Machine Learning Applications for Compression Strength After Low Velocity Impacted Carbon Fiber Composites

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Carbon fiber reinforced polymer (CFRP) composite structures are advanced engineering structures characterized by their impressive strength-to-weight ratio. However, these structures are weak in their out-of-plane direction in events such as impact loadings. Low velocity impacts (LVI), occurring under 10 m/s, often result in barely visible impact damage which can significantly reduce the strength of the composite material. These damages take the form of matrix cracks, fiber breaks, and delamination in the structure. Investigating the predictive capabilities and underlying factors that influence the LVI damage and post-impact compressive strength in composite structures is paramount. Machine learning algorithms and computational data science tools are employed to identify the key features contributing to structural resilience under impact loadings. The various material configurations, impactor shapes, and impact energies that affect various damage metrics (dent depth, delamination area, and delamination length) and how they contribute to the loss of compressive strength is studied. A dataset of over 400 individual datapoints is obtained and CAI reduction is binned into various target classes for the investigation. Impactor shape has a high correlation with the dent depth but has small contribution to the CAI strength. Delamination area and length increase with an increase in impact energy, and all show good correlation with a reduction in the material's residual strength. Predictive classification models, such as logistic regression, can make accurate predictions on CAI reduction up to 89%. Unraveling the intricate interplay of factors influencing LVI damage and CAI strength not only has the potential to revolutionize the design and optimization of composite structures but also promises to significantly enhance their performance and durability in real-world applications.

I. Introduction

There is a growing interest in the increased use of composite materials, specifically fiber-reinforced composites, such as carbon fiber reinforced polymer (CFRP) composites, because of their high strength-to-weight ratio. Although these materials are designed to be very strong in-plane, they exhibit weakness out-of-plane, particularly when subjected to transverse low-velocity impacts (LVI). Events such as LVI can result in barely visible impact damage (BVID), which manifests as internal damage in the forms of delamination between plies, matrix cracks, and fiber breakages. This damage has been shown to lead to reductions in the residual strength, prompting research into the behavior of compression after impact (CAI) to better understand how LVI affects the residual compressive strength of composite materials [1].

In response to this need, various efforts have been made to predict the CAI strength of CFRPs through analytical and numerical methods. For example, Soutis and Curtis [2,3] developed analytical models to predict the residual strength of damaged CFRP laminated composites using fracture toughness, albeit with unrealistic assumptions, such as modeling impact damage as an open hole in the specimen, resulting in large errors. Similarly, Tan *et al*. [4] and Sun *et al.* [5] explored numerical approaches to predict CAI strength with improved accuracy, although with time-intensive processes and accuracy heavily reliant on user input.

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As highlighted in a survey by Willard *et al*. [6], new emerging approaches are needed to solve complex science and engineering problems, and one such approach is state-of-the-art machine learning techniques. In particular, Hasebe *et al*. [7,8] applied a machine learning approach to predict the impactor shape, delamination area, and delamination length of CFRPs subjected to LVI, achieving an accuracy of approximately 80% by using dent depth and volume of indentation as features in the model, allowing inference of internal damages from visible damage.

In this paper, we employ a machine learning approach to investigate the CAI behavior of CFRPs after LVI. We collect a dataset of experimental data encompassing various layups, impactor shapes, impact energies, and measured impact damages, which are utilized to predict CAI retention strength.

II. Material and Methods

A. Data Collection

The dataset utilized in this study was obtained from experimental investigations conducted by the University of Tokyo [8], focusing on the low-velocity impact (LVI) and compression after impact (CAI) behavior of carbon fiber reinforced plastics (CFRPs). The experimental setup involved the use of various impactors, layup configurations, and impact energies to simulate different impact conditions. The LVI tests were performed using the Drop Tower Impact System CEAST 9350 (Instron Corporation), with specimens securely positioned between two plates to ensure stability during testing. For each impact condition, three specimens were prepared to capture the variability in response.

Following the LVI tests, comprehensive measurements of the external and internal damage inflicted on the CFRP specimens were conducted. External damage assessment involved the utilization of a wide area measurement system VR-5000 (Keyence Corporation), which provided detailed surface images and depth contour plots of the impacted regions. Additionally, the ultrasound C-scanning system HIS3 (KJTD Co., Ltd.) was employed to acquire internal damage images, allowing for a thorough evaluation of delamination area and length within the CFRP specimens.

The acquired dataset encompasses a diverse range of impact conditions and corresponding damage characteristics, facilitating in-depth analyses of the effects of impact parameters on CFRP performance.

B. Feature Selection

The feature selection process in this study encompasses a comprehensive array of parameters that influence the response of carbon fiber reinforced plastics (CFRPs) to low-velocity impact (LVI) and compression after impact (CAI) testing. Key features include layup configuration, impactor type, impact energy, and damage measurements.

The layup configuration of the CFRP specimens includes variations such as cross-ply and quasi-isotropic arrangements, with varying numbers of plies (8, 16, 20, and 24). These configurations play a crucial role in determining the mechanical properties and damage resistance of the composite material.

The impactor type, shown in Fig. 1, is another significant factor, with three different hemispherical shapes, two conical shapes, and a flat shape utilized during testing. Each type of impactor induces distinct damage patterns and severity levels in the CFRP specimens, contributing to the variability in response observed across different test conditions.

Figure 1

Fig. 1 Impactor shapes for low-velocity impact tests from [7].

The energy imparted during the impact tests represents another critical parameter influencing the extent and nature of damage sustained by the CFRP specimens. Various levels of impact energy were employed to simulate different real-world scenarios and assess the material's resilience under varying loading conditions.

Comprehensive measurements of damage parameters are shown in Fig. 2, including dent depth, delamination area, and delamination length, were conducted following the LVI tests. These measurements provide valuable insights into the structural integrity and damage tolerance of the CFRP specimens under impact loading, facilitating the assessment of material performance and the development of predictive models.

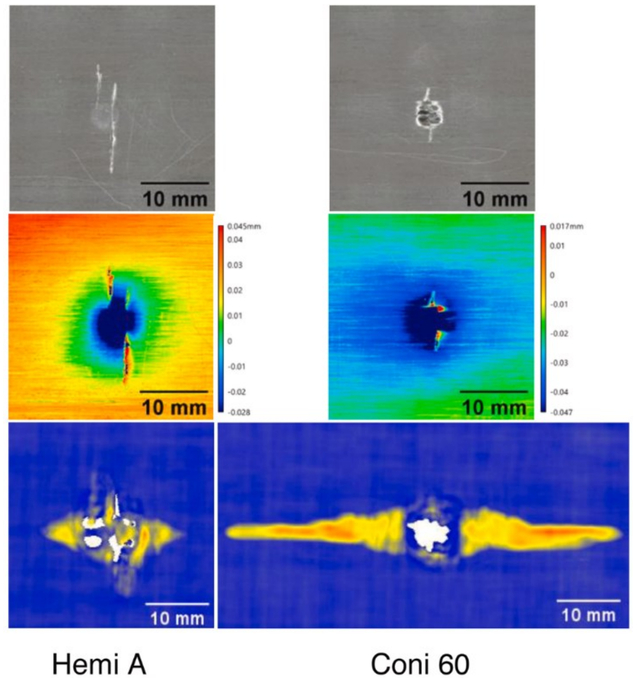

Fig. 2 Damage assessment for impact damage measurements: top to bottom, surface images, depth contour and C-scan images adapted from [7].

C. Data Pre-Processing

The raw experimental data obtained from the LVI and CAI testing underwent minimal pre-processing to ensure compatibility with machine learning algorithms. This section outlines the pre-processing steps used to prepare the dataset for subsequent analysis and model development.

One essential preprocessing step involved binning the CAI retention values into distinct classes to facilitate classification tasks. The CAI retention classes were categorized as follows: Non-impacted, 90% and above, 80-90%, 70-80%, 60-70% and below 60%. This classification scheme allowed for the categorization of specimens based on their CAI performance, enabling the development of predictive models to assess material strength and durability. The distribution of the classes is shown in Fig. 3 along with the given class name.

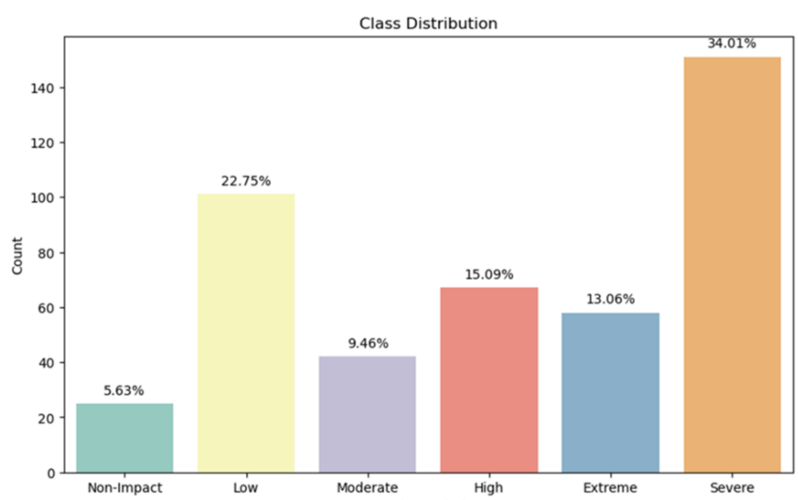

Fig. 3 Bar chart of distribution of the binned CAI retention classes.

Additionally, categorical variables such as layup configuration and impactor type were encoded using one-hot encoding to convert them into numerical representations suitable for machine learning algorithms. This process created binary columns for each category, indicating the presence or absence of a particular attribute.

Furthermore, feature scaling was performed using the StandardScaler to normalize the numerical features and ensure that all variables contributed equally to model training and evaluation. By scaling the features to have a mean of 0 and a standard deviation of 1, the impact of outliers and differences in feature magnitudes was mitigated, enhancing the stability and convergence of the machine learning models.

Overall, the preprocessing steps applied to the dataset aimed to enhance its suitability for training and evaluating machine learning models, facilitating the extraction of meaningful insights and the development of accurate predictive models for CFRP behavior under impact loading conditions.

D. Model Selection

For this study, logistic regression was chosen as the primary machine learning model for predicting the CAI class of CFRPs subjected to LVI. Logistic regression is well suited for classification tasks, making it an ideal choice for predicting CAI class categories.

The logistic regression model was implemented using the Saga solver with an l1 penalty. The l1 penalty, also known as Lasso regularization, helps in feature selection by encouraging sparsity in the model coefficients. This regularization technique can prevent overfitting and improve the generalization of the model to unseen data.

While the dataset size is modest, the choice of the Saga solver and l1 penalty was made to ensure robustness and interpretability of the model, particularly in handling potential multicollinearity among features and reducing the risk of overfitting. These specifications aim to provide a reliable predictive model for CAI class based on the impact damage characteristics of CFRPs, even with a smaller dataset.

III. Results and Discussion

A. Exploratory Data Analysis

The effect of impact energy on impact damage and CAI strength retention is explored in Fig. 4. As impact energy increases, the delamination area tends to increase, and strength retention also decreases as illustrated by the decreasing classes in Fig. 4. A subsection of the data stays under 200 mm^2 even as the impact energy increases and these data only have a low reduction in CAI strength. The data points primarily belong to the samples that were impactor with the flat impactor. This impactor shape caused the least impact damage with max delamination area and length of 152.83 mm^2 and 20.82 mm, as well as a max dent depth of 0.128 mm. A similar trend is observed for delamination length as with the delamination area, except for a group of data with lower impact energies that have larger delamination lengths. These specimens were all impacted by conical impactors and have high and extreme reductions in their CAI strength even though they were impacted at low energy levels. The biggest contributing factor to dent depth is impactor shape, as the conical impactors cause greatest dent depth. Flat impactors produce small to no dent depth, as well as the largest hemispherical impactor. The smaller the hemispherical impactor's diameter the greater the dent that is formed during impact. Dent depth has small correlation to the CAI classification as there is a lot of overlap across ranges of impact energy and dent depths below 0.75mm. Typically, above 0.75mm dent depth the CAI class falls into one of the greater reduction classes but still no clear groupings.

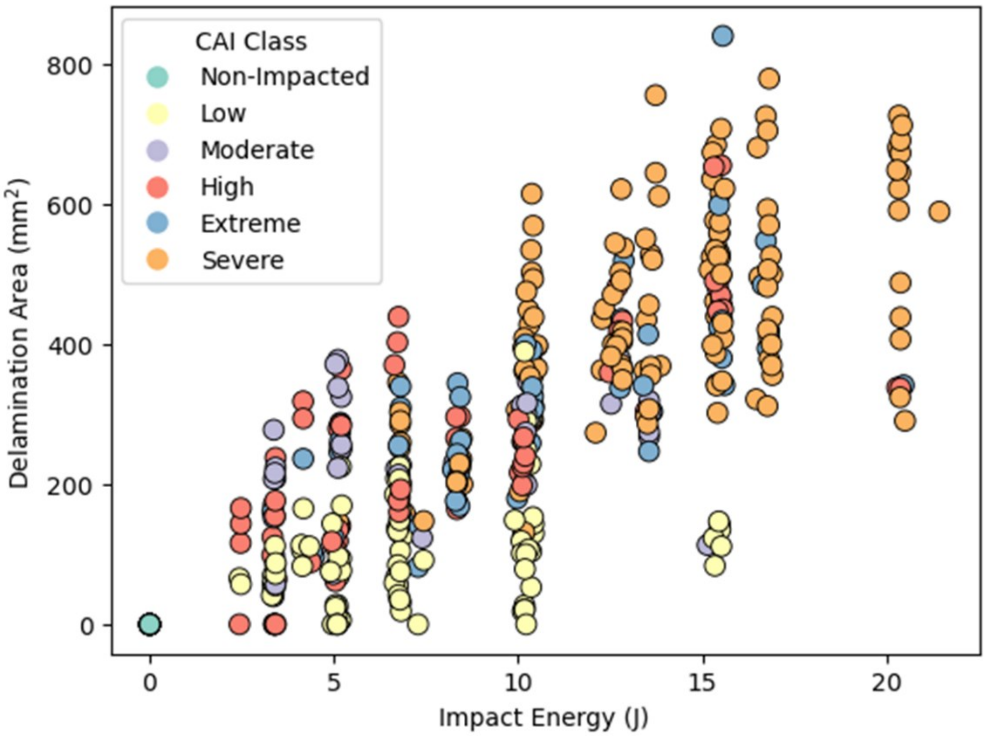

Fig. 4 Scatter plot of the delamination area versus impact energy showing reduction in CAI reduction classification.

Table 1 and 2 present the F-statistic and p-value for the relationships of the various impactor shapes and layup types with the different damages and CAI classes by performing a one-way analysis of variance (ANOVA). The hemispherical impactors have no significance on the delamination area and length whereas the two conical and flat impactors have high correlation, as shown by their high F-statistics and low p-values. Coni60 impactor has a significant effect on the dent depth as well, other impactors which showed significance include HemiB, HemiC, and flat. HemiA and Coni120 did not show a significant variation from the mean on dent depth illustrated by the low F-statistic and the high p-value. Impactor shapes that demonstrate a statistically significant difference for CAI retention class are the conical and flat impactors. Pristine class of impactors demonstrates the non-impacted samples and clearly have significant differences for all damages and strength retention. The analysis of layup types revealed interesting insights into their impact on various types of damage. While layup type did not show any significant effect on delamination length and dent depth across different thicknesses, indicating a consistent behavior regardless of layup configuration, the results for delamination area varied. Specifically, only C16 and Q16 layup types exhibited no significant differences in delamination area, which could be attributed to their intermediate thickness between the 8 and 24 thickness variants. This suggests that the effect of layup type on delamination area may be influenced by the specific thickness of the composite structure. The analysis of layup types in relation to CAI class reveals varying degrees of significance, suggesting the influence of layup configurations on the composite's CAI performance. Notably, two layup types, Q24 and R0, do not exhibit significant differences across CAI classes, indicating a consistent CAI resistance regardless of class variations. This consistency could be due to the robust structural design and material properties inherent in these layup configurations. On the contrary, other types show significant differences in CAI class distribution, reflecting the sensitivity of CAI performance to specific configuration characteristics such as fiber orientation, layer thickness, and stacking sequence.

Table 1: One-way ANOVA Results for Different Impactor Shapes on Damage Metrics and CAI Class.

Impactor Shape		Delamination Area	Delamination Length	Dent Depth	CAI Class
HemiA					
	F-statistic	0.3145	0.1329	17.10	1.190

	p-value	0.5752	0.7156	4.117	0.2758
HemiB					
	F-statistic	0.0508	2.813	29.55	5.3542
	p-value	0.8218	0.0941	8.288e-08	0.0210
HemiC					
	F-statistic	0.2118	3.107	6.988	2.400
	p-value	0.6456	0.0786	8.486e-03	0.1220
Coni60					
	F-statistic	18.14	39.17	257.3	37.96
	p-value	2.423e-05	7.969e-10	4.475e-46	1.424e-09
Coni120					
	F-statistic	11.46	19.18	0.0005	28.82
	p-value	7.649e-04	1.443e-05	0.9818	1.200e-07
Flat					
	F-statistic	53.27	22.01	25.79	49.93
	p-value	1.205e-12	3.533e-06	5.439e-07	5.604e-12
Pristine					
	F-statistic	51.44	93.18	19.52	79.51
	p-value	2.911e-12	3.189e-20	1.236e-05	1.086e-17

Table 2: One-way ANOVA Results for Different Layup Types on Damage Metrics and CAI Class.

Layup		Delamination Area	Delamination Length	Dent Depth	CAI Class
C8					
	F-statistic	36.58	1.195	0.3984	7.498
	p-value	2.864e-09	0.2748	0.5282	0.0064
C16					
	F-statistic	0.3899	0.6722	0.1516	5.928
	p-value	0.5327	0.4127	0.6972	0.0152
C24					
	F-statistic	8.0220	0.8998	0.1473	11.31
	p-value	0.0048	0.3433	0.7013	0.0008
Q8					
	F-statistic	14.86	0.0658	0.0078	31.79
	p-value	0.0001	0.7976	0.9296	2.899e-08
Q16					
	F-statistic	2.344	2.2425	0.1761	8.546
	p-value	0.1264	0.1349	0.6749	0.0036
Q24					
	F-statistic	7.065	0.0886	0.1234	0.0629
	p-value	0.0081	0.7661	0.7255	0.8021
R0					
	F-statistic	11.47	5.836	0.7148	2.697
	p-value	0.0008	0.0161	0.3982	0.1012
R45					
	F-statistic	2.824	2.107	0.0267	15.29
	p-value	0.0935	0.1473	0.8703	0.0001

B. Variability Analysis of Model Performance

Exploring the variability in model performance unveils crucial insights into the robustness and reliability of our machine learning approach. Assessing the stability and generalizability of predictive models is paramount for their effective deployment in real-world scenarios. the impact of random seeds and training percentages on model performance, offering valuable insights into model stability under diverse initialization conditions and training data sizes. Subsequently, histograms of training and testing accuracies for varying random seeds are presented in Fig. 5 that offer a visual representation of the distribution of model performance metrics. Lastly, an exploration into the variability in model accuracy across different training percentages in Fig. 6 provides a comprehensive view of how variations in the size of the training dataset influence model performance.

The histograms presented in Fig. 5 offer an exploration of the impact of random seed initialization on the accuracy of the logistic regression model, shedding light on the intricate relationship between initial conditions and model performance, particularly when considering the inclusion of damage features. This was achieved by executing the test/train split process using 1000 different random seeds, thereby capturing a comprehensive spectrum of potential initial conditions for model training and evaluation. The model without the damage features, shown in Fig. 5(a), has a range from 55% to 85% testing accuracy with a mean of 72.1% and standard deviation of 4.87%. Training accuracy is a much narrower distribution and slightly higher accuracy than that of testing with a mean of 77.3% and standard deviation of 1.36%. By including the damage features in the model, shown in Fig. 5(b), slightly higher testing and training mean accuracy is observed in the testing and training. A mean training accuracy of 78.7% is observed with a standard deviation of 1.22%, thus the damage features may have helped in predicting the CAI class. The test accuracy is a broader distribution with damage features, mean accuracy of 72.7% with 5.15% standard deviation.

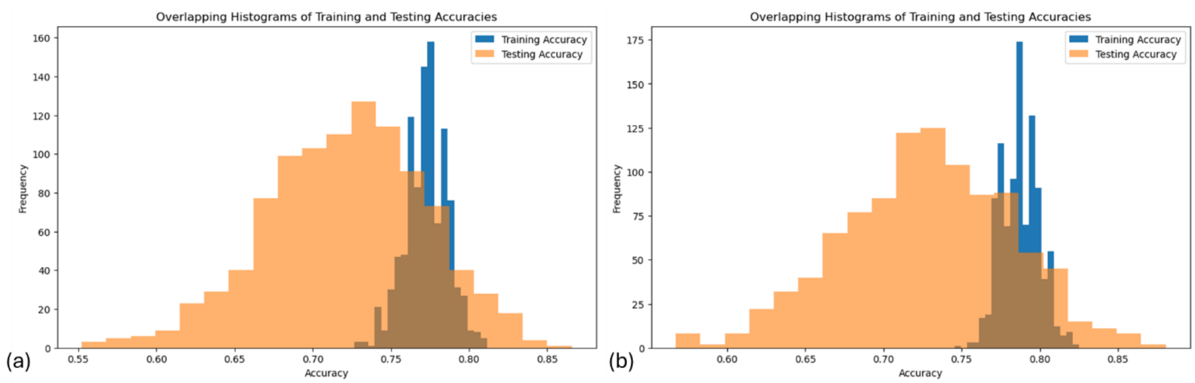

Fig. 5 Histograms of testing and training accuracies (a) without damage features and (b) with damage features across 1000 iterations of the logistic regression model, with a 15% testing split.

This approach was applied in a range of different test/train split percentages from 5 to 50%. Figure 6 shows the mean accuracies across the test/train split range with a 95% confidence interval. The mean training accuracy with and without damage shows little to no effect due to the test/train split. However, there is a clear trend in the accuracy of mean testing. There is a downward trend from 5 to 10% of data saved for testing, followed by an increase to 15%, and then a linear decrease as the test data size increases. At very low test sizes with small datasets, it is easy for classes to be absent from the test data, especially when the class distribution is unbalanced. This is why the model shows higher accuracy at 5%, which may be indicative of overfitting of the training data. The best balance is found between 12-15% of the data being saved for testing, as it prevents overfitting and ensures that all classes are represented in both the training and testing sets.

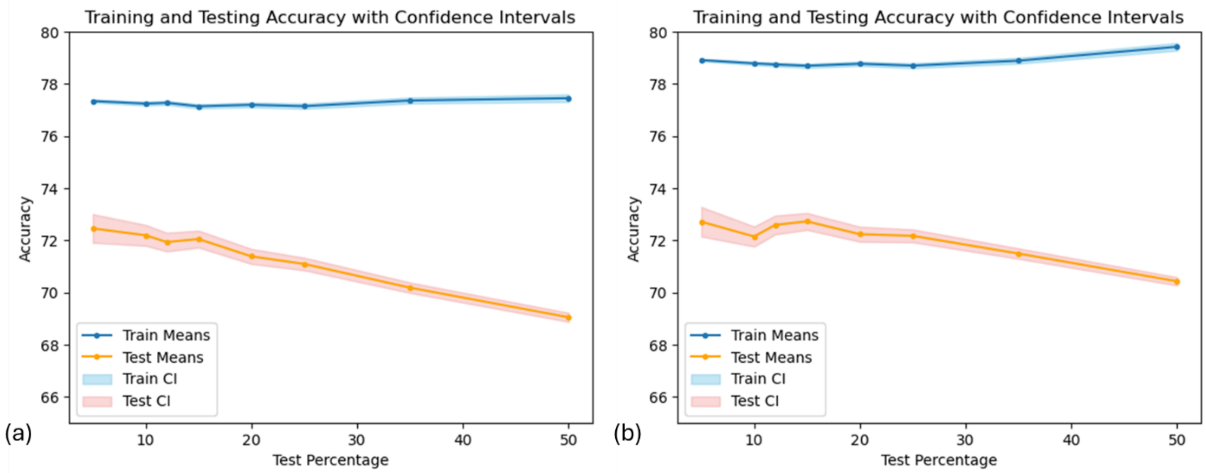

Fig. 6 Mean testing accuracies with 95% confidence intervals across varying test/train split percentages, (a) without damage features and (b) with damage features.

C. Assessment of Accuracy

Understanding the confusion matrix, a fundamental tool in classification analysis, is crucial to evaluating the performance of a model by presenting a detailed breakdown of predicted versus actual class labels, allowing for insights into classification errors and model efficacy. Figure 7 displays the confusion matrices for the logistic regression model with damage features at a 15% test split, showcasing the best-performing seed. In Figure 7, the confusion matrix corresponding to the random seed yielding the highest testing accuracy of 88.9% is depicted. The model shows great prediction power illustrated by the true predictions along the main diagonal. The few incorrect predictions typically fall one off diagonal meaning the prediction was off by one class, which could be due to the binning method or a specific feature giving the trained model trouble. Interestingly, the best trained model did not have non-impacted testing data, which will be shown to just allow easy predictions as opposed to helping in the training process. Even for the median and worst random state trained models, the incorrect predictions typically fall one or two classes off diagonal. This means that model is in fact learning the trend but the variation amongst the features is causing difficulty in learning with the dataset size.

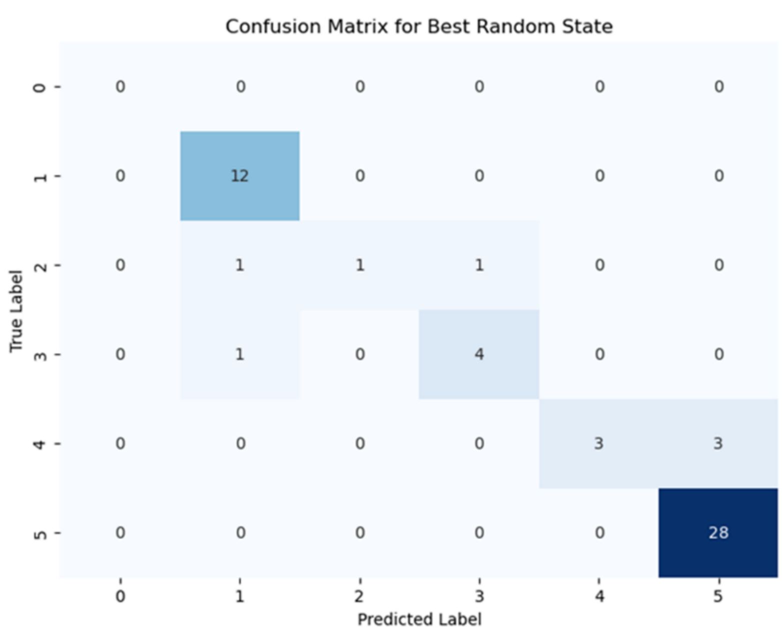

Fig. 7 Confusing matrices for the best random seed in the logistic regression model with damage features and 15% test size.

D. Feature Importance

The identification of significant features is crucial in understanding the underlying mechanisms of a predictive model. In this section, we dive into the feature importance of the characteristics of our logistic regression model, aiming to uncover the key variables driving its predictive performance. Figure 8 shows the feature importance of the best trained model. The model learned to look for the Pristine class in the impactor shape feature representing non-impacted specimens, this feature dominated the feature importance. The impact energy and delamination length are the next highest importance. As impact energy increases, the amount of damage induced on a specimen increases and thus reduces its residual strength. It is interesting that the delamination length has a higher importance in relation to the delamination area. This is since conical impactors caused large delamination lengths but relatively smaller delamination areas with a drop in CAI strength, as shown in Fig. 4, and thus influenced the model's training on CAI classification predictions. Of the damage features, dent depth has the smallest importance which has been demonstrated in literature to be of less importance. The importance across the layups and impactor shapes varies, but it seems the thinnest ply layups have higher importance than higher ply count layups. This could be telling that the model understands that thin plies typically do not retain strength after impact since a higher ratio of layers are damaged. HemiA and HemiB are of great importance in the model, even though the one-way ANOVA did not show significant importance with respect to the CAI classification, as shown in Table 1. The feature importance across the various performing models is similar to one another, with minor differences amongst the impactor shapes and layups. This may play into the high sensitivity of the training process with small datasets.

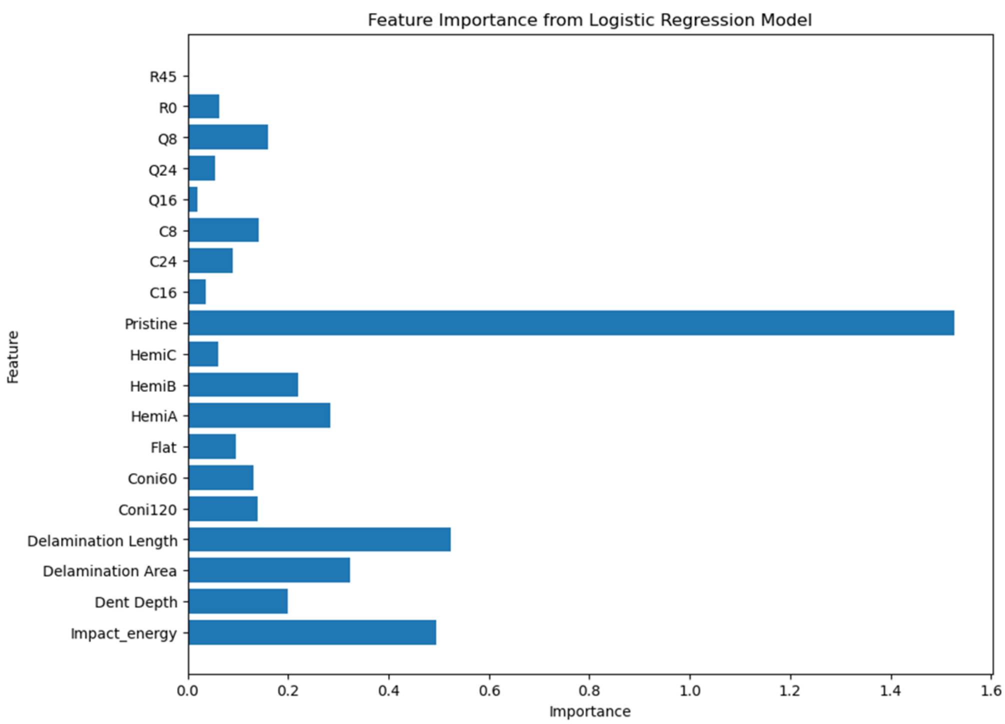

Fig. 8 Horizontal bar chart of importance for the best random seed in the logistic regression model with damage characteristics and 15% test size.

IV. Conclusion

In conclusion, this study provides valuable information on the impact of various factors on the CAI behavior of CFRPs after LVI. Through comprehensive analysis of impact damage metrics and CAI strength retention across different impactor shapes, layup types, and impact energies, significant correlations and trends have been identified. The findings highlight the critical role of impact energy in influencing delamination area and length, dent depth, and ultimately, CAI strength reduction. Notably, conical impactors exhibit a pronounced effect on delamination length and CAI reduction, underscoring the importance of impactor geometry in determining damage severity. Additionally, this investigation into layup types reveals nuanced differences in their impact on damage metrics and CAI class distribution, shedding light on the intricate relationship between layup configuration and composite performance.

Furthermore, feature importance analysis elucidates the key variables driving predictive accuracy, offering valuable insights for model refinement and optimization. Overall, this research contributes to a deeper understanding of the complex interplay between impact damage mechanisms and CAI behavior in CFRPs, paving the way for enhanced predictive models and informed design strategies in composite materials engineering.

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