAS and aircraft. The use of the common material database(s) that are needed for the design, development, manufacturing, testing, certification, qualification, equivalency and sustainment of aerospace vehicles is vital for the integrity and continued operational safety (COS) of aerospace vehicles. A number of companies can benefit from using the same data from this common database(s) without going through the complete and extensive manufacturing and testing of advanced composite structures. The use of ANN in the design, development, manufacturing, testing and certification of advanced composites for aerospace uses on the common material systems databases, by applying supervised machine learning via com-
puter vision technologies to compare the data with respect to the existing databases such as accident-incidents data, service difficulties reporting, design-manufacturing-testing data, etc., makes this novel methodology a promising technology to advance safety, integrity and the extended life of an aircraft, UAS and spacecraft.

Figure 2. Different failure modes of specimens with varying numbers of holes (redrawn [35]).

Figure 3. Final failure modes observed in sandwich panels for undamaged, damaged and repaired configurations (redrawn [35]).
Figure 4. Typical tensile test failure modes on solid laminate polymer composites (Reprinted, with permission, from ASTM D3039/D3039M-00, Standard Test Method for Tensile Properties of Polymer Matrix Composite Materials, copyright ASTM International. A copy of the complete standard may be obtained from www.astm.org) [36].

Figure 6 shows the proposed functional architecture for the use of ANN in the design, development, additive manufacturing, testing and certification of multifunctional composites for spacecraft, aircraft and UAS. As shown in Figure 6, the centralized material database(s) can be utilized and accessed by any of the numerous companies (Company A through Company n<sup>th</sup>) for a set of different material systems (Material-1 through Material m<sup>th</sup>) to be used in the aircraft, UAS and spacecraft projects. The use of ANN in the design, development, additive manufacturing and certification of multifunctional composites for spacecraft, aircraft and UAS, as shown in Figure 6, makes it more robust and comprehensive, thereby resulting in a digital data-centric assessment of the advanced composite structures for their suitability in aerospace applications as well as the continued operational safety (COS) of aerospace vehicles. This proposed methodology is applicable to both in-situ and off-site manufacturing. The use of the phrase “in-situ manufacturing” in this context is meant for the integrated design–manufacturing–testing technologies, in which the design, manufacturing and testing of the advanced composite structures take place at the same machine or equipment/tool with the help of the ANN. The use of ML, especially supervised machine learning, in the design, development, additive manufacturing and certification of multifunctional composites for spacecraft, aircraft and UAS makes it more streamlined compared with the traditional methodologies for aerospace vehicles. The operational, maintenance, inspection, accidents, incidents, service difficulties and other data from certification, qualification and equivalency, coupled with the supervised machine learning algorithm, makes this proposed methodology best suitable for the design,
development, additive manufacturing and certification of multifunctional composites for UAS, spacecraft and aircraft.

Figure 5. Proposed certification methodology for AI-enabled and additively manufactured multifunctional carbon fiber composites (modified-NCAMP-shared database process).

Figure 6. Proposed functional architecture as certification methodology for AI-enabled and additively manufactured multifunctional composites.

The proposed methodology, as shown in Figures 5 and 6, offers potential improvements and benefits to the overall safety, integrity and life of an aircraft, UAS and spacecraft due to the use of ANN in the design, development, additive manufacturing and testing, as well as the certification of multifunctional composites for spacecraft, UAS and aircraft. This proposed methodology for the use of ANN in the design, development, additive manufacturing and certification of multifunctional composites for spacecraft, aircraft and
UAS, coupled with the use of the existing structural health monitoring (SHM) and other health monitoring systems (OHMS), provide tremendous benefits and advantages to this new methodology over traditional methods and procedures. The scope of this novel methodology can also be applied to the OHMS to support the safety and integrity of aerospace vehicles.

3. Artificial Neural Network (ANN) Model for Structural Characterization

ML is used in the proposed methodology of this paper as a means of computational statistics for prediction using computers. ML algorithms use computational statistics to find patterns in data such as numbers, words, images, etc. The ML model is a mathematical model that takes available data for training and performs prediction on its own based on supervised, unsupervised or reinforcement learning. NN is a special type of ML that is inspired by the human neuron structure. See an example in Figure 7 for NN. The NN models are computing systems considered similar to biological neural networks that form human and animal brains. The NN is considered as a function with an input and a desired output, where an output is dependent on weighted inputs. The following are some of the types of validations using the ML model for the certification of coupled multifunctional properties of AI-enabled and additively manufactured multifunctional carbon fiber composites. The proposed new method converts the detailed experimental design, test plan, test matrix and other data, such as failure loads, failure modes, failure locations, material properties, processes, etc., into a simplified version of the computational model as shown in the below Table 1 as inputs, NN model and outputs. The method uses an ANN model for characterizing the strength of AI-enabled and additively manufactured multifunctional and continuous carbon fiber composite structures. Table 1 shows the list of inputs, ANN models, and the associated outputs. The use of ANN for a particular set of inputs determines the outputs. The anisotropic behavior and the defect vulnerabilities of the composite material systems due to variabilities in the material characterization properties make the composites more process dependent. The use of ANN in the design, development, additive manufacturing and certification of multifunctional composites for aircraft, drones and spacecraft appears to be the most desired application of ANN to achieve the safety, integrity and life extension of the aerospace vehicles, since the composite material systems are highly process-dependent. The use of ANN in the design, development, manufacturing, testing and certification of multifunctional composites for aerospace applications can be leveraged to minimize the presence of flaws and defects in the advanced composites that are inherently present due to environmental, material and processing factors.

![Figure 7. Structure of an artificial neural network (ANN) with 3 hidden layers.](image-url)
Table 1. Relationship amongst inputs, ANN and outputs of proposed methodology.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>ANN Model</th>
<th>Outputs</th>
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<tbody>
<tr>
<td>- Raw material</td>
<td></td>
<td>• Unifunctional and Multifunctional Material Properties</td>
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<tr>
<td>- Resin material</td>
<td></td>
<td>○ Structural</td>
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<tr>
<td>- AM techniques</td>
<td></td>
<td>○ Thermal</td>
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<tr>
<td>- Speed of AM machines in coupon fabrication</td>
<td></td>
<td>○ Electrical</td>
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<tr>
<td>- Temperature of the dispensed and multifunctional carbon fiber composites by AM machines</td>
<td></td>
<td>○ Electromagnetic Interference (EMI)</td>
</tr>
<tr>
<td>- Manufacturing processes</td>
<td></td>
<td>○ High-Intensity Radiated Fields (HIRF)</td>
</tr>
<tr>
<td>- Coupon composition</td>
<td></td>
<td>○ Viscosity</td>
</tr>
<tr>
<td>- AM locus orientations for coupon fabrication</td>
<td></td>
<td>○ Flammability</td>
</tr>
<tr>
<td>- No. of test coupons</td>
<td></td>
<td>○ Others</td>
</tr>
<tr>
<td>- Statistically sound test data</td>
<td></td>
<td>• Failure modes</td>
</tr>
<tr>
<td>- Test matrix</td>
<td></td>
<td>• Meets certification regulations</td>
</tr>
<tr>
<td>- Test plan</td>
<td></td>
<td>• No defects on AM parts</td>
</tr>
<tr>
<td>- Software version of the machines used</td>
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<tr>
<td>- Software assurance of the software used in AM machine</td>
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<td>- Calibration of AM machines</td>
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<td>- Calibration of testing machines</td>
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<td>- Environmental:</td>
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<td>(1) Cold Temperature Dry (CTD)</td>
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<td>(2) Room Temperature Dry (RTD)</td>
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<td>(3) Elevated Temperature Wet (ETW)</td>
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<td>(4) Elevated Temperature Dry (ETD)</td>
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<td>(5) Dry</td>
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</table>

Mathematically, as shown in Equation (1), the ANN function \( Y \) is known as a composition of other functions, \( f(Q_j) \), which can be further decomposed into other functions. The ANN function \( Y \), represented as a neural network structure with arrows depicting the relationships and dependencies between different functions, is shown below in Figure 7. The ANN computation is conducted within a fraction of a section depending on the computing architectures of the system and the number of hidden layers for the ANN. A typical ANN model includes a minimum of three layers: input, hidden and output. Each neuron in the ANN model performs a weighted summation of the inputs, which then passes a nonlinear activation function \( Q_j \), also called a neuron function, and finally, the data are fed out of the neural network through an output layer [37]. Figure 7 shows only three hidden layers for ANN computation. The use of the higher number of hidden ANN layers will yield a higher degree and complexity of the mathematical calculations, thereby resulting in robust outputs and the need for higher computing infrastructures.

3.1. Mathematical Approach for Artificial Neural Network (ANN) Model

The proposed methodology uses Supervised Learning in the ANN models, in which the ANN models are provided labeled input data and the desired output outcomes and results. The ANN models with learning techniques are instructed, using supervised learning techniques, on what to look for and what to deliver as an output. The ANN models are completely trained until they can achieve the expected performance to detect all the patterns and ANN neurons’ relationships with the weights and outputs. The trained ANN models produce the desired outputs, thereby leading to great results within the best optimized and efficient ways.

Mathematically, as shown in Equation (1), the ANN function \( Y \) is known as a composition of other functions \( f(Q_j) \), which can be further decomposed into other functions. The ANN model, as shown in Equation (1), Equation (2) and Equation (3), respectively,
can be trained by using three learning types: supervised learning, unsupervised learning and reinforcement learning. The process of training a system to perform a desired function is called supervised learning [38]. Unsupervised machine learning is defined as ML algorithms that are used for analyzing and clustering in order to find patterns in unlabeled data, e.g., in the clustering of samples [39]. Reinforcement learning involves learning what to do and how to map situations to actions for maximizing a numerical reward signal, in which an intelligent agent (algorithm) interacts with the environment [40].

The training/learning of the ANN model can be achieved by using various algorithms and adjusting its corresponding weights to obtain the desired outputs. The mathematical ANN model/architecture, as shown in Equation (1), is defined by the number of neurons and the interconnection of those neurons with weights and biases. The ANN model, as shown in Figure 7 and Equation (1), is defined on a set of input–output pairs and is trained to produce the desired output. The structure of each ANN model is represented as \((i, j, k)\), where \(i\) represents the number of nodes in the input layers, \(j\) is the number of nodes in the hidden layers, and \(k\) is the number of nodes in the output layers [41].

The net input (\(Q_j\)) is then passed through an activation function \(f()\), and the output \("(Y)"\) of the node is computed as:

\[
Y = w_{p0} + \sum_{j=1}^{m} \left( w_{pj} \right) \left( f \left( \sum_{i=1}^{n} (x_i)(w_{ij}) + (b_j) \right) \right),
\]

Equation (2): Outputs of the ANN model, where,
- \(p\) = the number of outputs \((p = 0\) if it is one); 
- \(f(Q_j)\) = the activation function.

The typically used activation functions in the ANN model are the Rectified Linear Units (ReLU), sigmoid, Hyperbolic tangent (tanh), etc. The ReLU function, as shown below in Equation (3), is the most common activation function. ‘ReLU’ is the abbreviation for the Rectified Linear Unit activation function [42]. It is frequently implemented in neural networks to accelerate the training and mitigate the disappearing gradient problem [42]. The value is returned by the “ReLU” activation function if the input is positive; otherwise, it is set to zero [42]. A sigmoid function is defined as a mathematical function with an “S” shaped curve, and it represents the logistic function, as shown below. The Sigmoid function, unlike the stepwise function, includes non-linearity in the ANN model. This implies that the outputs received from the neurons do not represent a linear combination.
of inputs and weights. This will support the nonlinear activation function for classifying and assisting the nonlinear decision boundaries in the data.

\[ f(Q_j) = \frac{1}{1 + e^{-Q_j}} \]  

Equation (3): ANN model with nonlinear weights.

Equation (3) shows that the complexity of the ANN model is dependent on the number of hidden layers and the learning accuracy of the ANN model. The accuracy is accomplished by increasing the number of hidden layers in ANN that causes a proportionate number of needed training repetitions. Figure 8 shows the typical process of ANN model training. In the typical process of ANN model training, the pass/fail criterion is defined as the threshold, and then the ANN is initialized. After that step is completed, the forward propagation is executed to calculate the error. The error calculation in this context is also known as a backward propagation. After that step in the ANN training process, ANN weights are updated to evaluate the ANN accuracy threshold. Once the ANN accuracy threshold is achieved, then the ANN model training process is completed. If the ANN accuracy threshold is not obtained, the forward propagation step is executed, and the whole step is repeated until the ANN model training is completed.

**Figure 8.** Typical ANN training process.

### 3.2. Evaluation Metrics for Artificial Neural Network (ANN) Validation

The failure modes, failure locations and failure types, as shown in Figure 2 [35] and Figure 3 [35], are used as an example in this section to analyze the below-listed evaluation metrics for the ANN validation and are listed below in Table 2. Table 2 shows the list of inputs and the associated ANN models and outputs. As shown in Table 2, the outputs are dependent on the ANN model and the corresponding inputs, since the anisotropy feature of the advanced composite structures makes them truly process-dependent. The process-dependency aspect of the advanced composite structures due to the presence of the inherent defects in the composite structures due to materials, processing, environmental factors, etc., makes the best application of the ANN in the design, development, additive manufacturing, testing and certification of multifunctional composites for aircraft, drones and spacecraft.

**Table 2.** Relationship amongst inputs, ANN and outputs.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>ANN Model</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input = scan of images of test specimens</td>
<td>ANN</td>
<td>Output = classes (class 1 through 6) of failure modes</td>
</tr>
</tbody>
</table>
The following parameters are used to support the analyses related to Table 3.
1. Fairness;
2. Relevancy denotes how well a retrieved document or set of documents meets the information need of the user [43];
3. Completeness;
4. Robustness;
5. Timing;
6. Correctness;
7. Accuracy (ACC): \( ACC = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + TN + FP + FN} \).

Where
False positive (FP) is a result that indicates that a given condition exists when it does not [44].
False negative (FN) is a test result which wrongly indicates that a condition does not hold [45].
True positive (TP) is a test result that correctly indicates the presence of a condition or characteristic [46].
True negative (TN) is a test result that correctly indicates the absence of a condition or characteristic [47].

### Table 3. Ground truths and predictions of ANN.

<table>
<thead>
<tr>
<th>Ground Truths</th>
<th>Predictions</th>
</tr>
</thead>
<tbody>
<tr>
<td>No DAMAGE</td>
<td>Class-1 = Failure Mode-1 = Failure modes (means fracture location, fracture loads in numerical values and orientation of fractures in the test specimen) in far field (away)</td>
</tr>
<tr>
<td>Center DAMAGE</td>
<td>Class-2 = Failure Mode-2 = Failure modes in center line with 0° failure locus orientation</td>
</tr>
<tr>
<td>Center DAMAGE and 1 Center Hole Repair</td>
<td>Class-3 = Failure Mode-3 = Failure modes in center line with 45° failure locus orientation</td>
</tr>
<tr>
<td>Center DAMAGE and 2 Holes Repair</td>
<td>Class-4 = Failure Mode-4 = Failure modes in circumference with 45° failure locus orientation</td>
</tr>
<tr>
<td>Center DAMAGE and 3 Center Holes Repair</td>
<td>Class-5 = Failure Mode-5 = Failure modes in far field (away) with 0° failure locus orientation, similar to No-DAMAGE test specimen</td>
</tr>
<tr>
<td>Center DAMAGE and 5 Center Holes Repair</td>
<td>Class-6 = Failure Mode-6 = Failure modes in far field (away) with 0° failure locus orientation, similar to No-DAMAGE test specimen</td>
</tr>
</tbody>
</table>

### 4. Conclusions and Future Work

In this paper, the use of ANN in the design, development, additive manufacturing, testing, testing and certification of multifunctional composites for aircraft, UAS and spacecraft was presented. Existing manufacturing technologies for multifunctional composites are not mature enough and have various drawbacks for their implementation on a commercial scale in aerospace applications. A few of the advanced manufacturing technologies, such as automated fiber placement (AFP), Advanced Robotics, Automated Tape Laying (ATL), etc., are not suitable for large and complex designs. Also, the existing trends in the use of ANN in advanced composite manufacturing have their own demerits in the areas of robustness and quality of data; proper execution of ANN; repeatability; maintaining variability tolerances; etc. Future work requires the exploration of the use of parallel high computing systems for the certification of AI-enabled and additively manufactured multifunctional carbon fiber composite structures for aerospace applications (aircraft, drones and spacecraft). Additional investigation can be conducted to evaluate the in situ additive
manufacturing (AM) of multifunctional composites for their use in low orbit, outer and deep space applications.

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