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Artificial Neural Network Based Prediction of Impact Loads and Thickness in CFRP and GFRP Composite Laminates

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Abstract

Recent technological advancements, particularly the integration of neural networks, have facilitated a predictive approach to complex engineering problems, especially those involving composite materials with directional properties. The scarcity of literature on predicting impact damage using experimental and ultrasonic flaw detection data motivated this study. Experimental assessment of impact damage on carbon fiber/epoxy (CFRP) and glass fiber/epoxy (GFRP) composites was conducted using low-velocity drop weight impact testing. Damage assessment employed an ultrasonic flaw detector with a single crystal wedge delay probe, capturing damaged data in A-scan format. Load vs. time data from impact testing and point-wise damage detection data from ultrasonic testing were used to develop a Feedforward artificial neural network (ANN) with two hidden layers (64 neurons each) and a one-neuron output layer. Training epochs ranged from 100 to 1000, resulting in a decreasing trend of mean absolute error (MAE) over time. The ANN model demonstrated consistent accuracy in predicting impact damage thickness and loads for both CFRP and GFRP. This predictive capability holds promise for anticipating potential failures in composite structures under impact loads, enabling preventive design measures and enhancing structural reliability. The model's versatility extends to incorporating C-Scan ultrasonic data, enhancing its utility in damage forecasting and mitigation strategies.

Keywords: Impact, damage, ultrasonic, ANN, prediction

INTRODUCTION

Composite materials combine distinct materials to enhance performance in aerospace, automotive, and sports equipment, leveraging strengths and mitigating weaknesses. Carbon fiber composites, using carbon fibers in epoxy resin, offer high stiffness and heat resistance for aerospace and high-performance applications. Glass fiber composites, with glass fibers in resin, provide strength and impact resistance for construction and consumer goods. Understanding composite impact damage is crucial for structural integrity, maintenance, and regulatory compliance in critical industries. Ultrasonic testing utilizes sound waves to detect defects and assess damage depth and extent within composites, offering real-time imaging and critical inspection capabilities in aerospace, automotive, renewable energy, and marine sectors. Neural networks mimic brain architecture to predict impact damage based on material properties and energy, enhancing composite design accuracy despite challenges like overfitting. Integrating neural networks with other models improves accuracy, benefiting aerospace, automotive, and structural engineering applications.

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Researchers have explored the impact response and performance of composite materials, advocating for further investigation into carbon fiber composites' impact behavior and factors like architecture and resin composition [1]. Drop weight impact experiments and computational modeling have been used to understand the correlation between experimental and numerical predictions of impact behavior, emphasizing the importance of refining computational models for reliability [2]. Studies on parameters influencing impact resistance and damage mechanics of composites highlight the need for optimization and quantification to enhance impact durability [3]. Hybrid laminates' impact behavior has been investigated, revealing the influence of hybridization and fabric structure [4]. Research underscores the importance of fabric architecture and resin toughness for low-velocity impact resistance and the development of resilient composites [5, 6]. Machine learning techniques in structural health monitoring (SHM) show potential but require further development and validation for effectiveness [7–9]. ANN models are increasingly used to predict impact behavior and damage progression, requiring improvement in precision and training efficiency [10]. Innovative damage identification methods, including deep neural networks, show promise but need refinement for practical use [8, 11–14]. Cheng *et al*. proposed a deep learning technique for automatic defect depth estimation using ultrasonic testing [15]. Overall, there is a gap in literature regarding ANN development for impact damage prediction using low-velocity drop weight impact tested composites and ultrasonic flaw detection, suggesting a promising area for future study.

The objectives of this study include:

i. To study the impact damage of composite laminate under low velocity drop weight impact.
ii. To detect damage induced due to impact loading in CFRP and GFRP composite laminates using ultrasonic test setup.
iii. To evaluate thickness of composite laminates using A-scan method with ultrasonic test setup.
iv. To develop an Artificial Neural Network (ANN) for predicting impact load and thickness of damaged sample based on data from experiment and ultrasonic flaw detection.

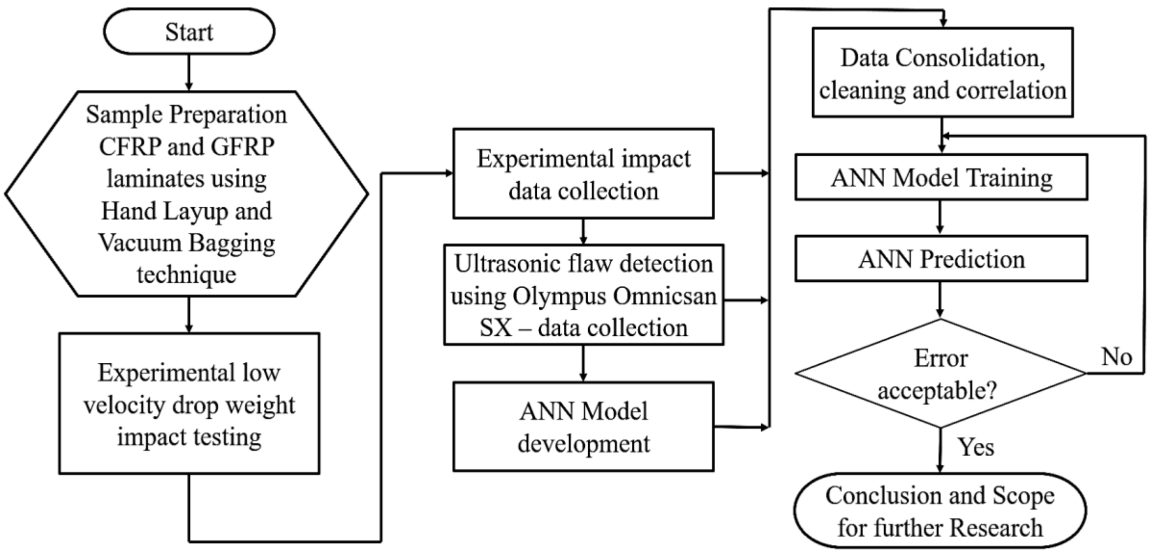


Figure 1. Flowchart for methodology employed in the study.

METHOD AND MATERIALS

As shown in Figure 1, The study involved manufacturing Carbon Fiber Reinforced Polymer (CFRP) and Glass Fiber Reinforced Polymer (GFRP) samples using hand lay-up and vacuum bagging techniques. Impact load, velocity, and energy were experimentally determined using a load cell and data acquisition system. Subsequently, an ultrasonic flaw detector was employed to detect damage, and data collected from this equipment was used to train an artificial neural network (ANN) model using TensorFlow. Predictions were made to estimate thickness and load at damaged and undamaged locations, with findings detailed in the conclusions, suggesting areas for further research. Drop weight impact testing was performed using a 4.1 kg impactor with a 12.7 mm hemispherical indenter, following ASTM D7136 standards at impact heights of 0.2, 0.3, and 0.4 m due to equipment limitations. Load vs. time and energy vs. time data were recorded using a load cell and data acquisition system. Ultrasonic flaw detection methodology using the Olympus Omni scan SX Ultrasonic flaw detector involved scanning impacted specimens with a single crystal wedge delay probe to identify flaws and capture amplitude signals for training and testing the ANN model.

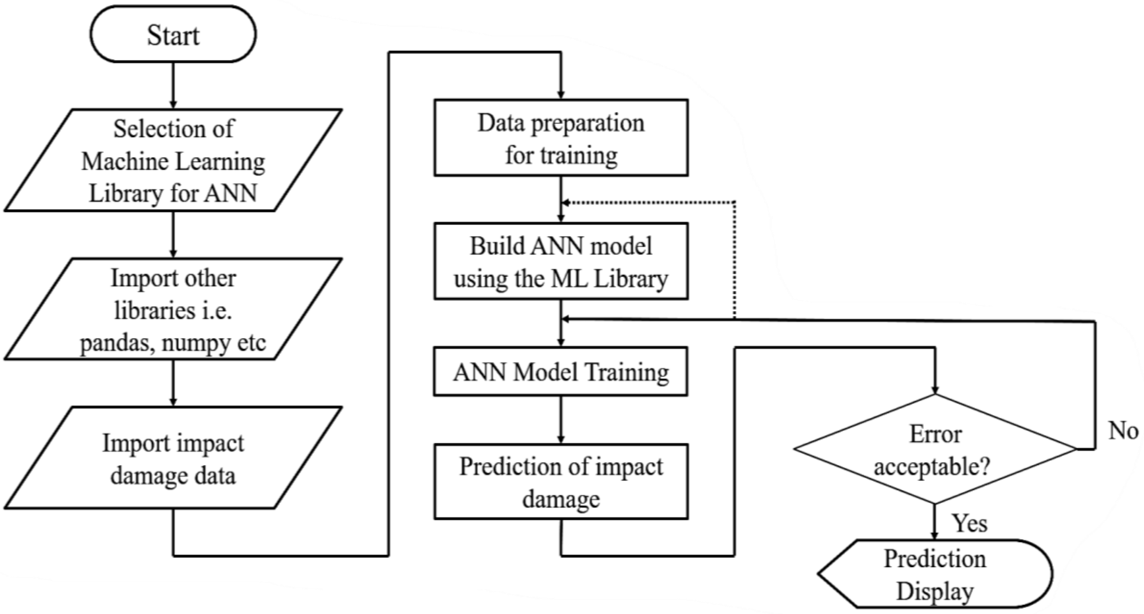


Figure 2. Flowchart for artificial neural network methodology.

The artificial neural network (ANN) was developed using the methodology as shown in Figure 2. After collecting the data, TensorFlow machine learning library was selected. The impact damage data was imported into the model and prepared for the model. A two-layer 64 neuron each model was considered in this study. The predictions were compared with the actual values and the error was determined and the results were obtained for further inferences.

The equipment as shown in Table 1 was used to drop the impact weight and cause the damage to the specimen, held by hold down toggle clamps [16]. The data acquisition system captured load vs. time data and corresponding distance data using the proximity sensors.

The specimen after impact damage have been depicted in Figures 3 and 4.

RESULTS AND DISCUSSION

Drop Weight Impact Testing

The CFRP and GFRP composite laminates were subjected to low-velocity drop weight impact, and the resulting damage is illustrated in Figures 3 and 4. This damage will be further investigated using non-destructive techniques, such as ultrasonic flaw detection, for composite materials.

Ultrasonic Flaw Detection

The Ultrasonic flaw detection set up consists of OLYMPUS Omniscan SX Ultrasonic flaw detector as shown in Figure 5, single crystal wedge delay contact probe of 10.00 MHz central frequency as shown in Figure 6 and connection cable. Contact testing using water as couplant in pulse echo mode shall be carried out. A-scan signal is a time history captured at a particular point on the sample specimen. A sample laminate is as shown in Figure 7.

Table 1. Instrumented drop weight impact testing equipment.

Sl No.	*Specimen Designation*	*Photo*	
		Top	*Bottom*
CFRP	*C1*		
	C2		
	C3		

Figure 3. Top and bottom images of impact damaged CFRP laminate.

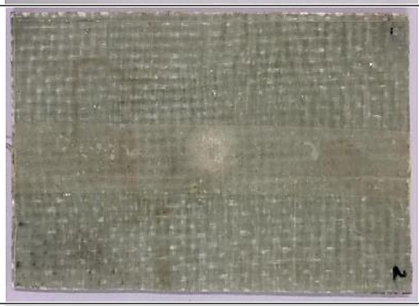
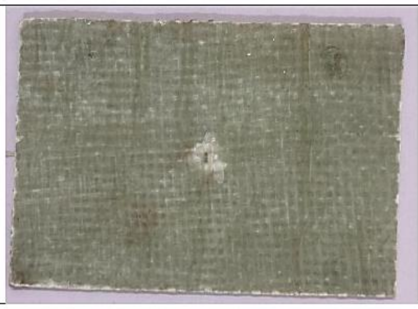
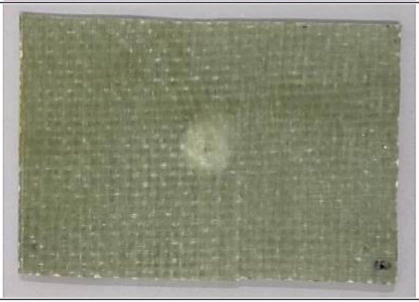
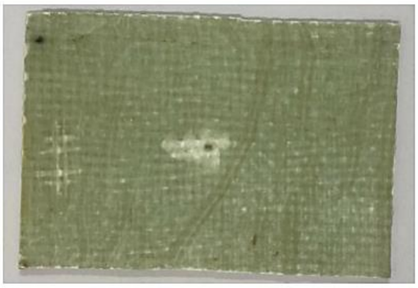
Sl. No.	*Specimen Designation*	*Photo*	
		Top	*Bottom*
1.	*G1*		
2.	*G2*		
3	*G3*		

Figure 4. Top and bottom images of impact damaged GFRP laminate.

Figure 5. OLYMPUS Omniscan SX ultrasonic flaw detector.

Figure 6. Single crystal wedge delay contact probe of 10.00 MHz frequency.

Figure 7. GFRP and CFRP Composite laminates subjected to impact damage.

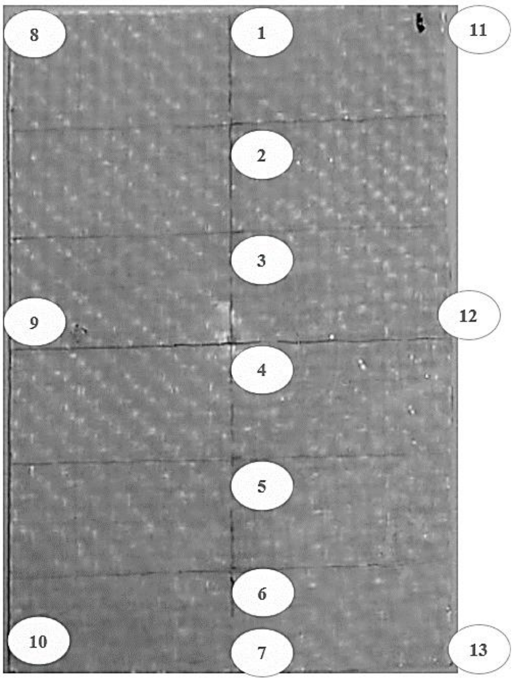
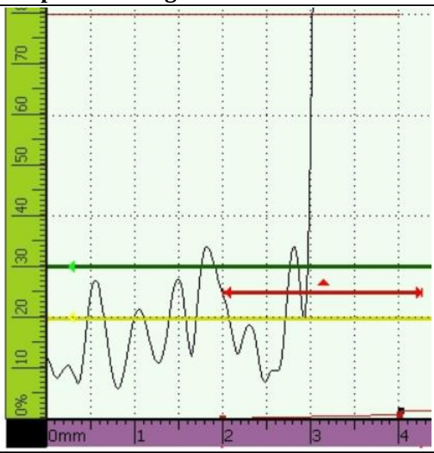
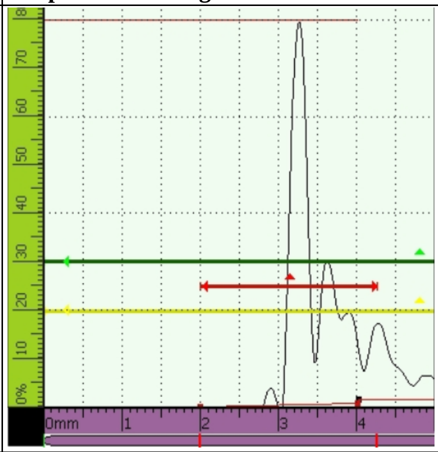
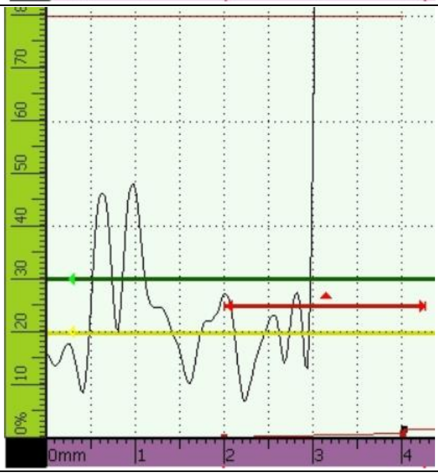
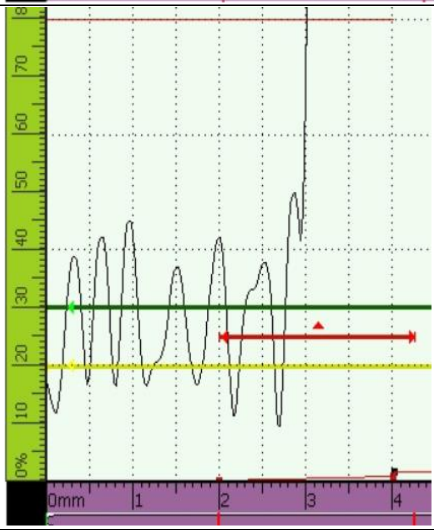
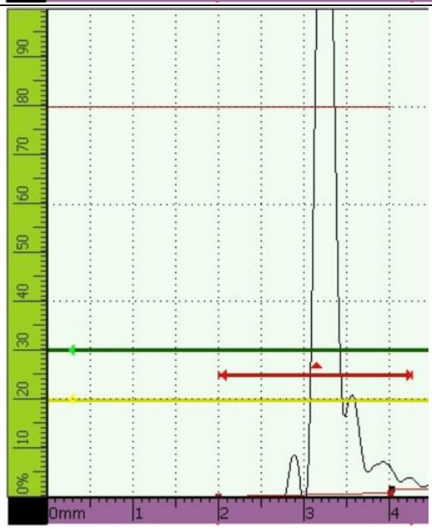


Figure 8. Marking of composite laminate for ultrasonic flaw detection.

The laminates were marked such that ultrasonic signals can be picked up at various locations. 13 such locations were identified for this study as shown in Figure 8. Further discretization can indeed help to refine the results. A procedure for flaw detection was developed in the process of training and learning the method of use.

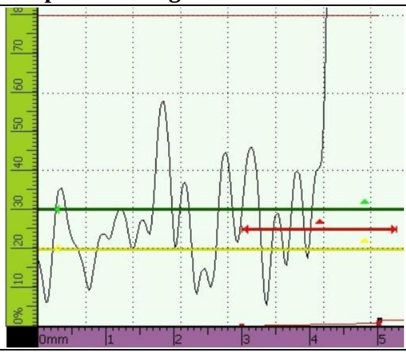
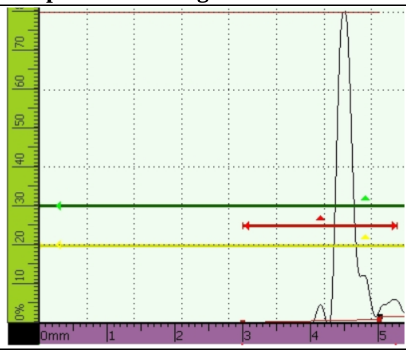
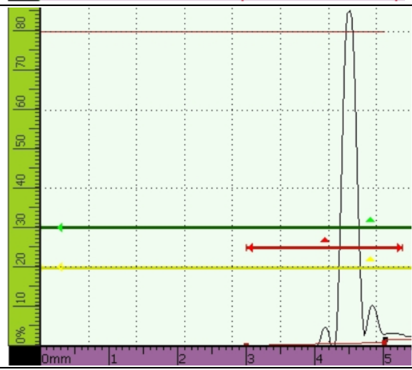
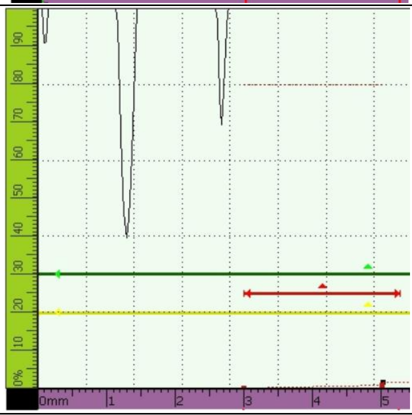
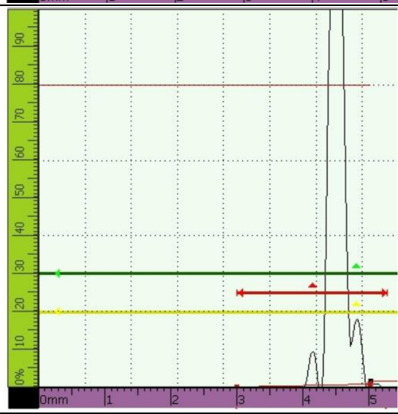
The outputs obtained from the ultrasonic flaw detection have been tabulated in Tables 2 and 3.

Table 2. CFRP flaw detection graphs.

Specimen	Output at damage	Output at undamaged location
C1		
C2		
C3		

The ultrasonic signal at damage exhibits agitation, indicating laminate irregularities that are well detected [17–19]. As the impact height increases, the detected thickness at damage decreases, reflecting greater penetration and reduced echo thickness. The thickness at the damage location is lower than the minimum undamaged thickness, indicating penetrative impact damage. These trends align with findings reported in the literature [17, 18].

Table 3. GFRP flaw detection graphs.

Specimen	Output at damage	Output at undamaged location
G1		
G2		
G3		

Similar trends between GFRP and CFRP data demonstrate measurement consistency, supporting subsequent use in ANN prediction models.

Development of Artificial Neural Network for Prediction

The objective is to use predictions to enhance design robustness and prevent failures by forecasting key damage parameters using available data. An Artificial Neural Network (ANN) is built using TensorFlow, a popular deep learning library developed by Google. The ANN model is structured as follows:

1. Sequential Model: Utilizing `tf.keras.Sequential()` to stack layers sequentially.
2. Dense Layers: The model consists of two dense layers:
   First dense layer (`Dense(64, activation='relu', input_shape=(X_train.shape[1],))`) with 64 neurons and ReLU activation, specifying input shape based on feature count.
   Second dense layer (`Dense(64, activation='relu')`) with 64 neurons and ReLU activation.
   Output layer (`Dense(1)`) with a single neuron for regression output.
3. Optimization and Loss Function: Compiled with 'adam' optimizer for efficient gradient descent and 'mse' (Mean Squared Error) loss function suitable for regression.

4. Model Training: Trained using `model.fit()` on training data (`X_train`, `y_train`) for a specified number of epochs (`epochs=1000`) to minimize MSE loss.
5. Evaluation: Model performance assessed on test data (`X_test`, `y_test`) using `model.evaluate()` with metrics like MSE and MAE (Mean Absolute Error).
6. Prediction: Trained model (`model.predict()`) used to make predictions (`predictions1`) on new input data (`new_input_data1`).

The ANN architecture features two layers with 64 neurons each, trained over a specified number of epochs. The model generalizes well to unseen data and aims to predict thickness or load. This approach combines TensorFlow's deep learning capabilities with conventional data splitting methods (80% training, 20% testing). The novelty lies in accurately predicting load and thickness values across different impact heights, demonstrating consistent accuracy and potential for future applications.

Using the ANN thus developed, the thickness and impact load values will be predicted by training the model using the experimental data and the ultrasonic flaw detection data. Following are the results of predictions in Tables 4–7 with a consolidated graphical summary given in Table 8.

Table 4. CFRP thickness prediction results.

Epochs	MAE	Actual thickness (mm)	Predicted thickness (mm)	Prediction Error (%)
100	0.6922	3.27	2.34	28.36
250	0.3783	3.27	3.07	6.04
500	0.2391	3.27	3.19	2.38
750	0.0533	3.27	3.31	1.21
1000	0.1729	3.27	3.25	0.59

The Ultrasonic Testing data was utilized as input for an ANN model to predict damage echo thickness based on amplitude [20]. An amplitude value of 72 corresponded to a detected thickness of 3.27 mm, validating the prediction. Training the model for 1000 epochs demonstrated a decreasing trend in mean absolute error (MAE), with optimal predictions observed between 500 and 750 epochs [21]. Using the Random Forest Machine Learning Algorithm, most thickness predictions exhibited errors of less than 1%, indicating reliable predictions. However, one prediction had an error of 9.47%, highlighting the need for further optimization [21].

Table 5. CFRP load prediction results.

Epochs	MAE	Actual load (kN)	Predicted load (kN)	Prediction Error (%)
100	0.1315	3.47	3.05	12.02
250	0.0939	3.47	3.52	1.38
500	0.0491	3.47	3.66	5.45
750	0.0492	3.47	3.57	2.75
1000	0.0523	3.47	3.61	3.93

The drop weight impact testing data was used as input for an ANN model to predict impact load at a specific instant for a 0.4 m impact height, based on data from 0.2 and 0.3 m impacts [20]. At 6.9 msec, the experimental load recorded was 3.47 kN, validating the prediction [21].

Table 6. GFRP thickness prediction results.

Epochs	MAE	Actual thickness (mm)	Predicted thickness (mm)	Prediction Error (%)
100	0.9725	4.51	3.04	32.57
250	0.9222	4.51	3.04	32.49
500	0.6900	4.51	3.38	24.96
750	0.6701	4.51	3.69	18.08
1000	0.5321	4.51	3.87	14.14

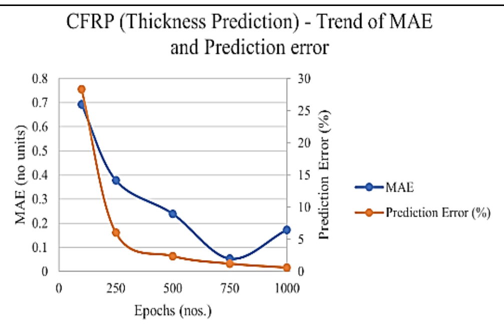
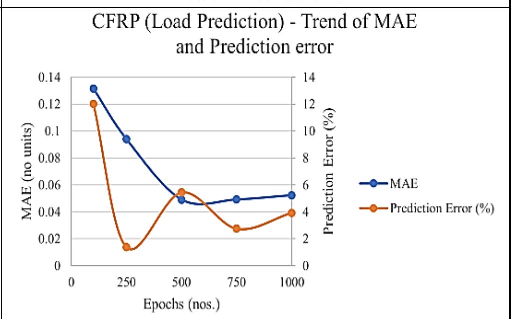
The Ultrasonic Testing data was utilized as input for an ANN model to predict damage echo thickness at a specific point given an amplitude [20]. For point 20 with an amplitude of 90, the actual detected value was 4.51 mm, validating the prediction. Training the model over 1000 epochs resulted in decreasing MAE, with optimal prediction observed at 1000 epochs [21]. The high error could be due to surface irregularities in the GFRP Laminate affecting signal consistency [21]. The Random Forest Machine Learning Algorithm predicted thicknesses with errors mostly below 1%, indicating faithful predictions, similar to trends observed in CFRP laminates.

Table 7. GFRP load prediction results.

Epochs	MAE	Actual load (kN)	Predicted load (kN)	Prediction Error (%)
100	0.2579	4.46	3.57	19.96
250	0.1153	4.46	4.43	0.64
500	0.0658	4.46	4.33	2.98
750	0.0495	4.46	4.42	0.86
1000	0.0448	4.46	4.47	0.14

The drop weight impact testing data was used to train an ANN model for predicting impact load at 0.4 m height based on data from 0.2 and 0.3 m heights [2]. At 6.9 msec, the equipment recorded a load value of 4.46 kN, validating the prediction. Training over 1000 epochs showed decreasing MAE, with optimal prediction around 1000 epochs [2]. High errors in some predictions may be due to the small test data magnitude. Most absolute differences between actual and predicted values were ≤0.1, indicating accurate predictions, similar to trends observed in CFRP laminates.

Table 8. Summary of trends of MAE and Prediction error for CFRP and GFRP.

<table>
<tr><th>Laminate</th><th>Thickness Predictions</th><th>Load Predictions</th></tr>
<tr><td>CFRP</td><td>
</td><td>
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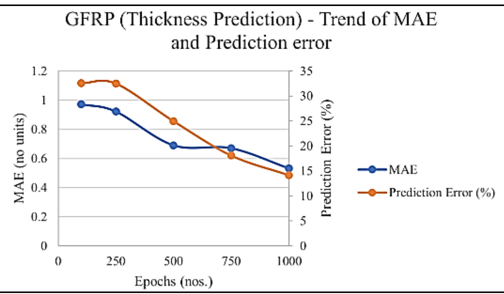
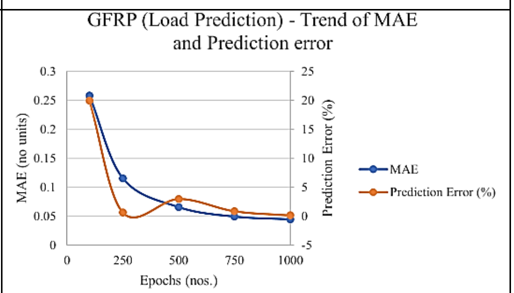
<tr><td>GFRP</td><td>
</td><td>
</td></tr>
</table>

On comparing the study carried by Le *et al*. [21] and the results obtained in this study, it can be inferred that there is a similarity between the corresponding graphs of CFRP and GFRP with respect to their trends. The ANN model performance is thus consistent as it shows decreasing trends in MAE [22] with increase in epochs for all the four predictions.

CONCLUSION

In this study, drop weight impact testing yielded data showing increased impact load and energy with higher impact heights. Ultrasonic flaw detection was understood, revealing clear damage presence through amplitude variations and reduced echo thickness with greater impact height, indicating more severe damage. Using TensorFlow, a feedforward ANN was trained to predict impact damage in CFRP and GFRP composites, achieving high accuracy (up to 99.41% for thickness and 99.86% for load) with increasing epochs, demonstrating reduced mean absolute error (MAE).

Future work should focus on refining the ANN model to further reduce prediction errors. Optimization of the Phased Array Wedge Probe with Encoder setup could enhance damage surface analysis accuracy and resolution. Refinement of the ANN to predict damage severity based on C-Scan data would advance damage assessment capabilities, supporting more effective maintenance and safety protocols for composite structures under impact loading.

CONFLICT OF INTEREST

The authors declare no conflicts of interest associated with this work.

Authors' Contribution

Gourav Vivek Kulkarni (Methodology, ANN Predictions, Writing original draft).

Ramesh S Sharma (Conceptualization, Ultrasonic flaw detection, Data Curation, Writing review & editing).

M N Vijaya Kumar (Ultrasonic flaw detection, Data Curation).

Sunith Babu L (Experimentation, Data Curation).

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