Optimizing Bulletproof Natural Fiber-Reinforced Polymer Composite Materials Using a Hybrid Computational Simulation and Machine Learning Approach

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https://hdl.handle.net/2324/7395558

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 11, pp.472-479, 2025-10-30. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

Optimizing Bulletproof Natural Fiber-Reinforced Polymer Composite Materials Using a Hybrid Computational Simulation and Machine Learning Approach

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Abstract: *This study investigates the optimization of natural fiber-reinforced polymer composite (NFRPCs) creation for bulletproof applications by integrating computational simulation and machine learning (ML). We incorporate abaca (Musa textilis) or pineapple leaf fibers (Piñatex), along with aramid and carbon fibers, into layered composite plates. Ballistic performance was modeled and predicted using simulated data from ANSYS Explicit Dynamics and validated through live bullet testing. ML models, such as Support Vector Machine (SVM) and Random Forest (RF) with optimized hyperparameters, achieved up to 80% prediction accuracy and an F1-score of 82% for abaca-reinforced composites, closely aligning with experimental results. However, lower prediction accuracy was observed for Piñatex-based composites, due to fiber variability and other factors identified in the study. This hybrid methodology highlights the potential of combining simulation and ML to reduce reliance on extensive live bullet testing, providing a data-driven pathway for the efficient development of high-performance bulletproof composite materials.*

Keywords: NFRPC; Ballistic plates; Machine Learning; Support Vector Machine; Random Forest

1. Introduction

Traditionally, ballistic plates and armor have relied on heavy ceramic or metal components, which often compromise mobility and lead to user fatigue [1-2]. This has driven interest in lightweight, high-performance alternatives, like fiber-reinforced polymer composites [3]. Additionally, effective ballistic plates require extensive research, iterative design, and comprehensive testing, which typically includes laboratory-scale ballistic tests, drop-weight impact tests, and full-scale field trials to evaluate performance under various threat levels and environmental conditions [4-5]. This process is time-consuming and expensive, limiting efficient exploration of the design space.

Natural fiber-reinforced polymer composites (NFRPCs) have emerged as a promising alternative in ballistic protection [6-7]. These materials are biodegradable and can be renewably sourced, addressing the high cost and environmental impact of traditional ballistic materials [8]. However, their utilization in ballistics has been constrained by inconsistencies in mechanical properties and moisture resistance [9]. Hybridizing natural fibers with synthetic fibers has shown potential to address these limitations, enabling the development of advanced bulletproof materials that combine sustainability with superior performance [10-11].

Advancements in finite element analysis (FEA) have significantly improved the efficiency of developing and optimizing ballistic plates [12-13]. By reducing reliance on extensive physical testing, FEA conserves time and resources while accurately predicting real-world performance [14-16].

The challenge is the accurate representation of material properties and dynamic impact behavior. Simulations often oversimplify microstructural interactions, leading to discrepancies between simulated and experimental outcomes [17-18]. Variability in material properties, particularly with natural fibers, introduces uncertainties in simulation results [19-20]. Machine learning (ML) offers a promising solution to enhance the accuracy and efficiency of simulations. ML algorithms can predict material properties and behaviors under various conditions, improving the fidelity of FEA models [21-22]. Integrating ML with FEA expedites the development of ballistic plates, leading to more effective and reliable protective gear [23].

This study integrates ML with ballistic impact simulation data from ANSYS Explicit Dynamics to optimize the layer composition of hybrid NFRPCs for bulletproof plate applications. The natural fibers selected were abaca (Musa textilis) or pineapple leaf fibers (Piñatex) due to their lightweight nature, proven mechanical durability and abundance in the Philippines. These fibers have gained attention for their potential in composite applications, notably as sustainable alternatives in engineering and defense [24]. Aramid fibers are widely recognized for their high tensile strength and superior impact resistance, making them a key material in protective equipment, while carbon fibers offer rigidity and lightweight advantages [25-26].

Logistic Regression (LR), Support Vector Machines (SVM), and Random Forest (RF) models, trained on ANSYS simulation data, validated against live ballistic impact test results, and evaluated for accuracy and resilience to data variability, predict the penetrability of composites based on the number of layers of each material in the composite. By integrating simulated and live testing data, the study reduces experimental costs while enhancing the generalizability of ML models.

2. Methodology

The development of predictive models began with fabricating composite plates composed of carbon, aramid, and the selected natural fibers. To evaluate the ballistic performance of these composites, penetration depth was collected through live tests and ANSYS.

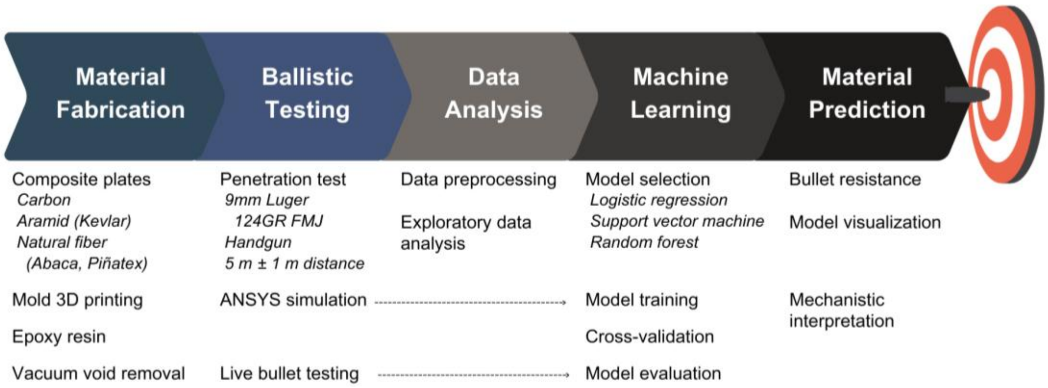

Figure 1. Methodology framework for the creation, testing, and modeling of NFRPC-based bulletproof material.

Explicit Dynamics simulations. The simulation data served as training data for ML models developed to predict the composite's ballistic resistance, classifying them as either resistant or penetrable. The performances of these ML models were validated against the experimental results from live tests to ensure reliability and generalizability. Figure 1 provides a visual representation of the framework employed for fabricating, testing, and modeling NFRPC-based bulletproof materials.

2.1 Composite Plate Fabrication

The plates were fabricated using a hand lay-up process, incorporating layers of aramid, carbon, and natural fibers to achieve the desired material configuration. Each fabric layer was impregnated with epoxy resin and meticulously stacked to ensure proper alignment and uniform resin distribution. The stacked layers were then sealed with a bagging film and subjected to vacuum-assisted curing for 24 hours. This step was crucial for eliminating air pockets, ensuring consistent consolidation, and minimizing void content, thereby enhancing the composite's mechanical and ballistic properties.

After curing, the composite plates were demolded and prepared for ballistic testing. To assess the influence of design parameters on ballistic performance, multiple plates were fabricated with varying configurations, such as the number of layers and total material thickness. These variations were designed to explore the balance between ballistic resistance, weight, and practicality for potential applications. The total composite thickness ranged from 11 to 32 mm, reflecting a trade-off between optimal protection and material manageability.

2.2 Ballistic Impact Investigation

The live bullet impact testing of the fabricated NFRPC plates was conducted using a one-shot penetration test for each plate. The test involved 9mm Luger 124GR FMJ ammunition fired from a handgun at a distance of 5.0 meters, following a modified version of the NIJ Standard IIIA 0101.06 [27]. Velocity readings were recorded at 2.5 meters from the plate, with adjustments made to account for potential inaccuracies caused by lead residue from the ammunition. The depth of penetration for each shot was then measured to evaluate the material's performance. Plates were classified as penetrable if the bullet fully exited the backplate and resistant if they exhibited only partial or no penetration.

The number of layers of carbon fiber, aramid, and natural fibers, the thickness of each material layer, the overall composite thickness, as well as the type of natural fiber used, were collected during testing. A total of nine plates were tested, consisting of five abaca-based composites and four Piñatex-based composites. The compositions of the plates varied in terms of the number of layers and the inclusion of synthetic fibers, with different total thicknesses. Figure 3 illustrates the test setup, along with sample images of a representative armor panel before testing and close-up views of the test results.

To expand the dataset for ML, bullet impact testing on various NFRPC material compositions was simulated using ANSYS Explicit Dynamics, a Finite Element Analysis (FEA) tool. This simulation modeled bullet penetration in composite materials, providing a cost-effective approach to supplement the live testing data [28-29]. The simulation setup consisted of NFRPC plates with a front layer of epoxy with a front layer of epoxy carbon woven fiber, a middle layer of aramid fiber, and a back layer of natural fiber. Figure 4 shows the composite geometry, layer configurations, and meshing parameters used in this study. The material properties for natural and aramid fibers were derived from experimental testing, while the properties of carbon fibers were sourced from the ANSYS Engineering Data database. The simulated bullet was modeled with a copper outer core and a lead inner core to meet Type IIIA armor specifications, with corresponding material properties also obtained from the ANSYS Engineering Data database.

The same data was also obtained from the simulations. Some results were adjusted to align with trends observed in the live testing, enhancing model fidelity. A total of 62 additional samples were generated through simulations, notably expanding the dataset. Among these, nine simulated samples replicated the exact compositions of the live-tested plates, providing a direct comparison to validate the accuracy and reliability of the simulation tool.

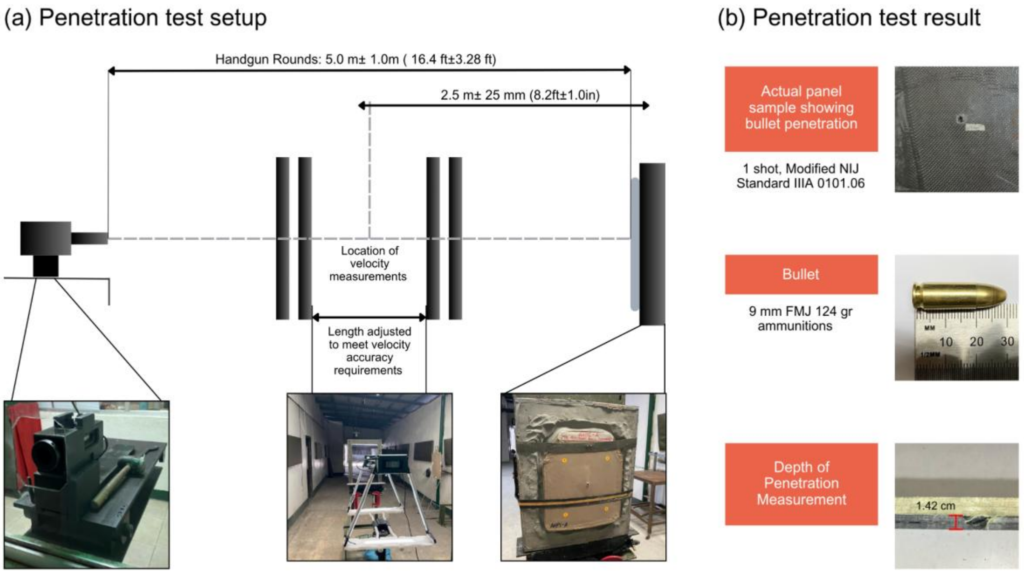

Figure 3. (a) One-shot penetration test with 9mm Luger 124GR FMJ, and (b) sample result from penetration test.

2.3 Data Preprocessing

Material penetrability during simulations was assessed using visual inspection and the backface signature (BFS) parameter, which quantifies the deformation or damage on the plate's backside after bullet impact [30-31]. A BFS threshold of ≥ 40 mm, based on ballistic resistance standards for body armor [27], was used to classify materials as penetrable. However, in cases where simulations showed no visible penetration despite exceeding this BFS threshold, likely due to calculation errors, the materials were still classified as penetrable to maintain consistency in evaluation.

Given the limited number of samples, a reduced set of features was selected for ML to minimize the risk of overfitting [32]. The selected features included carbon fiber thickness, aramid fiber thickness, natural fiber thickness, and the type of natural fiber, with bullet penetrability as the target variable. To streamline the analysis, the dataset was divided into two subsets based on the type of natural fiber. This separation allowed each machine learning model to focus specifically on the influence of material composition within a narrower scope, thereby enhancing predictive performance.

2.4 Machine Learning Model Selection

To identify the most effective ML model for predicting the ballistic resistance of composite materials, three candidate models were evaluated: Logistic Regression, SVM, and Random Forest. These models were selected due to their established effectiveness in classification tasks and their suitability for working with the limited simulation dataset available [27, 33-35]. Each model offered a distinct approach to classification, providing a robust basis for comparison in terms of their ability to classify material penetrability accurately.

Logistic regression was selected as the baseline model for its simplicity and interpretability. This supervised ML algorithm is a binary classifier. It applies the logistic (sigmoid) function to map numerical features into a probability between 0 and 1 [36]. This model assumes a linear relationship between the feature; thus, SVM was chosen as our nonlinear classification model.

SVM aims to find a hyperplane that separates different classes in the feature space [37]. It identifies "support vectors," the data points closest to the hyperplane that defines the optimal boundary. The kernel trick was used to map data points from their original feature space into higher dimensions, allowing for a linear decision boundary (hyperplane) that more effectively separates the classes [38]. Three kernel functions were evaluated: linear, radial basis function (RBF), and sigmoid. The linear kernel performs no transformation and directly maps input features to their original space. The RBF kernel uses the exponential function to calculate similarity between data points based on their distance, with a parameter to control the "spread" or influence of each data point. The sigmoid kernel applies the hyperbolic tangent function and uses a scaling parameter γ and a constant offset c for prediction [39]. SVM has demonstrated strong generalizability across a wide range of problems [40]. Its ability to perform well with small datasets makes it a good fit for the limited data available in this study [41].

Random Forest was also chosen due to its ability to handle complex and noisy data. It constructs multiple decision trees and combines their predictions to reduce overfitting, which is common with individual decision trees. As a probabilistic model, the RF builds classifiers on random subsets of the dataset, effectively improving generalization and robustness [42].

3. Results and Discussion

3.1 Model Decision Boundaries

To analyze the decision patterns of each ML model, material penetrability was predicted for various thicknesses of natural fiber, aramid, and carbon. Figures 5 and 6 illustrate the decision boundaries of the ML models for abaca-based and Piñatex-based composites. Resistant composites were marked in blue, while penetrable composites were marked in orange.

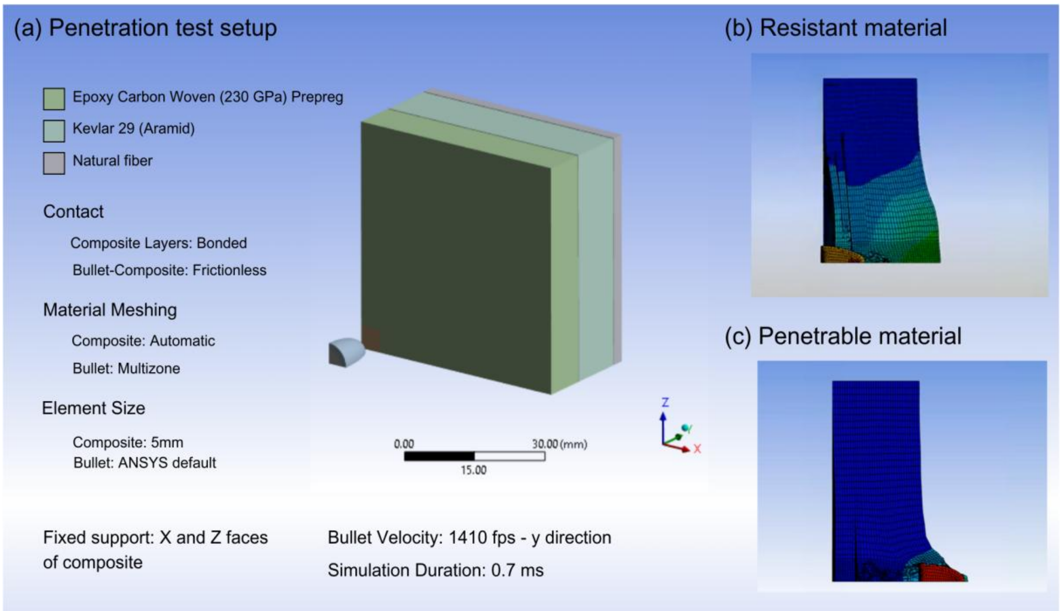

Figure 4. ANSYS Explicit Dynamics simulation for ballistic testing of NFRPC materials: (a) simulation setup, (b) example of a bullet being resisted, and (c) example of a bullet penetrating the composite.

For abaca-based NFRPCs, the SVM model found a curved, non-linear decision boundary, effectively distinguishing resistant from penetrable materials (Figure 5a). In contrast, the RF and LR models exhibited linear-like decision boundaries, with the RF model uniquely identifying a cluster of penetrable materials where *natural fiber thickness* < *14 mm*, *aramid thickness* > 12 *mm*, and *carbon thickness* < 6 *mm* as presented in Figures 5b and 5c.

For Piñatex-based NFRPCs, the decision boundaries across all models were nearly identical, forming a simple linear boundary at aramid thickness ≈ 4 *mm,* as shown in Figure 6. This outcome aligns with the simulated data, where penetrable materials were generally observed at *aramid thickness* < 4 *mm*, and resistant materials at *aramid thickness* > 4 *mm*. However, due to the discrepancies between the simulated and live data, the models inaccurately classified the live data.

These visualizations reveal the distinct clusters of material compositions with expected improved ballistic resistance. Dense blue areas indicate a greater likelihood of producing resistant composites, while predominantly orange areas may be avoided when creating bulletproof materials, as these compositions suggest weaker quality.

3.2 Model Performance

3.2.1 Optimal Hyperparameters

Before evaluating model performance on live test data, the models were assessed during training and optimized using Grid Search Cross Validation. The optimal hyperparameters for each model are listed in Table 3, while their validation performance is shown in Table 4.

For the LR model, the penalty type for both fiber types was set to L2 regularization, with the *C* value for abaca set higher than that for Piñatex. L2 regularization, also known as ridge regression, adds a penalty term (regularization parameter *C*) to the loss function based on the squared magnitude of the model's coefficients, which helps prevent overfitting by limiting large coefficients [43-44]. A higher *C* value means lower regularization strength, suggesting that the model for abaca was less regularized, thus allowing for a more complex fit compared to the model for Piñatex.

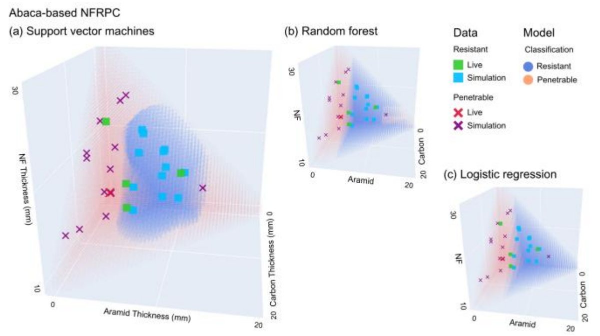

Figure 5. Decision boundaries for abaca-based NFRPCs: (a) SVM, (b) Random Forest, and (c) Logistic Regression models.

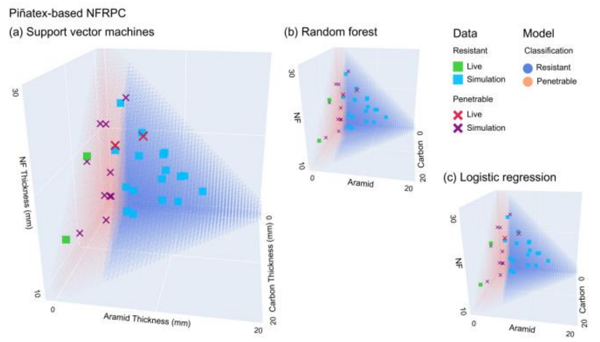

Figure 6. Decision boundaries for Piñatex-based NFRPCs: (a) SVM, (b) Random Forest, and (c) Logistic Regression models.

For SVM, L2 regularization was used as the default penalty type. In addition to optimizing the regularization parameter *C,* the kernel type and the kernel coefficient (*gamma*) were also fine-tuned. Similar to the LR results,

the *C* value for abaca was higher than for Piñatex. Furthermore, the model for abaca utilized the RBF kernel (with *gamma* = 0.1), which allows non-linear decision boundaries, as shown in Figure 5a. In contrast, only a linear kernel was used for Piñatex, which is evident in the simple linear boundary in Figure 6a.
Finally, for RF, the node splitting *criterion*, forest size (*n_estimators*), and ensemble fitting process (*warm_start*) were optimized. Both models for abaca and Piñatex used the *GINI* criterion, which is computationally cheaper than *Entropy*. Additionally, the *warm_start* parameter was enabled and allowed the model to add more trees to the ensemble without restarting. The RF model for abaca (*n_estimators = 8*) was slightly larger than for Piñatex (*n_estimators = 5*), which corresponds to a more complex decision boundary for abaca, as observed in Figures 5c and 6c.

Table 3. Optimal hyperparameters for each model on different natural fibers

Model	Hyperparameter	Abaca	Piñatex
Logistic Regression	C	0.6	0.1
	Penalty	L2	L2
SVM	C	2	1
	Gamma	0.1	-
	Kernel	RBF	Linear
Random Forest	Criterion	GINI	GINI
	Number of Estimators	8	5
	Warm Start	True	True

Table 4. Model performance for abaca and Piñatex datasets

Model	Metric	Abaca		Piñatex	
		CV	Test	CV	Test
Logistic Regression	Accuracy	0.92	0.60	0.90	0.25
	Precision		0.87		0.17
	Recall		0.60		0.25
	F1-score		0.63		0.20
SVM	Accuracy	0.97	0.80	0.90	0.25
	Precision		0.90		0.17
	Recall		0.80		0.25
	F1-score		0.82		0.20
Random Forest	Accuracy	0.97	0.80	0.87	0.25
	Precision		0.90		0.17
	Recall		0.80		0.25
	F1-score		0.82		0.20

3.2.2 Simulated Data

Based on the optimal hyperparameters shown in Table 3, the models' cross-validation performance was assessed using the simulated data. As shown in Table 4, all three models performed well during training, with cross-validation 0.92 to 0.97 accuracy for abaca and 0.87 to 0.90 accuracy for Piñatex. Among the models, the LR model exhibited the lowest performance for the abaca simulations, which is expected given that it produced the simplest model among the algorithms. Notably, the RF model demonstrated the weakest training performance on Piñatex.

3.2.3 Live Testing Data

To further evaluate model performance on unseen data, the models were tested using live bullet testing data, with the results summarized in Table 4. Overall, the models for abaca demonstrated better test performance (0.60 to 0.80 accuracy) compared to Piñatex (0.25 accuracy). Despite their different decision boundaries, both SVM and RF achieved the best performance for abaca with 0.80 accuracy, 0.90 precision, and 0.80 recall. The high precision and recall suggest that the models are effective in accurately predicting resistant materials and dependable in distinguishing between resistant and penetrable materials when abaca is used as the natural fiber layer.
In contrast, the models demonstrated significantly lower performance on the Piñatex dataset, achieving *0.25* accuracy and recall, *0.17* precision, and *0.20* F1-scores across all three models. The disparity between the simulated and live test accuracy for Piñatex could be a symptom that the models overfitted the training data. Unlike the abaca dataset, where classes exhibit clear clustering in both simulated and live test data, the resistant samples for Piñatex are noticeably more dispersed, as presented in Figure 6.
The low performance of Piñatex can also be attributed to the limitations of material modeling, which only provides approximations that may not capture the complexities of actual composite layers under dynamic conditions. Composite materials exhibit intricate behaviors such as anisotropic properties, inter-layer interactions, and rate-dependent responses, especially under bullet impact. Simulations often rely on simplified constitutive models and assumptions that may not fully replicate the mechanical responses, damage evolution, or failure modes observed in real-world scenarios. Manufacturing inconsistencies and complex failure mechanisms can lead to discrepancies between simulated and actual performance, emphasizing the need for model calibration and validation with experimental data to enhance accuracy.

3.3 Material Analysis

The variation in the ML model's performance between Piñatex and abaca fibers can be attributed to several factors, including differences in material behavior, such as abaca's higher shear modulus and Piñatex's greater tensile strength, as well as fiber-matrix interactions. Abaca fibers, characterized by a lower Young's modulus and higher shear modulus, provide significant flexibility and enhanced energy absorption through shear deformation, which are critical properties for mitigating the force of a bullet impact. This flexibility allows the composite material to deform more under impact, effectively spreading the force over a larger area and reducing the risk of penetration [45]. In addition, the fibrous network of abaca, combined with layers of carbon and aramid fibers known for their exceptional tensile strength and durability, performs well in composite structures under high-stress conditions.

In contrast, Piñatex fibers, with their higher Young's modulus, offer greater stiffness and resistance to tensile deformation, which creates an effective barrier against penetration. However, their lower shear modulus makes them less efficient in dissipating shear forces during impact. Consequently, the overall performance of Piñatex fibers in a ballistic layered construct may be less effective than abaca fibers due to their reduced ability to handle shear stresses typically encountered in composite materials during impact events.

Furthermore, fabrication limitations, such as inconsistencies in resin distribution and fiber placement during composite manufacturing, can introduce variability in the material's characteristics [46]. For example, non-uniform resin distribution, presence of voids and delaminations, or inconsistent fiber volume fractions within the composite can result in variations in mechanical properties such as stiffness and strength, leading to unpredictable performance under ballistic impact. These inconsistencies present challenges in developing accurate and reliable predictive models for such materials.

4. Limitations and Future Work

This study is limited by the small dataset size, which includes only 9 live bullet tests (4 Piñatex; 5 abaca) and 62 simulated data points (32 Piñatex, 30 abaca). While more data is desirable for improving model accuracy, fabricating bulletproof NFRPC plates is both time-consuming and costly. Even simulations for replicating real-life ballistic tests can demand substantial computing resources and time to generate large datasets. With such a small dataset, the model tends to overfit and struggles to generalize, as observed in the Piñatex results.

Balancing model complexity to manage the bias-variance trade-off is essential when optimizing hyperparameters. In this study, only a limited number of hyperparameters were optimized, and future work could benefit from exploring additional ones. For instance, testing different kernel functions for the SVM or utilizing larger RFs could improve performance. Furthermore, feature engineering could enhance model fitting.

Further limitations stem from the specific testing conditions and simulation settings, including the choice of bullet and gun type, the composite's proximity to the testing setup, the shooting angle, and the physical composition properties used in the simulation. While controlling these external factors is essential for obtaining accurate results, it is equally important for models to capture the physical behavior of materials under dynamic conditions effectively.

Given these constraints, future studies should focus on expanding the dataset by incorporating a larger and more diverse range of both simulated and live test data. Employing advanced simulation methods, such as finite element modeling with enhanced material calibration, would help reduce discrepancies between simulated and live test data. Additionally, the integration of multi-objective optimization methods would enable the exploration of composite designs that balance ballistic resistance with other critical factors, such as weight, cost, and durability. Finally, further development of the hybrid computational simulation and ML approach for NFRPC in bulletproof applications is strongly encouraged.

5. Summary and Conclusion

In summary, this study demonstrates the practical application of ML combined with simulations in the development of bulletproof materials. The approach showed promising results, particularly with abaca fibers, where ML models effectively predicted the penetrability of the composites. However, challenges were encountered when using Piñatex, which are stated in the limitations outlined earlier.

ML models, optimized with hyperparameters, achieved high performance, with accuracy reaching up to 80% and F1-scores as high as 82% for the abaca-based composites. Notably, the SVM and RF models exhibited these metrics, highlighting the potential of ML in supporting or replacing traditional testing methods in exploring the design space of bulletproof composites, but further refinement is necessary to improve model performance across a range of fiber types.

The high predictive accuracy and F1-scores achieved for abaca-based composites suggest that ML can be a valuable tool in simulating material penetrability prior to conducting extensive physical tests. While abaca fibers showed strong predictability, Piñatex presented challenges in terms of prediction accuracy, likely due to material variability and other fiber-specific factors.

Future research will focus on refining models to better account for fiber variability, expanding to other natural fiber-reinforced composites, and optimizing algorithms for enhanced robustness. This approach offers a promising pathway to developing sustainable, cost-effective materials for protective applications.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

Acknowledgment

The authors gratefully acknowledge the Department of Science and Technology – Philippine Council for Industry, Energy and Emerging Technology Research and Development (DOST–PCIEERD) and the UP Engineering Research and Development Foundation, Inc. (UP ERDFI) for their generous funding and support of

this project. The authors would also like to extend their appreciation to Mr. John Henry Galino and Mr. Isaiah Nikolo Gonzales for the initial gathering of the research data.

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