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Design of composite rectangular tubes for optimum crashworthiness performance via experimental and ANN techniques

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ABSTRACT

This paper examines the crashworthiness performance of composite rectangular tubes using experimental and artificial neural network (ANN) techniques. Based on experimentally obtained values of different crashworthiness parameters under various loading conditions, ANN models are constructed to identify the optimum cross-sectional aspect ratio of cotton fiber/epoxy laminated composite to achieve the targeted mechanical properties such as load carrying and energy absorption capability. Experimental findings show that axially and laterally loaded rectangular tubes were significantly affected by their aspect ratio. Furthermore, the predictions obtained from the ANN models showed consistency with the experimental data. In addition, the developed ANN captured the complicated nonlinear relationship among crashworthiness parameters to obtain insight into the practical design of the composite materials.

1. Introduction

Composite materials from natural fibers have recently created worldwide interest as they provide advantages like low weight, good fatigue strength, resistance to corrosion, quick mounting, etc. [1–4]. Cotton fiber/epoxy laminated composite is such material composed of cotton fiber and epoxy resin. The resin protects the fiber and retains its intended shape, reinforcing the overall resin structures. Using cotton fiber as reinforcement might prove worthwhile compared to synthetic fibers such as glass since cotton fiber is lighter, abundant, safe to work with, and economical. Composite materials may provide better technological and economic benefits in the applied sectors without losing efficiency and safety [5].

The capacity to absorb energy is critical for manufacturing rail automobiles, cars, and aero vehicles, particularly during crash incidents or scenarios [6–11]. Effective use of composite materials can boost the energy absorption mechanism of the automobile and aviation industries to dissipate kinetic energy during an emergency collision. Structure's integrity and crashworthiness heavily rely on its materials type and its shape. The standard shapes used in the industry nowadays are hexagonal tubes used in making honeycomb structures and circular tubes. Researchers are exploring the usage of rectangular tubes because it is far easier to fabricate, it reduces manufacturing time and labor costs [12,13]. However, it is also essential to investigate the considered rectangular tubes' crashworthiness performance when subjected to the quasi-static crushing test.

Researchers estimate the crashworthiness using specific mechanical parameters (e.g., load carrying and energy absorption capability) by conducting a quasi-static axial crushing load test on samples. Most researchers are involved in analyzing natural fiber-reinforced polymer composites through a variety of experiments and material characterization. The materials designer must first obtain mechanical characteristics appropriate for the intended application; this is achieved by conducting several random sample tests under different loading conditions. These experimental techniques are found in the literature for composite materials, but due to the lack of complete understanding of the mechanical parameters, it is very tedious to find the optimum composite structure and geometry through experimental investigation alone [11]. Whereas machine learning algorithms can efficiently perform this task if necessary experimental data are used to build an accurate and reliable predictive model, ultimately providing a feasible configuration of alternative composite materials [3,4]. Combining experimental and ANN techniques falls under the scope of computer-aided smart manufacturing; and will be a more cost-effective approach and more time-efficient to support the design of future experimental work.

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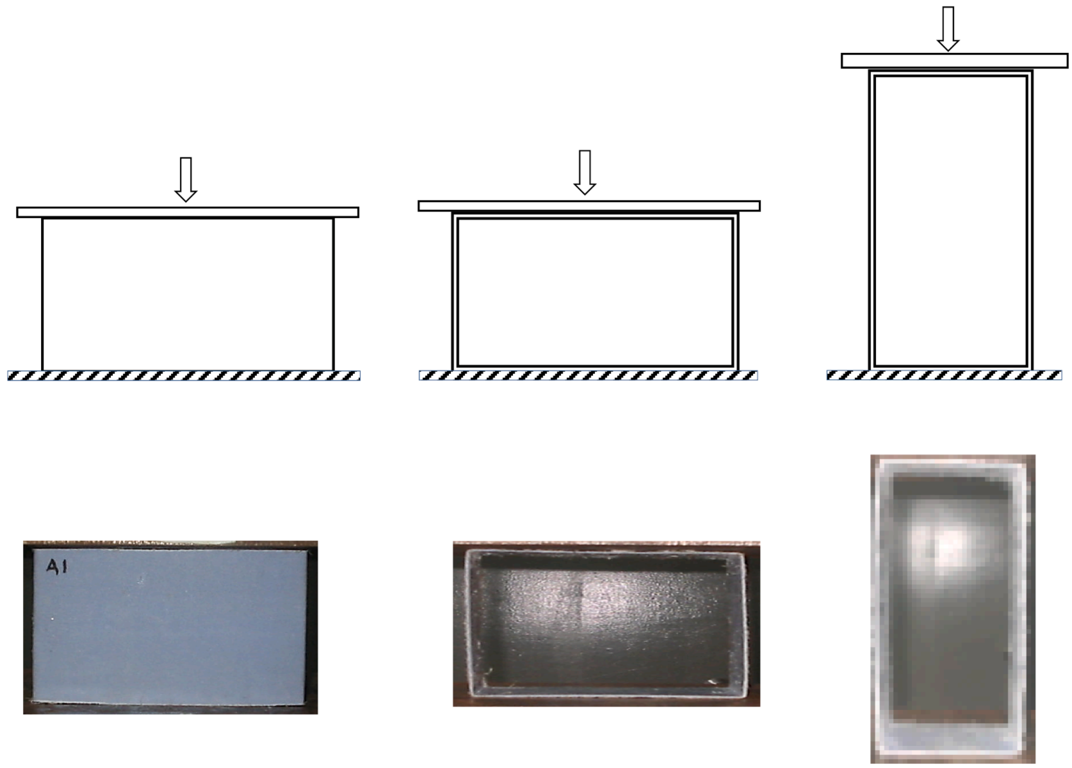

Fig. 1a. Loading conditions (i) axial crushing, (ii) A-side lateral crushing, and (iii) B-side lateral crushing.

Table 1a
Geometric description of the cotton/epoxy rectangular tubes.

ID	Length, a (mm)	Width, b (mm)	Aspect ratio, a/b	Mass, M (g)	Area, A (m^2)
A	153	153	1.00	105.667	0.001177
B	165	140	1.18	102.367	0.001173
C	180	126	1.40	103.863	0.001177
D	193	114	1.67	102.323	0.001181
E	208	98	2.00	115.167	0.001177

Predictive data-driven models can make the computer-aided production of natural fiber composites easier. Artificial Neural Networks application (ANNs) has been considered a common method of defining nonlinear systems [14–16]. ANNs exceed other nonlinear techniques of system recognition, like fuzzy systems or evolutionary algorithms, when an industrial system model is complicated yet typically requires a less powerful computing approach [14]. ANNs are powerful machine learning adaptive algorithms that enable users to develop complicated relationships between nonlinear variables [17,18]. The neural network recognition model (identifier) understands the uncertain mechanism as the training progresses [16]. Thus, it removes the need for physical modeling, learning by instances, called data-driven modeling. This benefit makes ANN machine resources very attractive in engineering applications where the problem is scarce or incomplete, but experimental measurements are readily accessible [7,8,19–32].

Nonetheless, the application of ANN models to forecast cotton reinforced composite fiber structure is relatively limited. In composite materials, ANN models were used to forecast particular characteristics and not to predict the configuration of composite materials. However, Kazi et al. showed lately that the ANN model could estimate the optimum filling content of cotton fiber while achieving the targeted mechanical objectives [4], and this sort of method can be widely applied to different materials and circumstances, as long as required experimental data are provided.

The work presented here intends to demonstrate how machine learning algorithms like ANN can develop an intelligent system to produce a fiber-intensified composite material that meets the required crash resistance quality while using a minimum set of experimental work. The predictive ANN models and methodology are intended to assist future material designers in considering composites laminated with cotton fiber/epoxide as an adjustable energy absorber in diverse applications. In particular, the model will minimize the experimental characterization efforts.

2. Research statement

Designing automotive body structures under dynamic loadings is crucial to achieving maximum safety [33]. Research engineers involved in the automobile, aircraft, spacecraft, and nuclear industries have given considerable attention to enhancing energy absorbing capacities and stroke length per unit mass using composite structures to absorb more energy and provide safety for passengers [11,12,34–37]. The geometry of the composite structures has been recognized as a crucial parameter that plays a significant role in load-bearing and energy absorption. Nevertheless, obtaining this optimal shape by tests alone is complicated and lengthy, mainly because of the lack of a good connection between crash resistance characteristics and the materials' geometry. This limitation can be overcome by leveraging machine learning algorithms like ANN to establish a relationship between these nonlinear attributes and identify the targeted mechanical properties through minimal experimental efforts.

Hence, the study aims to examine the crashworthiness performance of composite rectangular tubes using experimental and artificial neural network techniques for advanced industry 4.0 applications under different loading conditions through quasi-static crushing tests and machine learning algorithms. Three loading conditions are applied to test the rectangular tubes with five different cross-sectional aspect ratios during the quasi-static crushing test, as shown in Fig. 1a. The first condition is the axial crushing (Ax), while the second and third are the A-side lateral crushing (ALt) and the B-side lateral crushing (BLt),

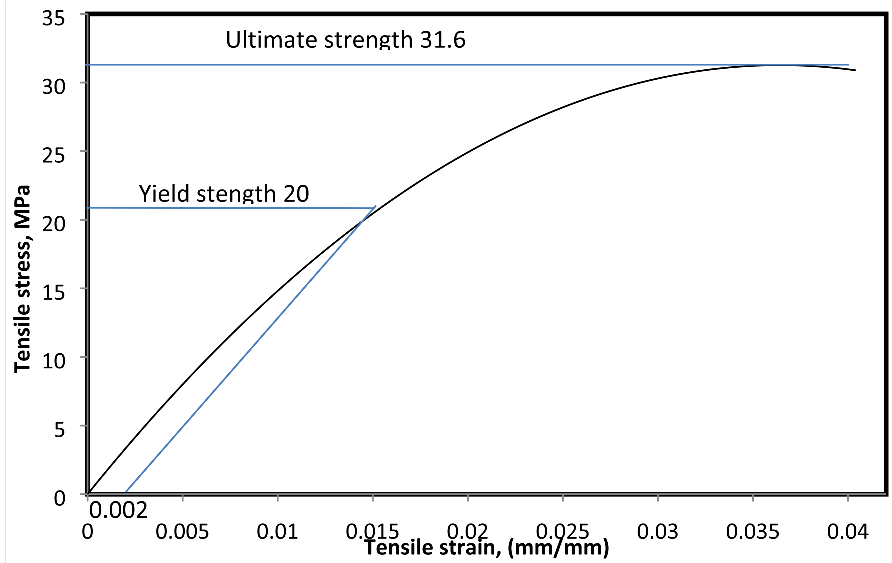

Fig 1b. Tensile stress–strain response of cotton fiber-reinforced composite.

Table 1b
Tensile test specimen data for cotton/epoxy.

Young's modulus (GPa)	Yield strength (MPa)	Ultimate strength (MPa)	Fracture strain mm/mm	Resilience (kJ/m^3)	Toughness (kJ/m^3)
1.46 ± 8e-2	20.5 ± 1.6	31.6 ± 1	0.04 ± 1e-3	168.5 ± 4	876.6 ± 4

respectively. Thus, the samples investigated in this research are rectangular tubes with five different cross-sectional aspect ratios (a/b), ranging from 1.0 to 2.0, as shown in Table 1a.

The objective is to build predictive ANN models that can forecast the best cross-section aspect ratio (a/b) for each crushing behavior while meeting the mechanical characteristics specified in Table 3. In choosing these targeted crashworthiness properties, it was assumed that designers are trying to maximize the parameters based on the initial experimental values obtained, and it should be flexible enough to find the optimum composite structure based on the designer/manufacturer's requirements. The ANN models are trained based on the sample experimental data of five different cross-sectional aspect ratios (a/b) shown in Table 1a to form a correlation between mechanical properties. Such a model will support intelligent product designers by reducing the need to conduct physical experiments for all aspect ratios (Fig 1b).

3. Experimental program

3.1. Material investigated

The rectangular tubes' wall was made from woven cotton fiber/epoxy resin composite, with six layers of cotton fiber on each specimen. The ratio of epoxy hardener to epoxide resin was 17 parts to 100 parts. Therefore, a single 300 mm high rectangular tube required about 250 ml epoxy resin and 3657.6 mm × 300 mm of cotton cloth. The tensile behavior of cotton fabric (0/90o) reinforced epoxy was carried out using an MTS machine (Fig. 1b). ASTM D 638-0215 was used for determining

Table 2
Crashworthiness parameters of cotton fiber composite rectangular tubes.

ID	a/b	Initial Crush Load (kN)	Average Crush Load (kN)	Total Energy Absorbed (J)	Specific Energy (kJ/kg)	Crush Force Efficiency (kN/kN)	Stroke Efficiency (mm/mm)
Axially Loaded Tubes							
AA	1.00	5.410	3.224	255.900	2.422	0.596	0.866
BB	1.18	5.421	2.919	237.175	2.317	0.539	0.890
CC	1.40	3.533	2.005	157.830	1.520	0.567	0.882
DD	1.67	5.324	2.804	220.469	2.155	0.527	0.876
EE	2.00	6.025	3.295	271.808	2.360	0.547	0.874
FF	2.57	4.795	2.540	206.633	2.059	0.530	0.901
Laterally crushed Rectangular Tubes on Side "A"							
AA	1.00	0.193	0.241	35.192	0.333	1.247	0.953
BB	1.18	0.247	0.280	37.799	0.369	1.136	0.963
CC	1.40	0.261	0.309	36.942	0.356	1.187	0.947
DD	1.67	0.210	0.169	18.547	0.181	0.803	0.964
EE	2.00	0.109	0.132	12.173	0.106	1.216	0.941
FF	2.57	0.249	0.235	17.934	0.179	0.943	0.953
Laterally crushed Rectangular Tubes on Side "B"							
AA	1.00	0.374	0.363	54.117	0.512	0.970	0.974
BB	1.18	0.351	0.352	52.776	0.516	1.003	0.908
CC	1.40	0.313	0.307	46.095	0.444	0.981	0.833
DD	1.67	0.202	0.230	41.384	0.404	1.142	0.932
EE	2.00	0.261	0.288	56.825	0.493	1.100	0.950
FF	2.57	0.249	0.254	52.499	0.523	1.020	0.908

Fig. 2a. Effect of Aspect Ratio (a/b) on the Load-Displacement Curve of axially Crushed tubes.

Fig. 2b. Crushing history of axially crushed tubes with different aspect ratios.

their tensile strength. Table 1b summarizes the results obtained from a tensile test in the longitude fiber direction of cotton/epoxy.

3.2. *Quasi-static crushing test*

The static crushing test was carried out on a universal hydraulic servo machine of the MTS series with a load-carrying capacity of 100 kN. Before the test was carried out, steel platens were paralleled. All specimens were crushed at a 15 mm/min speed up to 95% of their initial length. The machine computerized data acquisition system automatically recorded Load-displacement curves. Three replicate tests were done to obtain an average result. In addition, photographs of the specimen under loading were taken to provide the history of their crushing process (see Fig. 2b, Fig. 3b and Fig. 4b). Table 2 lists the experimental values of crashworthiness parameters of cotton fiber composite rectangular tubes under axial crushing (Ax), A-side lateral crushing (ALt), and B-side lateral crushing (BLt).

3.2.1. *Crushing history of axially crushed tubes*

The load–displacement behavior and crushing history of axially crushed tubes with different aspect ratios are shown in Figs. 2a and 2b, respectively. All axially crushed specimens with different aspect ratios were observed to absorb the energy in a progressive failure mode. The curve reveals that tubes initially resist the applied load linearly as an elastic material. As a result, the tube walls deflect inward at the B-side, deflecting outward at the A-side. This deflection was noticed as a drop in

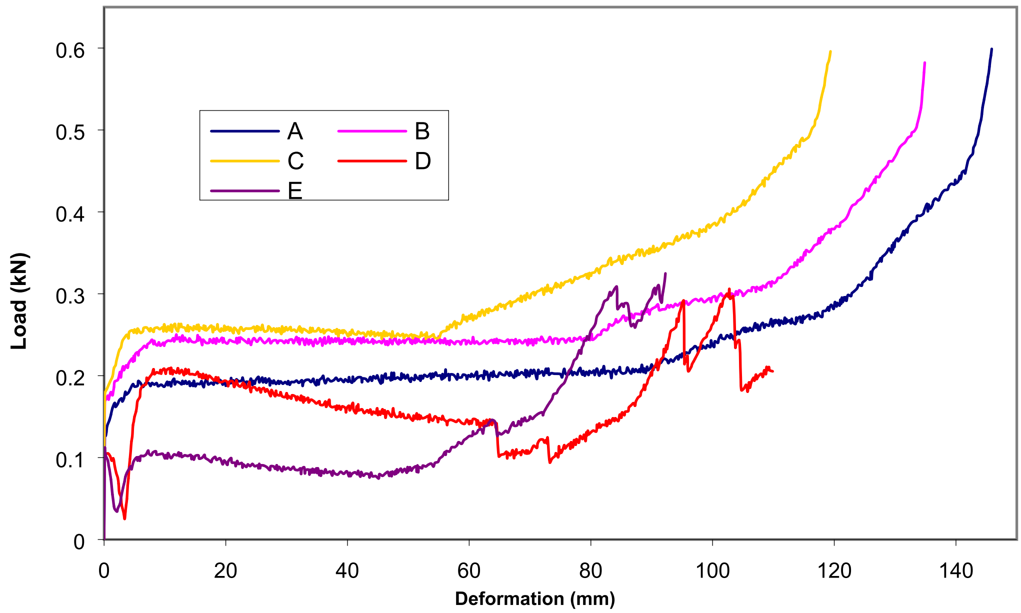

Fig. 3a. Effect of aspect ratio (a/b) on the load–displacement curve of laterally crushed tubes.

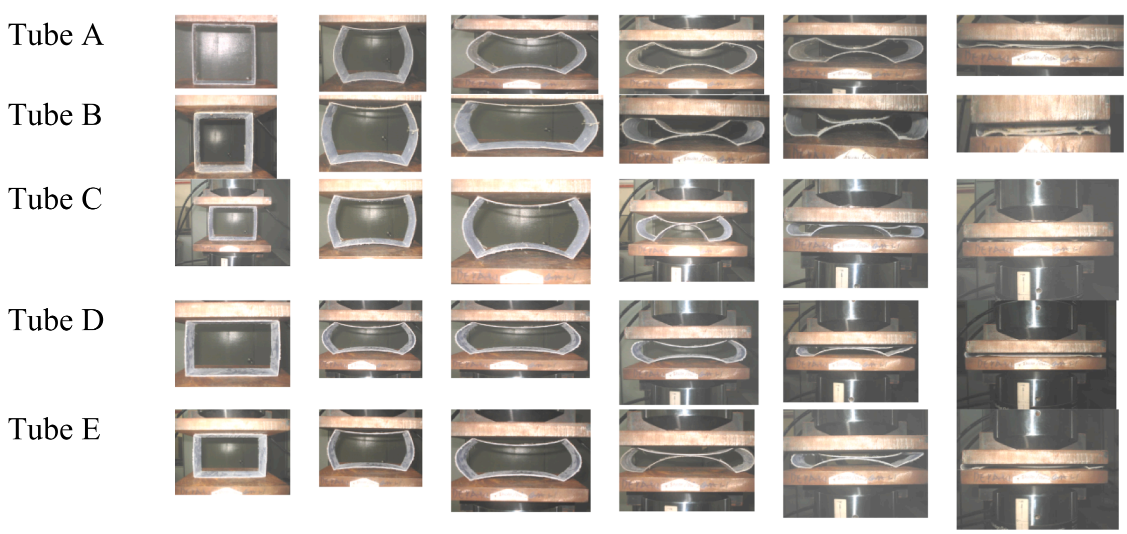

Fig. 3b. Crushing history of laterally crushed rectangular tubes on Side “A”.

the load–displacement curve. As loading proceeded, the tube kept collapsing progressively, and matrix cracking began to occur. The continuation of the compression load caused local buckling to occur at the top end and shear at the corners of the tube. In addition, the folding mechanism and hinges formulation-like metals were observed. This highly resilient and elastic properties of cotton caused a hybrid failure mode in cotton/epoxy composite tubes. The load–displacement curve continues to decrease till compaction of the tube occurs, where it starts increasing rapidly.

3.2.2. Crushing history of laterally crushed tubes on sides “A and B”

The load–displacement behavior of laterally crushed specimens differs from that of axially crushed specimens. Figs. 3a, 4a and 3b; 4b represent the load–displacement curves and the crushing history of laterally crushed cotton/epoxy composite tubes, respectively. The load–displacement curves for all laterally crushed specimens, regardless of which side, follow similar trends. When the compression process was started, the tube immediately began deforming without excessively resisting the applied load. Hence, the curve does not show a clear initial peak and drop, like axially loaded specimens. The upper and bottom surfaces of the tube, in contact with loading plates, can be seen as beams loaded along the whole length by a uniform distribution of the load. This load of compression causes the beams to bend and columns to buckle. With the compression progress, the contact area gradually decreases until only the corners contact the plate. As the distortion advances, the tube columns constantly move outwards due to the heavy arm (a continuous rise in the distance between the load and centroid point of the distorting column). The compression causes the buckling of the vertical side to progress until it becomes almost flat and comes in contact with the platen. The load–displacement curve tends to increase when the top and bottom sides contact each other. Continuing deformation causes the side walls to crack at a mid-height, clearly seen as a sudden curve drop. Finally, because of tube compaction, the load displacement starts increasing rapidly.

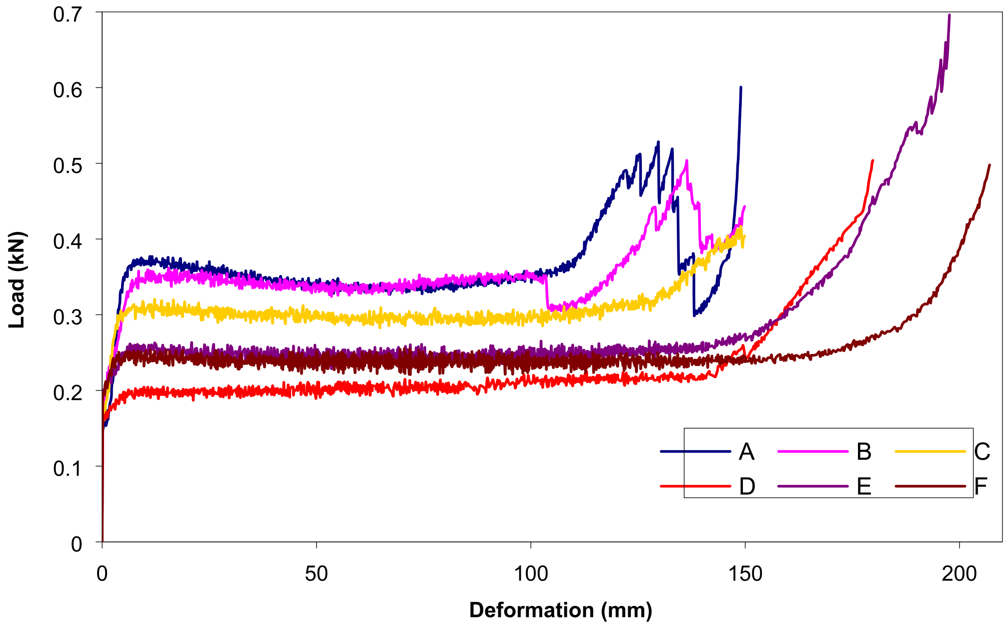

Fig. 4a. Effect of aspect ratio (a/b) on the load–displacement curve of laterally crushed tubes.

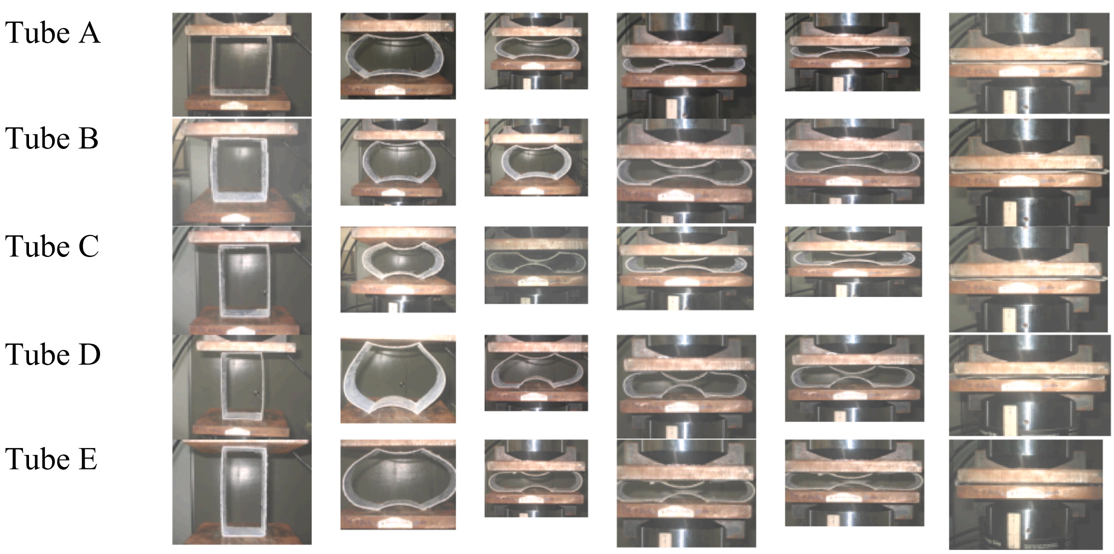

Fig. 4b. Crushing history of laterally crushed rectangular tubes on Side "B".

Table 3
Targeted crashworthiness properties and their values for an automotive application.

Targeted crashworthiness parameters	Axial crushing	A-side crushing	B-side crushing
Initial crush load (kN)	6.025	0.261	0.374
Average crush load (kN)	3.295	0.309	0.363
Total energy absorbed (J)	271.808	37.799	56.825
Specific energy (kJ/kg)	2.422	0.369	0.516
Crush force efficiency (kN/kN)	0.596	1.247	1.142
Stroke efficiency (mm/mm)	0.901	0.964	0.974

The maximum values of each targeted crashworthiness property are summarized in Table 3 from the experimental results listed in Table 2. These values are set as the targeted crashworthiness properties for the desired automotive application in this work. It is assumed that designers are willing to obtain the maximum crashworthiness performance for each type of loading condition in their end-use.

4. Configuration of ANN models

4.1. The necessity of machine learning algorithm

The findings of experiments showed that the cross-sectional aspect ratio substantially influenced the load transport and energy absorbance capacity. However, the sample tubes' crashworthiness parameters (e.g., initial crush load, average crush load, total energy absorbed, specific

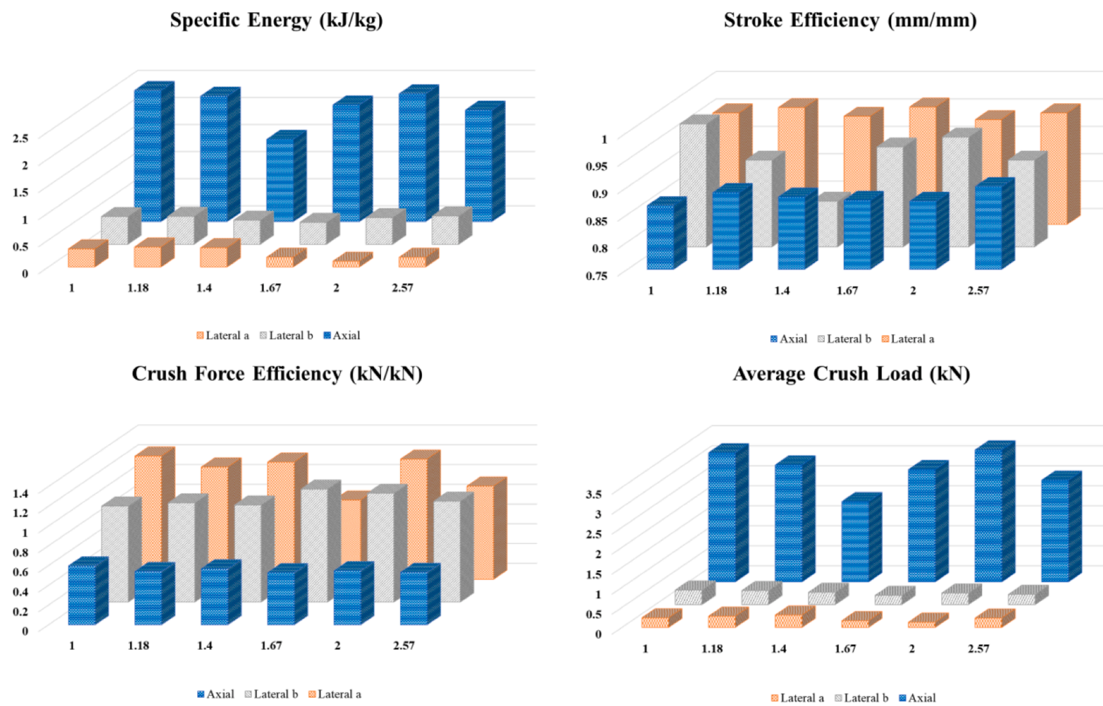

Fig. 5. Nonlinear nature of crashworthiness parameters of cotton fiber composite rectangular tubes for different aspect ratios under different loading conditions.

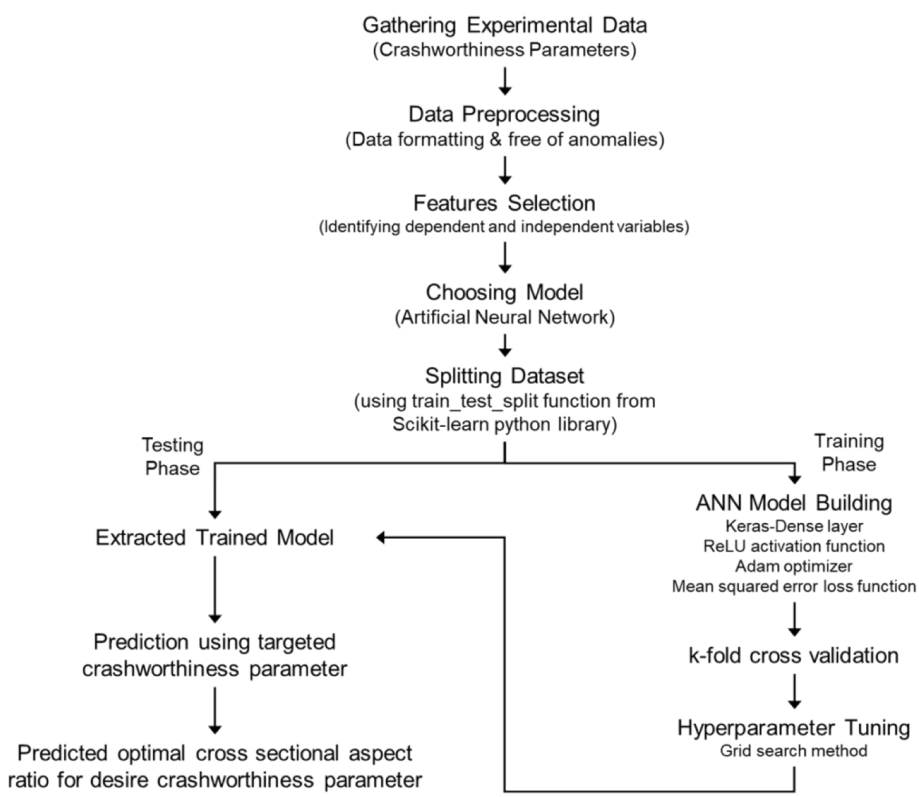

Fig. 6. Proposed methodology to develop predictive ANN models.

energy, crush force efficiency, and stroke efficiency) showed nonlinear and conflicting behavior (see Fig. 5). For example, the initial crush load of the tested axially loaded tubes has no direct pattern when increasing the aspect ratio. Furthermore, the relationship between initial crush load and aspect ratio is not similar for lateral loading conditions. The same is true for other parameters in the other loading conditions. The conflicting nature of the properties (as seen in Fig. 5) makes it difficult to predict an accurate composite structure at the desired maximum crashworthiness performance. Hence, ANN is used to develop an enhanced machine learning method that can provide insights into the complicated relationship among those parameters and for the effective design of the composite materials.

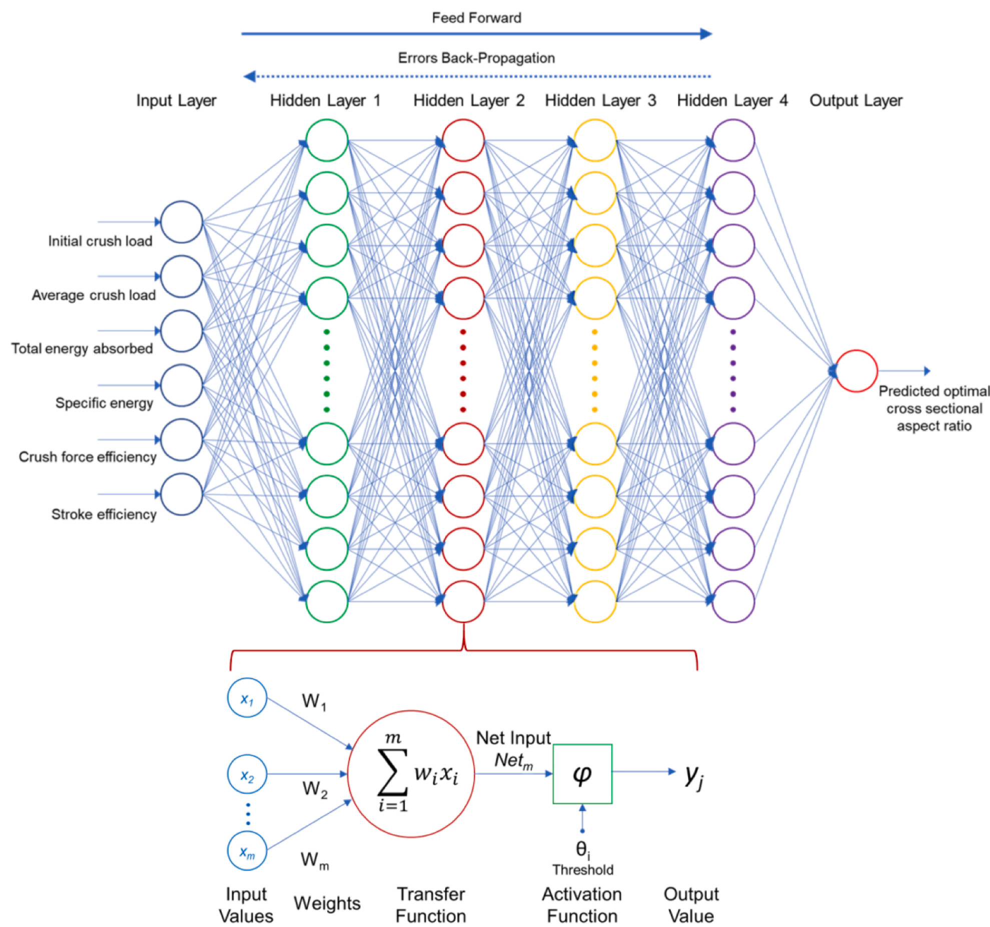

Fig. 7. The structure of the ANN models stacked to forecast the best cross-sectional aspect ratio.

Table 4
Model validation of ANN Model-1.

Crushing types	The aspect ratio of the real sample	ANN predicted aspect ratio				
		Prediction 1	Prediction 2	Prediction 3	Prediction 4	Prediction 5
Axial crushing	1	0.995	1.008	1.007	1.002	1.015
	1.18	1.269	1.207	1.234	1.268	1.228
	1.4	1.403	1.412	1.422	1.418	1.412
	1.67	1.685	1.66	1.653	1.678	1.672
	2	2.016	2.015	2.042	2.032	2.018
Train score		1.09×10^{-04}	7.56×10^{-05}	3.92×10^{-04}	1.97×10^{-04}	7.82×10^{-05}
Test score		0.0019	2.55×10^{-04}	0.0012	0.0021	6.83×10^{-04}

Table 5
Model validation of ANN Model-2.

Crushing types	The aspect ratio of the real sample	ANN predicted aspect ratio				
		Prediction 1	Prediction 2	Prediction 3	Prediction 4	Prediction 5
A-side crushing	1	1.031	1.071	0.999	1	1
	1.18	1.215	1.259	1.18	1.18	1.18
	1.4	1.428	1.471	1.4	1.4	1.4
	1.67	1.683	1.703	1.67	1.67	1.67
	2	2.008	2.023	2	2	2
Train score		5.26×10^{-04}	0.0028	1.84×10^{-11}	4.94×10^{-11}	4.31×10^{-08}
Test score		6.63×10^{-04}	0.0037	1.99×10^{-07}	5.11×10^{-08}	1.97×10^{-08}

4.2. Strategic steps for ANN models development

Three separate artificial neural networks (ANN) models are developed for predicting the optimal aspect ratio for the three types of loading conditions, achieving the targeted crashworthiness parameters (referred to in Table 3). Model-1 was for axial crushing, Model-2 was for A-side lateral crushing, and Model-3 was for B-side lateral crushing. Traditional regression/optimization methods were not suitable for such prediction

Table 6
Model validation of ANN Model-3.

Crushing types	The aspect ratio of the real sample	ANN predicted aspect ratio				
		Prediction 1	Prediction 2	Prediction 3	Prediction 4	Prediction 5
B-side crushing	1	0.999	1	1	0.996	1.013
	1.18	1.182	1.18	1.18	1.187	1.199
	1.4	1.4	1.4	1.4	1.397	1.398
	1.67	1.67	1.67	1.67	1.670	1.681
	2	2.001	2	2	2	2.014
Train score		2.99×10^{-06}	1.25×10^{-12}	8.89×10^{-11}	2.66×10^{-08}	2.72×10^{-04}
Test score		1.10×10^{-06}	3.97×10^{-11}	1.26×10^{-10}	1.64×10^{-05}	1.53×10^{-04}

due to the data point limitation. Therefore, a supervised machine learning algorithm like ANN was the choice. ANN model with suitable hidden layers simplifies the work because the hidden layers are neurons conditioned to the proper weight and activating function using the suitable learning algorithms – the critical elements in an ANN model. Neurons usually have an adjustable learning weight. The weight in every link enhances or reduces the signal intensity. In addition, neurons may possess a threshold to signal if the overall signal crosses the threshold. As ANN aims to imitate the way people learn, it works as an adaptive data processing system that may modify the topology of their network or internal information that flows over the training phase. The convergence theorem confirms the neural network's perfect architecture, depending on the selection criterion (such as mean squared error loss function).

The strategic steps for designing the ANN models and efficiency tests are outlined in Fig. 6. The three main phases of any machine learning activity are followed to create an ANN model based on the collected experimental and material characteristics data: (1) pre-processing data, (2) prediction model construction and training, and (3) model validation by compliance with training dataset validation and assessment for the pre-trained test dataset. The detailed stepwise description of the ANN model configuration is available in our previous publications [2–4]. The same procedures are followed here to finalize our predictive ANN models.

The key challenge with the model was to design the suitable architecture (i.e., the number of hidden layers, epoch, batch size, etc.). The developed models' parameter values (i.e., node weights, bias, etc.) were learned from the forward and backpropagation algorithms. The objective of training a neural network was to find a very complex function (i.e., activation function) that mapped one set to another; the set and mapping depended entirely on the problem we were trying to solve.

The lower part of Fig. 7 shows a neural element and a relation between the input vector x_i^m and output vector y_j^{m+1}. The structure of a single node consisted of inputs, weights, and bias. In the learning process, these parameters were changed to produce the complex function which solves the problem. The model for ANN was made with the TensorFlow's Keras-Dense layer. Dense carried out the procedure in the following way:

$$Output = activation(dot(input, kernel) + bias \tag{1}$$

$$y_j^{m+1} = \varphi\left(\sum_{i=1}^{m} w_{ij}^n x_i^m\right) + b_{ij} \tag{2}$$

where the *input* was an input-data function, *activation* meant an element-wise activation function passed as the activation argument, the *kernel* was a weights matrix created by the layer, the *dot* represented the numpy dot product of all input and its corresponding weights, and *bias* was a bias vector created by the layer (only applicable if use_bias was True). The rectified linear unit (ReLU) activation function was used during the layers' construction. ReLU was a well-used, robust estimator that could simultaneously activate all neurons. Here defines the ReLU activation function:

$$f(x) = 0; for x < 0 \tag{3}$$

$$f(x) = x; for x \geq 0 \tag{4}$$

During compiling the model, both 'adam' and 'rmsprop' optimizers of TensorFlow were tested, and 'mean_squared_error' (MSE) was used as the loss function. An optimizer is a tool that will update the weights to minimize the errors by backpropagating the loss into the neural network. The optimal iteration and regression were taken into account with MSE values.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y - \hat{y})^2 \tag{5}$$

where y was the measured output and ŷ was the predicted output of the training or test dataset. The error was minimized by the shift in weights as follows:

$$\Delta w_{ij}^n = -\eta \frac{\partial MSE}{\partial w_{ij}^n} \tag{6}$$

where η was the learning rate, the optimum number of the ANN structure (number of neurons, number of hidden layers, activation function) was achieved by the hyperparameter tuning method.

While developing three separate models, the ANN architectures (i.e., number of hidden layers and number of neurons in each layer) were kept identical to extract some added benefits later. It will allow researchers the freedom to merge these three models to further investigate the best results in crushability in all types of scenarios. Note that the same ANN architectural design does not confirm the same model because of the different combination of node weights, bias values, transfer function, and activation functions among the nodes depending on their nonlinear interactions (see Fig. 7).

Nevertheless, numerous additional parameters have been modified to direct the learning phase, known as the hyperparameter (e.g., choice of the optimizer, type of activation function, number of k-fold cross-validation). These hyperparameters must be adjusted to enable the model to resolve the specified master learning problem better. Here, TensorFlow was utilized to discover the proper model architecture with the grid search hyperparameter tuning approach.

The model for ANN was made with the TensorFlow's Keras-Dense layer. The optimum structure of the ANN models derived using the given concept consists of six input neurons in the input layer, four hidden layers, one output layer, and two hundred neurons in each hidden layer. It was challenging to identify the right combination of hidden layers and their neurons with minimal error and the highest accuracy while constructing the neural network. The 'train_test_split' function (part of the Scikit-Learn python data science library) was used for splitting data arrays into two subsets: training data (80%) and testing data (20%). During the development of the layers, the rectified linear activation unit (ReLU) function was utilized. In compiling the model, both 'adam' and 'rmsprop' optimizers of TensorFlow are tested, and 'mean_squared_error' (MSE) is used as the loss function. An optimizer is a tool that will update the weights to minimize the errors by back-propagating the loss into the neural network. During training, the dropout method was utilized to avoid the overfitting problem.

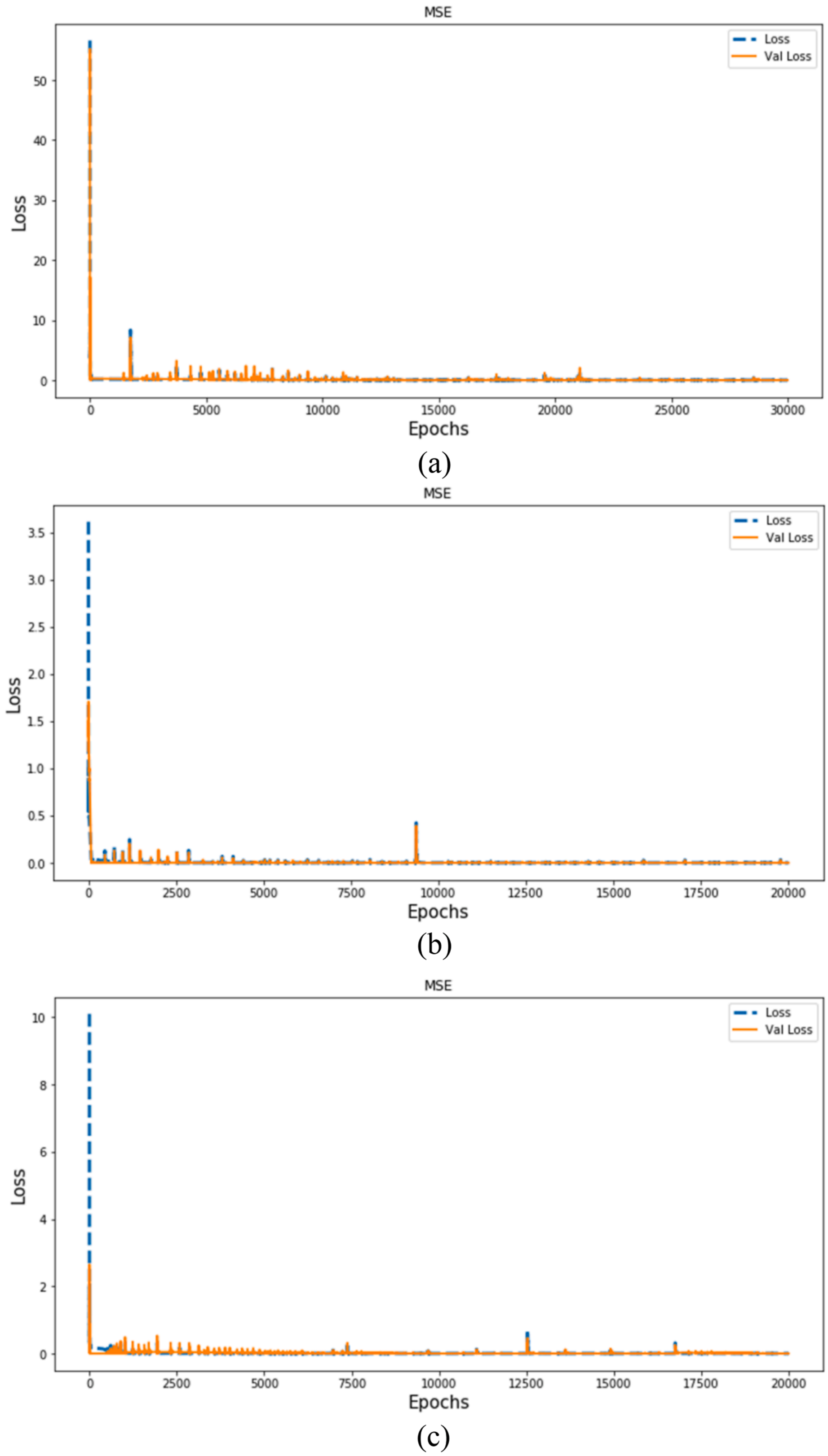

Fig. 8. Improved loss functions values throughout the epochs for (a) axial crushing, (b) lateral A-side crushing, and (c) lateral B-side crushing during prediction 1.

The generated ANN models are evaluated during the prediction phase to forecast the optimum aspect ratio for axial crushing, A-side crushing, and B-side crushing independently to reach specified crashworthiness parameters. Those models are tested numerous times to verify the precision and reliability of the optimum sample configuration produced. The precise models are also evaluated based on train and test scores. Sections 5.1 and 5.2 provide comprehensive results.

Table 7
Robustness of predicted optimal aspect ratio for targeted crashworthiness parameters using the developed ANN models.

Crushing types	Predicted aspect ratio (a/b)					The average predicted aspect ratio (a/b)	Standard deviation (σ)
	Prediction 1	Prediction 2	Prediction 3	Prediction 4	Prediction 5		
Axial crushing (ANN Model-1)	1.814	1.742	1.785	1.806	1.766	**1.783**	±0.026
A-side crushing (ANN Model-2)	1.407	1.452	1.378	1.374	1.360	**1.394**	±0.033
B-side crushing (ANN Model-3)	1.393	1.398	1.431	1.392	1.383	**1.399**	±0.016

The bold values are the average predicted aspect ratio of the five predictions.

5. Results and discussion

5.1. Performance evaluation of ANN Model-1

ANN Model-1 was developed to capture the nonlinear relationship of the crushing load, energy absorption, specific energy, and stroke efficiency of the rectangular tubes subjected to axial crushing. After training the Model-1 using the experimentally measured property values, the developed model's performance was validated by comparing the predictive aspect ratio with the actual aspect ratio of the samples (ranging from 1 to 2 in the random interval as per the experimental procedure). The model's accuracy is tested at least five times for each forecast and to determine if the model was under/over fitted or not. In Table 4, the summarized prediction results are given for the axial crushing. The predicted aspect ratio by the ANN Model-1 was not rooted to any specific value, which implies that the model was not overfitted due to the higher number of neurons and hidden layer, which was crucial for this case. In addition, each type of prediction's training score and test score were very low, reflecting the higher accuracy of the developed model. Thus, the developed model was validated with the axial crushing experimental values. As the model was accurate enough to forecast the aspect ratio, the model's usefulness was improved by predicting the optimal aspect ratio for the rectangular tubes to reach the highest crash resistance (see section 5.4 for more details).

5.2. Performance evaluation of ANN Model-2

Similarly, ANN Model-2 was built using the same approach mentioned in section 4 for the lateral A-side. It was seen that ANN Model-2 could predict the experimental aspect ratio of the real samples when the experimental values of the crashworthiness parameters were used as the input. The loss function values for the testing and training phase were near zero (see Table 5), indicating high model precision. The fluctuations in the predicted values over multiple runs of the forecast reflected the model's flexibility, as it was not rooted in any specific training data point during the prediction phase. This Model-2 was used further to predict the optimal cross-sectional aspect ratio for the targeted crashworthiness performance.

5.3. Performance evaluation of ANN Model-3

ANN Model-3 is developed for the lateral B-side crushing of the considered composite structure. Like Model-1 and Model-2, it is validated using the experimental data. The accuracy of the Model-3 was satisfactory in terms of both training and testing scores (see Table 6). In addition, the experimental sample aspect ratio is predicted quite accurately using the developed model, and the model application is further explored by predicting the optimal configuration of the rectangular tubes.

In Fig. 8, loss function modifications are displayed across the epochs. The variation of loss-function values becomes small over epochs. Initially, the values of training loss and validation loss are more prominent for all situations; subsequently, ANN models can reduce the values of the loss function, which implies that the model can minimize the errors. This might be related to the stochastic nature of the ANN models; however, the algorithm reduces these fluctuations. Therefore, the model performance and the stop criteria must be carefully monitored and halted before steady results are achieved. For brevity, the loss function's progression over the epochs is shown only for one prediction, but a similar pattern was observed for all five predictive cases (prediction 1 to prediction 5 in Table 4, Table 5, and Table 6).

5.4. The optimal cross-sectional aspect ratio for targeted crashworthiness parameters

ANN models specified in Section 5.1, Section 5.2, and Section 5.3 have been stored into a disk using the Keras script, along with associated structural information (weights and bias values of the transfer functions for all nodes), which can be used further without performing the entire procedure. This technique optimizes the simulation and allows users to predict the optimal cross-sectional aspect ratio using the same ANN models. The optimal aspect ratio was found for each type of loading condition averaging five different predictions, listed in Table 7. For axial crushing, 1.783 was obtained as the optimal aspect ratio for the given properties. For the lateral A-side and B-side crushing, the values were found as 1.394 and 1.399, respectively. The standard deviation of the projected values for any particular load situation is relatively low (as shown in Table 7), showing that the models were efficient with the relationship formed between the studied mechanical characteristics. The time required for adjusting the hyperparameter and k-fold cross-validation was discovered to be quite challenging since the data points were low, while the number of neurons and periods was manipulated in order to identify the best ANN structure.

This ability to predict using the developed ANN models will be very useful for researchers or product designers that seek to identify the optimal configuration of the rectangular composite structure. They have the flexibility to adjust any particular mechanical property and see it affect the final result of crash strength.

6. Conclusion

In this work, three new ANN models have been developed in the TensorFlow backend using the Keras library in Python to predict the optimal cross-sectional aspect ratio of the rectangular tubes for three different crushing loads (e.g., axial crushing, A-side lateral crushing, B-side lateral crushing). The models are used to gain an insight into the nonlinear and conflicting behavior of the crashworthiness parameters. For this purpose, the effects of cross-sectional aspect ratio (five different cross-sectional aspect ratios (a/b), ranging from 1.00 to 2.00) of sample rectangular tubes on mechanical properties (i.e., load carrying and energy absorption capability) of cotton fiber/epoxy laminated composite have been investigated both by experiment and by the machine learning algorithm. The experimental results demonstrate that the cross-sectional aspect ratio impacts the load transport and energy absorption capacity substantially. The developed ANN models successfully predict the optimal aspect ratio for each loading condition (1.783 for axial crushing, 1.394 for A-side lateral crushing, 1.399 for B-side lateral crushing) with minimal errors (standard deviation was ±0.026, ±0.033, and ±0.016 for ANN Model-1, 2 & 3 respectively) based on their given targeted maximum crashworthiness parameters. The estimated optimal values are very much in line with the experimental insights pattern in terms of nonlinearity. Furthermore, the developed model allows the designer to evaluate any other values of the crashworthiness parameter within the training range to obtain the desired aspect ratio. This predictive model can benefit smart manufacturing and industry 4.0 applications using cotton fiber/epoxy laminated composite, ultimately reducing the manufacturing cost and time.

CRediT authorship contribution statement

Monzure-Khoda Kazi: Methodology, Software, Data curation, Validation. **Fadwa Eljack:** Supervision, Resources, Funding acquisition. **E. Mahdi:** Supervision, Resources, Validation.

Declaration of Competing Interest

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 paper.

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