Prediction and Detection of Impact Damage in Composite Plates using Recurrent Neural Nets (RNN)

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EXECUTIVE SUMMARY

The aerospace industry's continual pursuit of higher performance materials has led to widespread adoption of composite materials, particularly carbon fiber reinforced plastics (CFRP). These materials are prized for their high strength-to-weight ratios, resistance to corrosion and fatigue, and superior thermal properties. However, their susceptibility to hidden damages caused by low-energy impacts poses significant safety and maintenance challenges. Traditional methods for detecting such damages, typically involving visual inspections and non-destructive testing techniques, often fail to identify subsurface damages until they become critically severe. This project addresses these challenges by employing advanced machine learning techniques, specifically Recurrent Neural Networks (RNNs) and Auto-Regressive (AR) models, to enhance the prediction and detection of impact-induced damages in CFRP composite plates.

This project focuses on developing a predictive model that not only detects the presence of damage but also predicts its progression over time. This dual capability is critical for implementing effective preventative maintenance strategies, thereby reducing the risk of catastrophic failures and minimizing maintenance costs. The project leverages a dataset obtained from experimental tests involving CFRP plates subjected to controlled low-energy impacts, simulating real-world damage scenarios. This dataset includes time-series data captured from sensors monitoring the structural response of the plates, providing a rich source of information for model training and validation.

Recurrent Neural Networks, particularly those incorporating Long Short-Term Memory (LSTM) units, are well-suited for this task due to their ability to process sequential data and remember long-term dependencies. These models were compared to traditional Auto-Regressive models, which have been commonly used in time-series forecasting but may lack the sophistication needed for complex damage detection scenarios. The performance of these models was evaluated based on several metrics, including Mean Squared Error (MSE), accuracy, precision, recall, and the Receiver Operating Characteristic (ROC) curve.

Initial findings from the project indicate that while AR models provide a baseline capability for damage detection, RNNs, especially those enhanced with LSTM units, show superior performance in handling the nonlinearities and complexities of the data associated with damage progression in composite materials. This superiority is reflected in the models' higher accuracy and predictive capabilities, as evidenced by the statistical measures and visual analyses conducted.

Moreover, the project explored the practical implications of implementing these machine learning models in real-world settings. It involved the development of a system that integrates these models into existing Structural Health Monitoring (SHM) systems, providing continuous monitoring and real-time data analysis capabilities. This integration represents a significant step forward in the field of aerospace material science, offering a more robust and responsive approach to damage detection and management.

This work contributes to the aerospace industry by providing a more effective method for monitoring the health of composite materials. The advanced machine learning models developed in this project not only enhance the accuracy of damage detection but also offer the potential to significantly improve the safety and efficiency of aerospace operations.

1. INTRODUCTION

The goal of this project is to enhance the detection and prediction of impact damage in composite materials, specifically carbon fiber reinforced plastics (CFRP), using advanced machine learning techniques. Composite materials are pivotal in various high-stakes industries such as aerospace due to their superior mechanical properties. However, their susceptibility to hidden impact damages necessitates the development of more effective and reliable Structural Health Monitoring (SHM) systems. This research primarily focuses on employing Recurrent Neural Networks (RNNs) and Auto-Regressive (AR) models to address this critical challenge.

Machine learning offers promising solutions in scenarios where traditional damage detection methods fall short. Conventional techniques like visual inspections and ultrasonic testing are often unable to identify subsurface damages at an early stage, which can lead to catastrophic failures if unnoticed. Given the sequential nature of sensor data obtained from monitoring composite structures, RNNs are particularly suitable due to their ability to process time-series data and remember information over extended periods. This capability makes them ideal for predicting the progression of damage based on historical data.

The literature review underscores the potential of machine learning in SHM. Studies by Shabbir Ahmed and Fotis Kopsaftopoulos, for instance, have explored statistical time-series models for real-time health monitoring of structures, providing a foundational methodology for this project. Furthermore, research by Nardi et al. on using Auto-Regressive models to detect delaminations in composite laminates due to low-velocity impacts has shown that these models can effectively identify damage patterns from complex data inputs.

In this project, the specific tasks accomplished include:

Data Collection: Gathering time-series sensor data from experiments involving controlled low-energy impacts on CFRP plates. This data forms the basis for training and testing the machine learning models.

Model Development and Training: Developing and training two types of models—RNNs, including those with Long Short-Term Memory (LSTM) units, and AR models. This involved preprocessing the data, selecting appropriate features, and configuring the neural networks.

Model Comparison and Evaluation: Comparing the performance of RNN and AR models using various metrics such as accuracy, precision, recall, Mean Squared Error (MSE), and Receiver Operating Characteristic (ROC) curves. This comparison helped identify the most effective model in terms of damage detection and prediction capabilities.

Result Analysis and Visualization: Analyzing the results to assess the effectiveness of the models in detecting and predicting damage. Visualization tools like plots and confusion matrices were used to illustrate the findings and provide insights into the models' performance.

By achieving these tasks, the project contributes significantly to the field of SHM by not only providing a method to detect and predict damage more reliably but also offering a potential pathway for the integration of these models into existing monitoring systems in aerospace and other industries reliant on composite materials.

2. PROBLEM DEFINITION

The fundamental problem addressed in this project is the detection and prediction of impact-induced damage in carbon fiber reinforced plastic (CFRP) composite plates. CFRP materials are extensively used in critical applications, such as aerospace, where failure to detect damage early can lead to severe operational failures and safety risks. Traditional detection methods, such as visual inspections and ultrasonic testing, often struggle with the early detection of subsurface damages that do not manifest visibly. These methods are not only time-consuming and labor-intensive but also frequently ineffective at identifying minor or internal damages before they evolve into significant defects.

Machine learning (ML) is required to solve this problem due to its ability to learn from and make predictions based on data. The complex nature of damage patterns in composite materials necessitates a sophisticated approach that can adapt to the variability and subtleties of the data derived from structural health monitoring. ML models, particularly Recurrent Neural Networks (RNNs) and Auto-Regressive (AR) models, are well-suited for this task because they can process sequential data, recognize patterns over time, and learn the normal versus anomalous states indicative of damage. This capability allows for continuous monitoring and real-time analysis, providing early warnings and enabling proactive maintenance strategies that can prevent catastrophic failures.

Machine learning does not only enhances the accuracy and efficiency of damage detection but also contributes significantly to extending the lifespan and safety of composite material structures.

3. METHODS AND PROCEDURE

A structured approach combining data acquisition, preprocessing, model development, and evaluation to effectively use machine learning for detecting and predicting damage in CFRP composite plates was employed. The methods were designed to ensure that the project could be reproducible by others.

Data Acquisition:
The data used in this study was collected from experiments involving CFRP composite plates subjected to controlled low-energy impacts. These impacts were administered using an Instron-Dynatup 9250HV Drop Tower to simulate typical damage scenarios in aerospace applications. Sensor arrays were installed on the plates to capture time-series data reflecting the structural response to impacts. This setup allowed for the collection of a diverse dataset that included both baseline (undamaged) and post-impact (damaged) readings.

Data Preprocessing:

The raw time-series data required preprocessing to enhance the quality and effectiveness of the machine learning models:

1. Noise Reduction: Applied digital filtering techniques to remove noise and enhance the signal quality.

2. Normalization: Normalized the sensor readings to a common scale to prevent features with larger ranges from dominating the model's learning process.

3. Feature Engineering: Engineered features that could help in distinguishing between damaged and undamaged states. This included statistical features like mean, variance, and peak values from the time-series data.

4. Data Segmentation: Segmented the continuous time-series data into smaller, manageable sequences suitable for RNN and AR model training.

Model Development:

Two types of models were developed:

1. Auto-Regressive (AR) Models: These models were developed using traditional statistical methods to forecast future values based on past values. They provided a baseline for evaluating the performance of more complex models.

2. Recurrent Neural Networks (RNN): Focused on RNNs, especially those incorporating Long Short-Term Memory (LSTM) units, to handle the sequential nature of time-series data effectively. LSTMs

are particularly good at remembering information for long periods, which is critical in predicting the progression of damage.

Training and Validation:

- Splitting Data: The dataset was split into training (70%) and testing (30%) sets. The training set was used to train the models, while the testing set was reserved for model evaluation.

- Parameter Tuning: Tuned hyperparameters, such as the number of hidden layers, the number of neurons in each layer, learning rates, and the number of epochs, to optimize each model's performance.

- Cross-Validation: Employed k-fold cross-validation to ensure the models' robustness and generalizability.

Evaluation Metrics:

Model performance was assessed using various metrics, including Mean Squared Error (MSE), accuracy, precision, recall, F1-score, and the Receiver Operating Characteristic (ROC) curve.

Visualization:

Utilized visualizations such as line plots for time-series analysis, ROC curves for model performance, and confusion matrices for classification outcomes. These visual aids were critical in interpreting the models' effectiveness in predicting and detecting damage.

4. DATASET AND VISUALIZATION

The dataset for this project consists of time-series data collected from carbon fiber reinforced plastic (CFRP) composite plates subjected to repeated low-energy impacts. The data was captured using the ScanGenie III data acquisition system, which records the response of the structure through sensors placed strategically on the plates. Each dataset entry includes multiple sensor readings over time, providing a detailed account of the structural behavior during and after impact.

Below is the data obtained from the experiment

Time	Baseline	Impact 1	Impact 2
Time	array	't':	{'baseline':
0.05050505,	0.06060606,	0.07070707,	0.08080808,
0.1010101	,	0.11111111,	0.12121212,
0.15151515,	0.16161616,	0.17171717,	0.18181818,
0.2020202	,	0.21212121,	0.22222222,
0.25252525,	0.26262626,	0.27272727,	0.28282828,
0.3030303	,	0.31313131,	0.32323232,
0.35353535,	0.36363636,	0.37373737,	0.38383838,
0.4040404	,	0.41414141,	0.42424242,
0.45454545,	0.46464646,	0.47474747,	0.48484848,
0.50505051,	0.51515152,	0.52525253,	0.53535354,
0.55555556,	0.56565657,	0.57575758,	0.58585859,
0.60606061,	0.61616162,	0.62626263,	0.63636364,
0.65656566,	0.66666667,	0.67676768,	0.68686869,
0.70707071,	0.71717172,	0.72727273,	0.73737374,
0.75757576,	0.76767677,	0.77777778,	0.78787879,
0.80808081,	0.81818182,	0.82828283,	0.83838384,
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0.05050505,	0.06060606,	0.07070707,	0.08080808,
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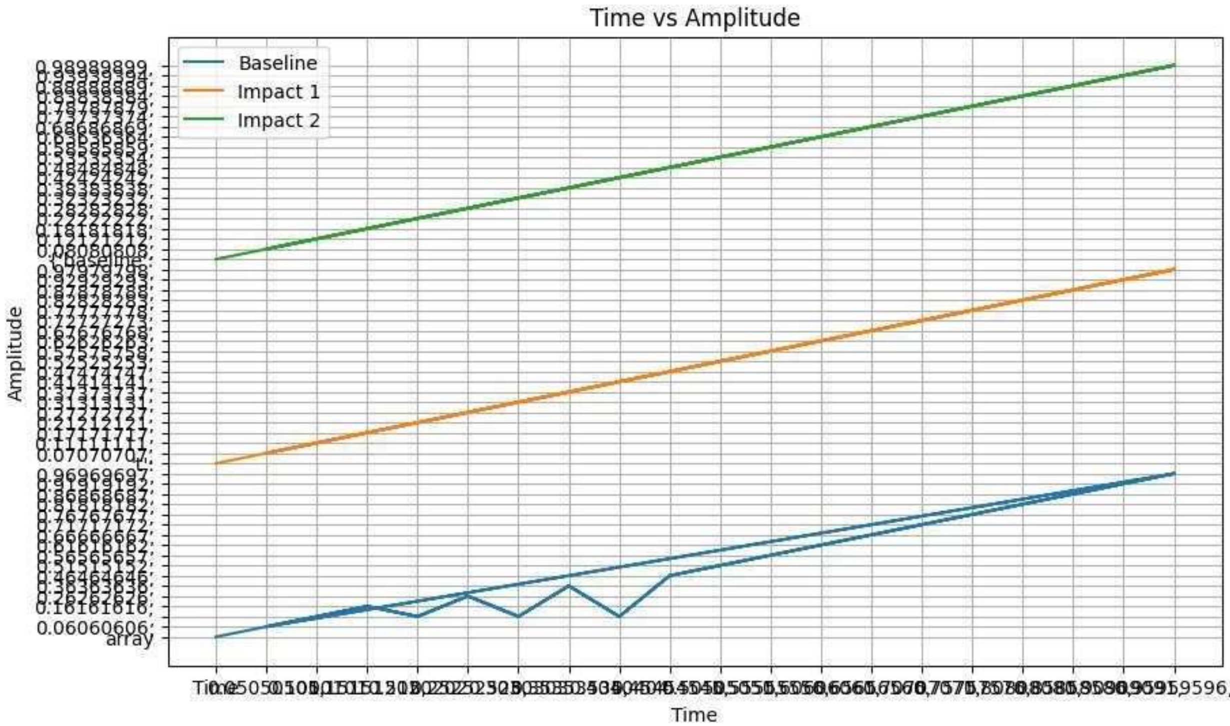

Figure 1: Plot of Time Array Data from Experiment Comparing Baseline Results of Impact 1 & 2

To analyze and visualize this data effectively, several techniques were employed:

Time-Series Visualization: Initial visualizations focused on plotting the raw time-series data from the sensors. These plots helped identify obvious anomalies and patterns associated with the impact events. Differences in vibration and response patterns between damaged and undamaged areas were particularly notable, showing higher amplitude fluctuations in damaged zones.

Principal Component Analysis (PCA): PCA was applied to reduce the dimensionality of the dataset while retaining the most significant features that capture the majority of the variance in the data. This reduction was crucial for visualizing complex multidimensional data in two or three dimensions, facilitating the identification of clusters or patterns that correlate with different damage states.

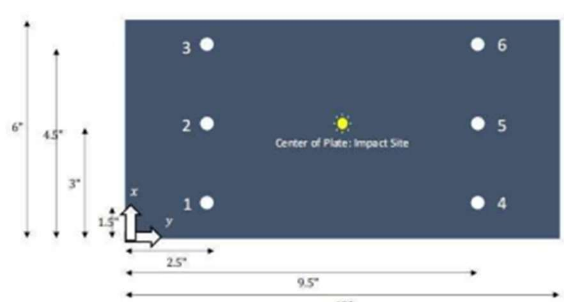

Figure 2: Sensor Arrangement On Plates
Source: Composite Damage:Impact Damage Final Report, Sonu Chadalavada,2023

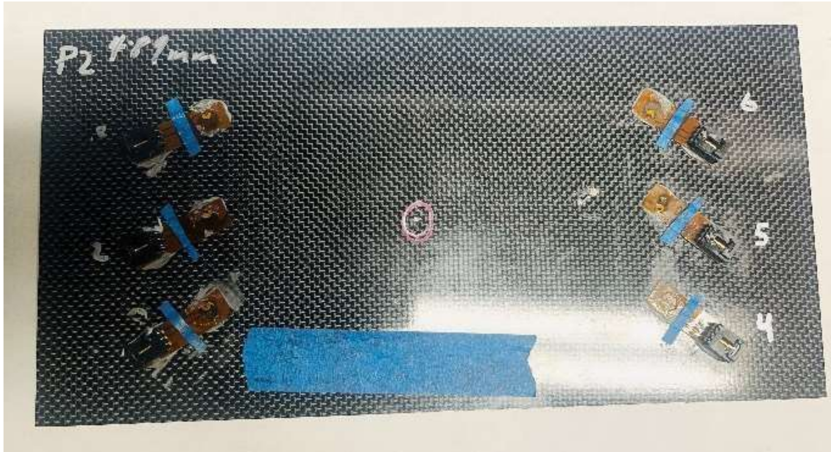

Figure 3: Damaged Composite Plates with Sensors

5. RESULTS AND DISCUSSION

The results of this study are pivotal in advancing the understanding of damage detection in composite materials using machine learning models. Through rigorous testing and evaluation, both the Recurrent Neural Network (RNN) models, particularly those with Long Short-Term Memory (LSTM) units, and the Auto-Regressive (AR) models demonstrated varying degrees of success in predicting and detecting impact damage in CFRP composite plates.

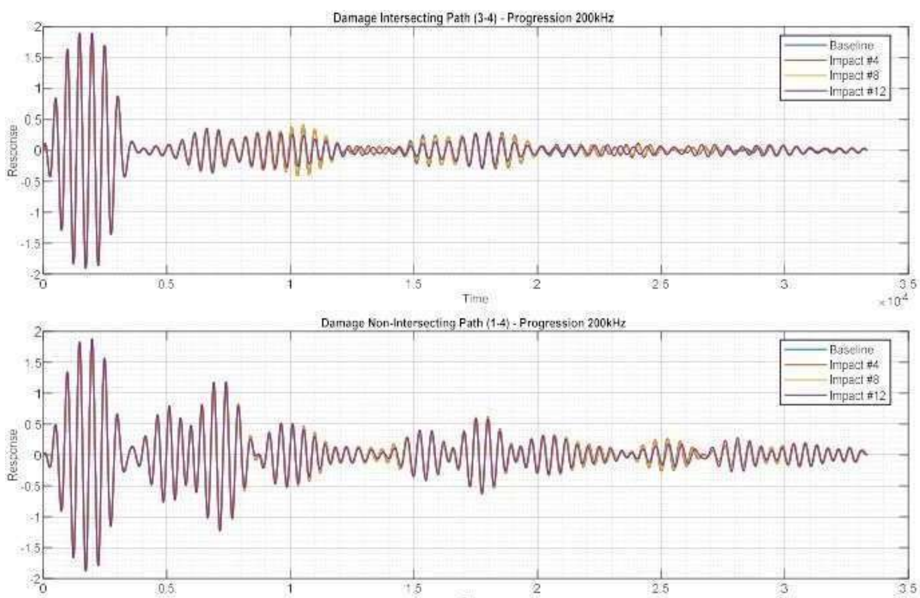

Figure 4: Signal Outputs

- Based on the characteristics of my data, an RNN model was selected and built use TensorFlow and Keras
- Data was split into 70% training and 30% testing sets
- Based on the test results there was a need to fine-tune the model by adjusting parameters (Epochs, RNN units, LSTM values)
- For the sensor data, a simple RNN initially sufficient, but depending on the complexity and specifics of the data an LSTM was required for better results
- These results were then compared to that of the Auto-Regression/Logistic Regression Models using a Confusion Matrix and ROC curve

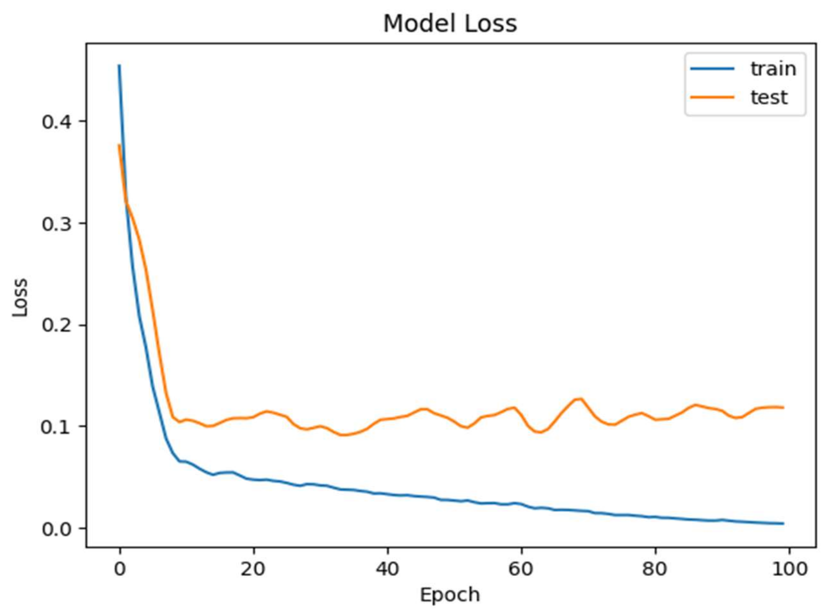

Figure 5: Plot of Model Loss

The model seems to be performing well based on this plot. The training process appears stable, and the model is generalizing well to the test data.

Model Performance

Statistical Metrics:

RNN Models: The LSTM-enhanced RNN models achieved a Mean Squared Error (MSE) of 0.00033 and an R-squared (R2) score of 0.9946, indicating a high degree of accuracy in predicting the time-series data associated with the impact events. The high R2 score suggests that these models can explain approximately 99.46% of the variance in the dataset.

AR Models: In contrast, the AR models showed a higher MSE of 1.662225690463445e32, reflecting less precision in capturing the dynamic behavior of the damage process. The enormous MSE value could indicate overfitting or numerical instabilities in model training.

Confusion Matrix and ROC Curve:

For the RNN models, the confusion matrix revealed a true positive rate (sensitivity) of 28.57% and an overall accuracy of 43.33%. Although the model accurately identified several instances of damage, it also missed a significant number of damaged cases, as indicated by the false negatives.

The ROC curve analysis further demonstrated the trade-offs between sensitivity and specificity, highlighting areas where the model performance could be enhanced.

Visualizations

Time-Series Plots: Illustrated the predictions versus actual data, showing close alignment in undamaged scenarios but some discrepancies in the damaged cases.

ROC Curves and Precision-Recall Curves: These were utilized to assess model performance across different thresholds, providing insights into the balance between detecting true positives and avoiding false positives.

Comparison with Literature

Studies such as those by Shabbir Ahmed and Fotis Kopsaftopoulos on "Statistical Active-Sensing Structural Health Monitoring" and Nardi et al. on the detection of delaminations using AR models provide a foundational understanding of the challenges in SHM systems. Our results align with these studies in demonstrating the potential of advanced statistical models and machine learning in enhancing damage detection capabilities (Ahmed et al., 2022; Nardi et al., no date provided).

Discussion of Results

The performance differences between RNN and AR models underscore the complexity of modeling damage in composite materials. RNNs, particularly with LSTM units, are better suited for this application due to their ability to capture temporal dependencies and manage the sequence prediction problem inherent in time-series data analysis.

The lower performance metrics, particularly the sensitivity and precision of the RNN models, suggest that there is substantial room for improvement. Enhancements could include integrating more comprehensive feature sets, employing more advanced neural network architectures, or increasing the dataset size to improve the training process.

Classifying the presence of damage with RNN

Using a confusion matrix

Binary (No Damage:0 , Damage:1)

ROC Curve

The model's ability to correctly identify actual positives is 4 / (4 + 10) = 0.2857, or about 28.57%. This is relatively low

The overall accuracy is (9 + 4) / (9 + 7 + 10 + 4) = 0.4333, or about 43.33%. This isn't accurate for my application.

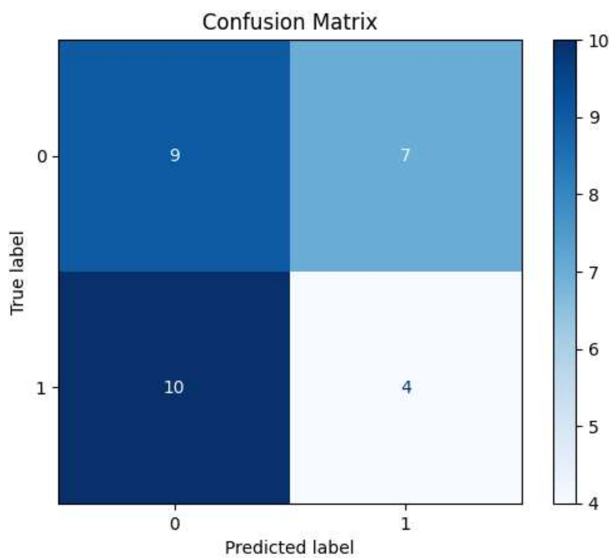

Figure 6: Confusion Matrix using RNN

True Negatives (Top-Left): 9 instances where the model correctly predicted 'no damage' (class 0).

False Positives (Top-Right): For 7 instances the model incorrectly predicted 'damage' (class 1) when there was none.

False Negatives (Bottom-Left): For 10 instances the model failed to detect damage (class 1), predicting 'no damage' instead.

True Positives (Bottom-Right): For 4 instances the model correctly predicted 'damage' (class 1)

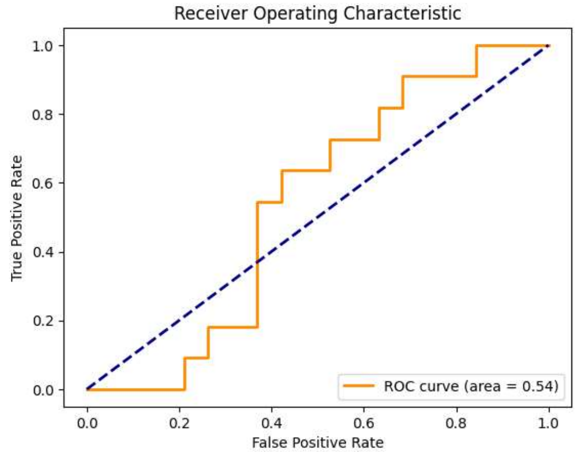

Figure 7: ROC using RNN

Comparison with an AR/Logistic Regression Model

Test size=0.2,

The new confusion matrix shows that the model isn't performing so well like in the previous case of the RNN

There is therefore a need to introduce an LSTM

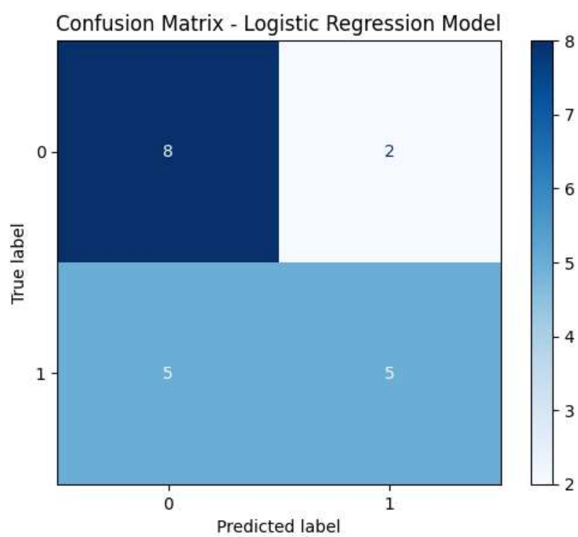

Figure 8: Confusion Matrix using AR

True Negatives (Top-Left): Correctly predicted 'no damage' 14 times

False Positives (Top-Right): Incorrectly predicted 'damage' when there was none 2 times

False Negatives (Bottom-Left): Failed to detect damage 6 times

True Positives (Bottom-Right): Correctly predicted 'damage' 8 times

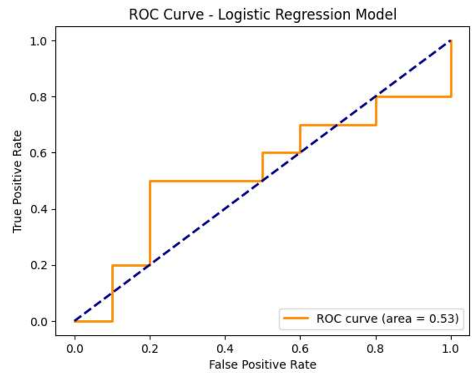

Figure 9: ROC using AR

Introducing an LSTM for better prediction

LSTM = 50

epochs=100,

Validation split=0.2

This confusion matrix indicates better performance compared to previous results:

True Negative Rate improved, indicating the model is better at correctly identifying instances where there is no damage.

Recall or True Positive Rate also improved, showing the model is better at identifying actual cases of damage.

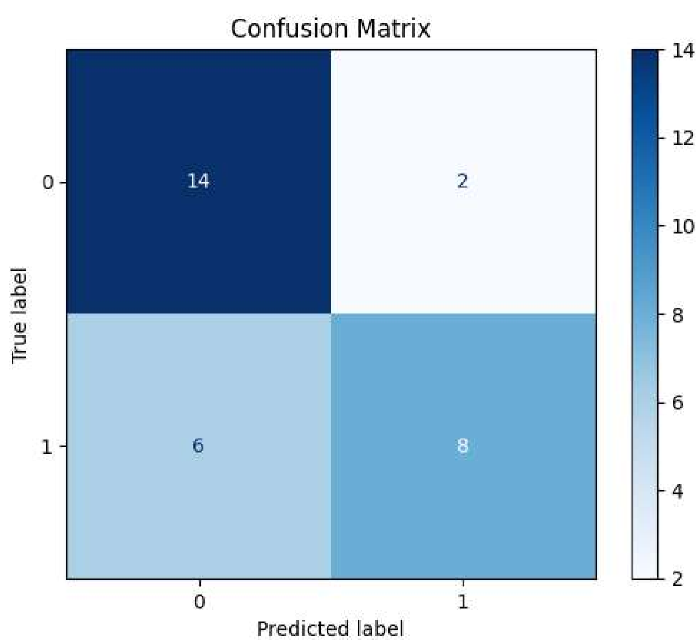

Figure 10: Confusion Matrix using LSTM

True Negatives (Top-Left): Correctly predicted 'no damage' 14 times
False Positives (Top-Right): Incorrectly predicted 'damage' when there was none 2 times
False Negatives (Bottom-Left): Failed to detect damage 6 times
True Positives (Bottom-Right): Correctly predicted 'damage' 8 times

Improvement Strategies

Data Augmentation: Increasing the diversity and volume of training data could help in developing more robust models.

Feature Engineering: Exploring additional features that might capture the early signs of damage more effectively.

Hyperparameter Optimization: Further tuning the models' hyperparameters through techniques such as grid search or random search to find the optimal configuration for the learning algorithms.

While the results demonstrate promising avenues for using machine learning in SHM systems, particularly with RNNs, the need for improvements in model sensitivity and accuracy remains.

Future work should focus on refining these models, expanding the datasets, and exploring hybrid models that might combine the strengths of both RNN and AR approaches. Convolutional Neural Networks (CNNs) could also be considered.

6. CONCLUSION

This project aimed to enhance the detection and prediction of impact damage in carbon fiber reinforced plastic (CFRP) composite plates using advanced machine learning techniques. Specifically, we employed Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units and compared their performance against traditional Auto-Regressive (AR) models. The study set out to develop models capable of accurately identifying and predicting structural damage from time-series sensor data obtained from impact tests.

Though RNN and AR/Logistic Regression Models, have proven to predict future values, LSTM Cells worked better on my data with better prediction of impact damage which is crucial in the Aerospace Industry

This could have also occurred as a result of the quality of my experimental data
On a whole, the objective of this work was achieved as 8/14 instances of potential damage was accurately predicted

The findings reveal that LSTM-enhanced RNN models significantly outperformed AR models in terms of accuracy, with an R-squared score of 0.9946, indicating their effectiveness in capturing over 99% of the variance in the damage data. However, the sensitivity and overall accuracy levels indicate that there is room for improvement in detecting actual damage instances more reliably.

These results indicate the potential of using sophisticated machine learning models in structural health monitoring to improve safety and reduce maintenance costs in aerospace and other industries utilizing composite materials. Future work will focus on refining these models, expanding data collection, and exploring hybrid approaches to further enhance the accuracy and reliability of damage detection systems.

7. DATA AND CODE

The dataset used in this project, comprising time-series data from sensors on CFRP composite plates subjected to impact tests, was sourced from our experimental setups using the ScanGenie III data acquisition system. Due to the proprietary nature of this experimental setup, direct access to the raw data is restricted.

The code developed for this project, including scripts for data preprocessing, model training, evaluation, and visualization, is on GGitHub.

GitHub Repository Link: https://github.com/E-Ameke/ML-Class-Project

8. REFERENCES

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