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Enhancing Drilling Performance in Self-Healing Composites with Machine Learning Approaches

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ABSTRACT

Machining fiber-reinforced plastic (FRP) materials is a big challenge to overcome lot of difficulties in achieving adequate quality for better and acceptable range in assembling process. FRP machining is still a crucial step in achieving quick part assembly while maintaining exact geometric tolerances. However, a variety of machining-induced defects (like matrix -smearing, thermal deterioration and delamination) frequently occur because of the heterogeneous structure. In this paper 3-Gly-cidoxy-propyl-tri-methoxy-silane (KH560) treated carbon fiber-reinforced plastic (CFRP) laminate is investigation for delamination during drilling with L9 orthogonal array and experiments were created by selecting control elements that influence the delamination factor and maximum cutting force. Peel-up and push out delamination was carried out using microscope.1000 rpm cutting speed, 15 feed and 85^0 point angle showed to be optimum. Machine learning (ML) algorithms exhibiting exceptional performance and concluded Random Forest (RF) algorithms is better among others based on computational complexity.

Keywords: Carbon fiber delamination; CFRP drilling; Machine learning techniques; Predictive analysis

NOMENCLATURE

CFRP	: Carbon fiber reinforced polymer
ML	: Machine learning
BPNN	: Back propagation neural networks
RF	: Random Forest
KH560	: 3-Gly-cidoxy-propyl-tri-methoxy-silane
Fd	: Delamination factor
FRP	: Fiber-reinforced plastic
FESEM	: Field Emission Scanning Electron Microscope
ANN	: Artificial neural networks
NSGA-II	: Non-dominated Sorting Genetic Algorithm
GPR	: Gaussian Process Regression
SVM	: Support vector machines
Tg	: Glass transition temperature

1. INTRODUCTION

The intricate nature of CFRP drilling can result in catastrophic failure within the structure's real load-bearing capacity, as evidenced by disaster depicted from past damage. A quantitative assessment of layered damage can be based on simulation results, which can successfully forecast modes failure of materials during drilling[1]. The effect of feed rate on thrust force is greater. At increasing feed rate levels, greater thrust force was achieved. Furthermore, it is discovered that employing cryogenic drilling can reduce torque by up to 24.46 %[2]. The numerical models estimated peeling force effectively makes up for the drilling tests' limitations. At 135°, the peeling force reaches its peak, which causes significant peel-up delamination. Furthermore, calculated findings support the possibility of further developing the analytical model of delamination[3]. To predict delamination factor (Fd) drilling of CFRP laminates, establish a Gaussian process regression model. Feed, drill size, and speed are some variables used to find quality of the finished work piece for a wide range of machining operations[4]. The ANN model validates itself by displaying effective connection of trained and testing datasets. Most significant total variance among experimental and ANN projected Fd was determined as 1.46 % and 12.5 % for the training and testing respectively[5]. Feed is the most important continuous variable in cutting, independent of drill tool size and material thickness.

The thickness of the material is crucial if peel-up delamination occurs in the drilled composites. It is evident that when the feed increases, the delamination increases regardless of the material's characteristics or the size of the drill bit[6]. Three machine learning algorithms methods compared; it was determined that SVM had the greatest prediction performance. It required less samples and had good prediction exactness for discrete along with continuous location and size parameters. The FRP damaged beams were predicted ten times using "back propagation neural networks", "extreme learning machines, and support vector machines algorithms". The mean absolute errors of these predictions are 2.69 %, 1.55 %, and 1.22 %, while the accuracy of the interface predictions is

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33.33 %, 83.33 %, and 100 %[7]. Fd has been predicted using machine learning algorithms. Random forests, SVM, XG Boost, and linear regression models have all been compared and assessed using a range of KPIs. XG Boost produced the best forecast of all the models, and multiple KPIs were used to validate it. In terms of performance, the XG Boost model closely trails random forests. It was determined that when critical parameters for CFRP drilling process, XG Boost machine learning model performs the best in accurately predicting the Fd[8]. Delamination recognition in any laminate was developed using random forest and artificial neural network techniques. To accurately represent experimental data, FEM models with a variety of artificial noise were used to generate data even with 10 % noise in the input signals performs exceptionally well in predicting delamination of laminated composites[9].

Molecular traceless quadrupole moment and molecular average hexadecapole moment as input features, Gaussian Process Regression (GPR) model predicts glass Transition temperature (Tg) of polymers. This model exhibits excellent accuracy and stability, demonstrating the potential of GPR in comprehending and simulating the connection between Tg and basic quantum chemical parameters. It is adaptable and works with polymers that have Tg values that are both below and above room temperature[11]. Singular Spectrum Analysis (SSA) calculated a complete delamination damage prediction method using data from multiple sensors in drilling, including “force, torque, temperature, vibration, and hole exit”. SSA positive result on random removal export delamination that has been smoothed out, and the forecast error is decreased by more than 39 % when compared to the usual regression technique. The suggested approach generates time series prediction data utilized for the purpose of estimating the amount of delamination damage that will be caused by the hole that will be drilled[12]. ANN prediction of drilling response variable Both the push force and the exit-delamination force ought to be reduced. in CFRP drilling to guarantee the quality of the hole while ensuring that the Material Removal Rate (MRR) is raised for efficiency Increase overall performance, the parameters of the Non-dominated Sorting Genetic Algorithm (NSGA-II) are modified to fulfil the constraint requirement[13].

Prediction of crucial delamination situation in drilling of CFRP laminates utilizing two analytical CTF models presented with discrete cutting states, that is, up to the point when the drill actually makes contact with the laminate. There is an increase in both TC and T when the chisel edge length and feed rate are increased. Due to the fact that TC grows at a higher rate than T, the chisel edge is responsible for a significant portion of the thrust force and has a significant impact on cutting performance. Drilling at a reduced feed rate using a drill with a shorter chisel edge length might help reduce delamination. Variable feed rate drilling is a viable drilling approach for avoiding delamination while maintaining productivity[14]. Push-out delamination during laminate composite drilling is analysed experimentally and numerically. Based on experimental data, a more straightforward simulation model is created, and an explicit dynamic element method is used to simulate damage progression used to optical microscopy and X-ray computed tomography are used to assess damage evolution[15].

2. METHODOLOGY

CF 12K woven is used and bought from Toray Advanced materials-korea, resin Araldite LY-556 by Huntsman combination of Aradur HY-951. Silane treatment agent “3-glycidyl ether oxy-propyl-tri-methoxy-silane (KH560)” tensile strength of 515Mpa, tensile modulus 234, percentage of elongation 2.2 and density 1.79 kg/m3. Laminate is prepared with surface sizing by modifying surface using KH-560 silane treatment 5 % later hand lay-up process followed by vacuum bagging technique to solidify later post curing in autoclave.

2.1 KH-560 Treatment Progression

KH560 was dissolved in a mixed solvent consisting of a 95:5 weight ratio of ethanol and deionized water. KH560 solutions with 5 % is prepared. The pH of the afore mentioned solutions was adjusted to 5 with the addition of acetic acid to aid hydrolysis of silane coupling agent. Subsequently, the solutions treated a 60 min. ultrasonication. In water, KH-560 undergoes hydrolysis process to cause reactive silanol clusters, with methanol released as a byproduct. Silanol groups can undergo condensation with hydroxyl groups on surfaces of diverse inorganic materials (substrates or pigments/fillers) to establish chemical connections.

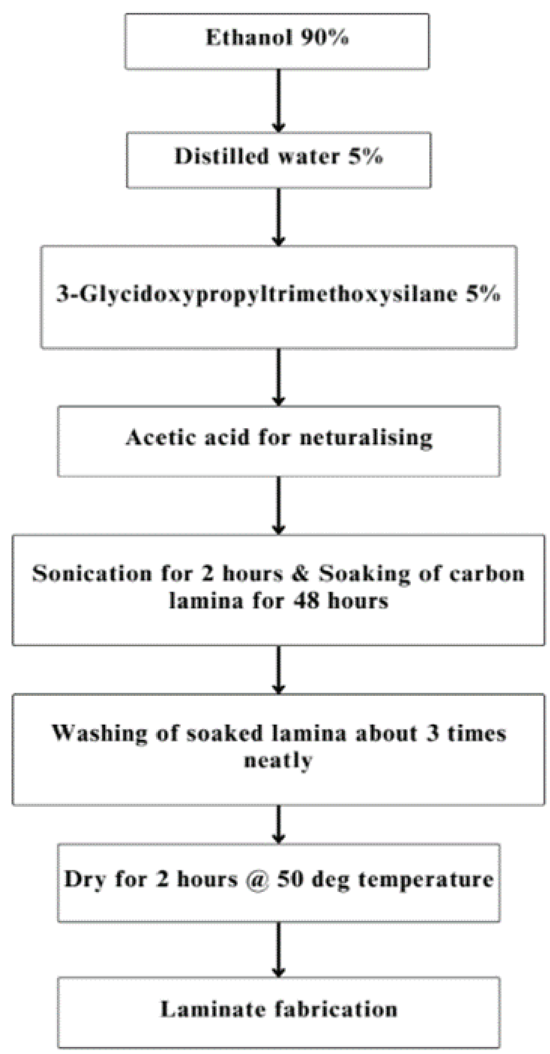
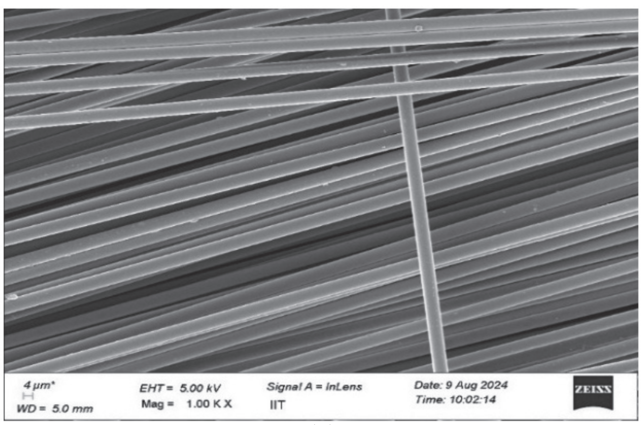


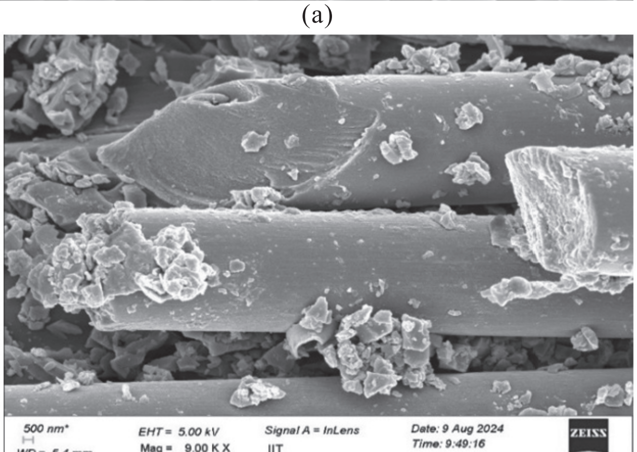
Figure 1. Methodology of KH-560.

Epoxy groups are catalyzed by acidic or basic conditions, allowing them to react with compatible polymers (containing primary amines, hydroxyls, carboxyl, epoxy groups, etc.), thereby facilitating the coupling and bonding between inorganic fillers and organic polymer materials through afore mentioned dual reactions. KH-560 self-healing materials mixes with polymers that possess self-healing functions via its epoxy groups, providing self-healing characteristics to materials. Precision control over material properties is possible by altering the amount of KH-560 and reaction conditions, allowing production of smart materials with specified procedure in Fig. 1.

Figure 2. Hand lay-up process.



(a)



(b)

Figure 3. (a) FESEM image of pre-fabrication; and (b) Post testing sample.

Figure 2 Illustrates hand lay-up set up for fabrication using vacuum bagging, adhering to a precise sequence: initial laminas are trimmed as per dimensions, followed by the calculation of the requisite number of laminas in accordance with ASTM testing standards.

From Fig. 3(a) represents fiber after Kh 560 treatment without fabrication in Fig. 3(b) shows laminate after testing for mechanical characterisation for its bonding behaviour. Surface included tiny, square and circular dendritic holes that seemed to be stiff, improving resin storage during the creation of polymer matrix. Upon fabrication in use of engineering applications sample needs to be either machined or drilled which is inevitable process due to errors in all criteria it may get catastrophic failure generally due to delamination.

Subsequently, the laminas are stacked with binders interspersed, and vacuum process commences until laminate is prepared. Upon testing for mechanical sustainability surface morphology of treated fiber is tested using Field Emission Scanning Electron Microscope (FESEM) at magnifications of 4 and 200 µm. Later machining operation is performed with drilling critical parameters considered from various literatures and developed DOE using Minitab Taguchi technique L9 orthogonal array as shown in Table 1.

Table 1. DOE(L9) orthogonal array

Experiment	Cutting speed (rpm)	Feed (mm/min)	Point angle (deg)
1	500	10	85º
2	500	15	118º
3	500	20	135º
4	750	10	118º
5	750	15	135º
6	750	20	85º
7	1000	10	135º
8	1000	15	85º
9	1000	20	118º

Drilling is carried on a BMV60+ TC24(mm) 3-axis vertical machining Centre VMC 285.5 mm (L) ×150 mm (W)× 3 mm (T), straight shank twist drill bit with two flutes post drilling hoemonitored and evaluated delamination factor using digital microscope of 5-megapixel camera.

3. RESULTS AND DISCUSSION

The effect of thrust force in Fig. 4 during drilling FRP materials, with varying drill diameter, spindle speed, and feed rate are studied and investigated and explained

From experimental analysis drilling parameters its effects on laminates resulted cutting speed and point angle plays a major role which directly effects delamination. The thrust force falls as the cutting speed rises from 500 rpm to 1000 rpm. Since too much force might result in fiber pull-out and delamination at the hole exit, lower thrust force often leads to lower delamination. Since there is less thrust force at higher cutting speeds, delamination is minimised.

The thrust force vs. point angle graph shows that increasing the point angle tends to marginally increase thrust force. While a wider angle may increase stress concentration, a lower point angle produces a sharper tool tip, reducing axial force and delamination. In order to minimize delamination, a lower point angle of 85° is preferable.

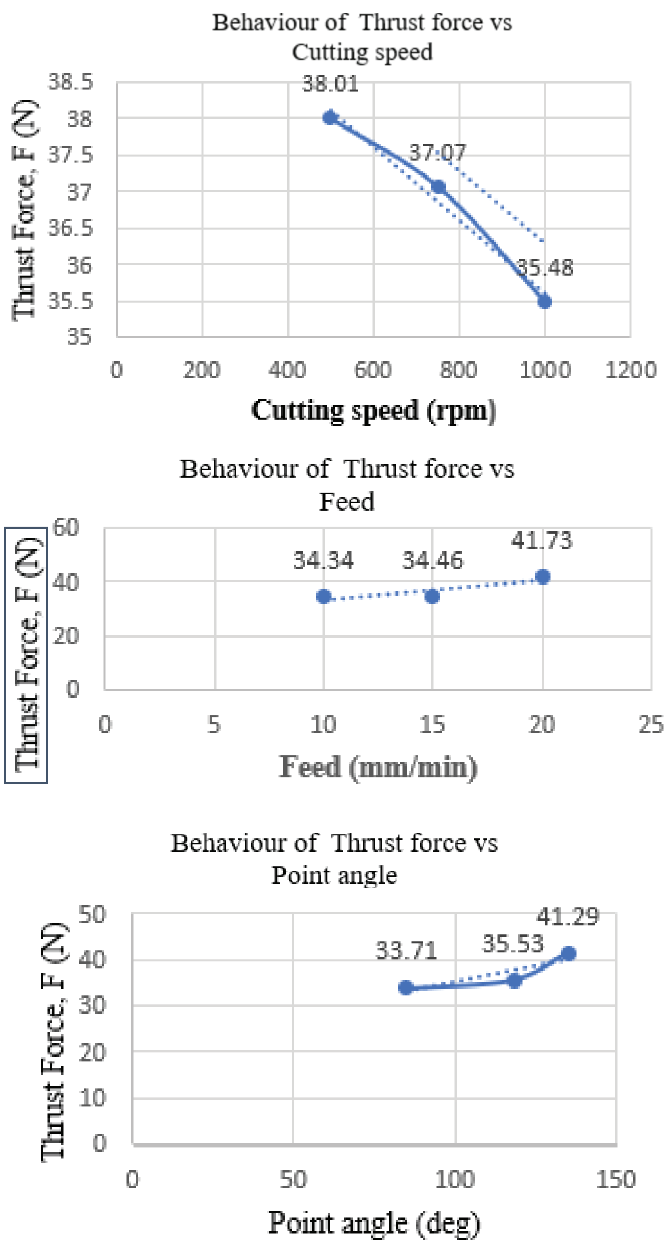


Figure 4. Cutting parameters versus thrust force.

An excessive amount of thrust force is produced by a high feed rate, which results in an increase in the amount of fiber push-out and hole damage. Delamination is reduced when feed rates are lowered to 10 mm per min.

The effect of torque in Fig. 5 during drilling FRP materials, with varying drill diameter, spindle speed, and feed rate are studied and investigated and explained.

A decrease in torque occurs whenever the cutting speed is increased. The torque is lowered when the cutting speed is increased, most likely because there is less friction and cutting resistance. When the cutting speed is increased to 1000 revolutions per min., torque is decreased, which results in smoother drilling and less tool wear. The higher the feed rate,

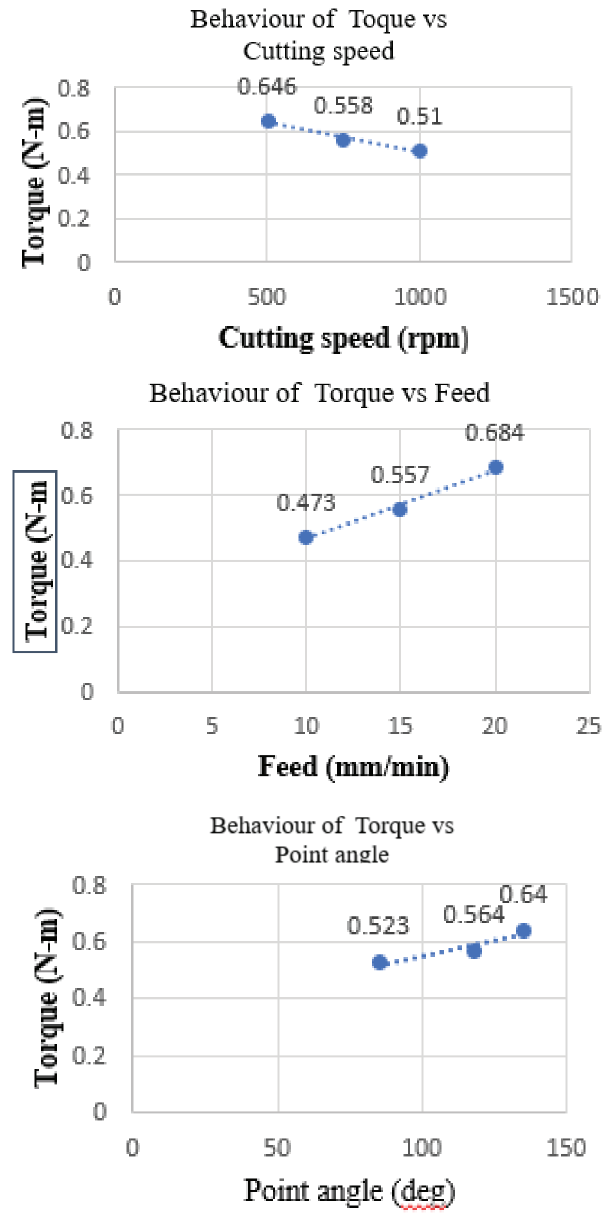


Figure 5. Cutting parameters versus torque.

the greater the cutting resistance, which in turn necessitates a greater amount of force in order to pierce the CFRP material. When the feed rate is reduced to 10 mm per min., torque is reduced, which in turn helps prevent excessive tool wear and damage. There is a reduction in torque when the point angle is smaller (85°), which makes drilling easier and more efficient.

From Fig. 6 it is concluded by increasing the cutting speed, amount of delamination reduces. Increased cutting speeds result in a reduction in thrust force, which in turn leads to a decrease in fiber pull-out and delamination. Delamination is increased when feed rates are increased. When the feed rate is increased, the thrust force also increases, which, as a result of excessive cutting pressure, makes delamination worse. Higher delamination is the result of a point angle that is lower (85°). Cutting forces are distributed over a wider region when the point angle is increased. This reduces stress concentration at hole exit, which in turn minimizes the amount of fiber breakage that occurs.

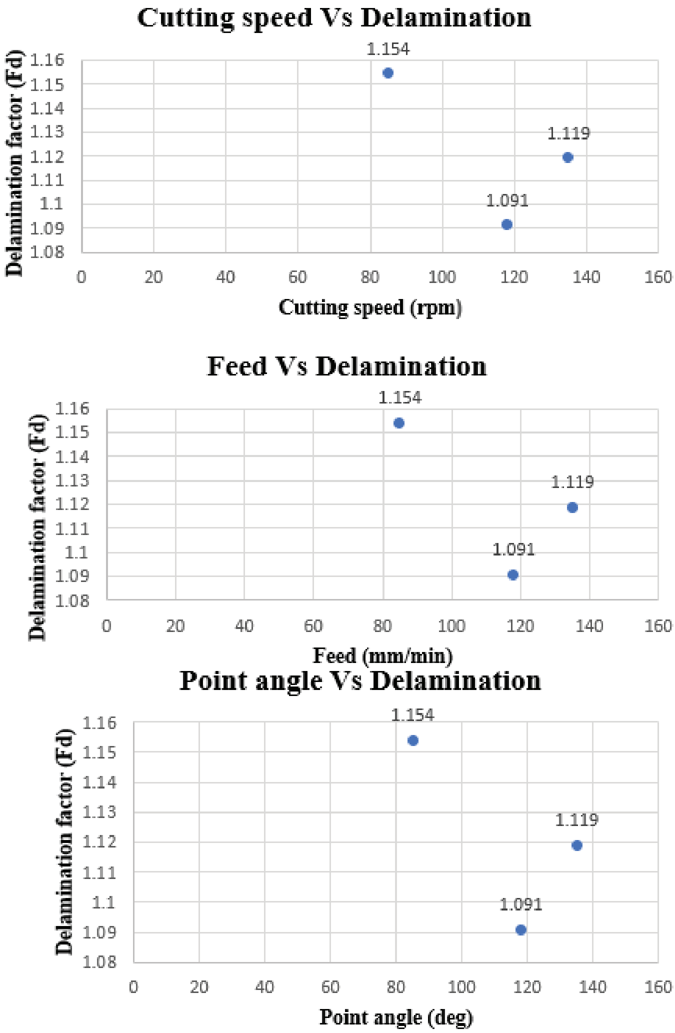


Figure 6. Delamination versus cutting parameters.

Table 2. Predicted values vs experiment values

Fd	RF	GB	ANN	XG B
1.11	1.10	1.10	1.12	1.10
1.12	1.12	1.12	1.12	1.12
1.13	1.13	1.13	1.12	1.13
1.04	1.05	1.05	1.04	1.04
1.21	1.21	1.21	1.21	1.21
1.21	1.21	1.21	1.22	1.20
1.02	1.02	1.02	1.02	1.02
1.01	1.01	1.01	1.01	1.01
1.12	1.13	1.13	1.12	1.12

4. MACHINE LEARNING ALGORITHM

Random Forest (RF), XG Boost, Gradient Boosting (GB), and Artificial Neural Networks (ANN), and process are showed in Fig. 6. Feed rate, point angle, and cutting speed are the independent variables lead to delamination. In ML collection of decision trees that were regularly trained using bagging process make up the "forest" it generates. The bagging method's basic concept is that more learning models lead to better outcomes. The hyperparameters of a RF are extremely like those of a decision tree or bagging predictor. GB is a method that creates decision trees iteratively, fixing the mistakes of the previous tree with each new one. The parameters that were set during training have a greater impact outcome. The three types of layers in an ANN are input, hidden, and output. Weighted connections bind every neuron in one layer to every other layer's neuron. These connections are altered in accordance with the input during training phase.

Thrust force and torque are important metrics in traditional drilling research, which mostly focuses on how process variables affect drilling forces and hole quality is tedious and iterative process which may not be effective.so, predictive analysis shown in Table 2.

Predictive analysis using RF shown in Fig.7 testing algorithm and training model testing R-squared (R2) values showed exceptional performance in predicting delamination with testing dataset R2 of 0.9882372 and training R2 of 0.9987537 and about 98.82 % of variance in testing dataset, indicating that it works extraordinarily well on unseen data, according to testing R2 value of 0.9882372.

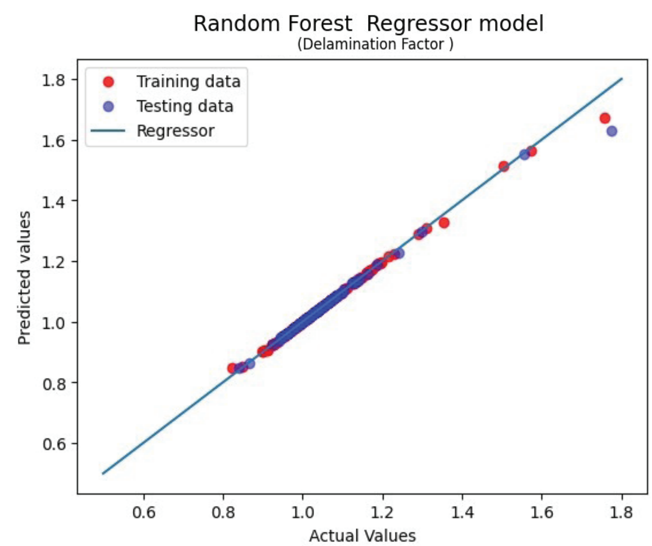


Figure.7 Actual Vs predicted delamination-RF.

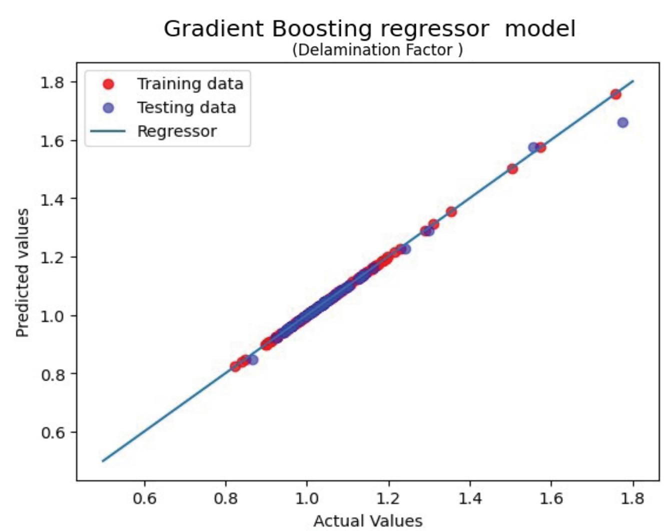


Figure 8. Actual vs predicted delamination-GB.

GB has testing R2 value of 0.9868453, model shows almost 98.68 % of variation in testing dataset, demonstrating its excellent performance on unseen data shown in Fig. 8.

XG Boosting algorithm requires more computational power to use, which increases overall cost of model but there is no significant performance improvement compared to other models shown in Fig. 9, so even XG boosting can solve more complex problems it is not economical for this experimental data for which required level of accurate predictions can be possible with other models.

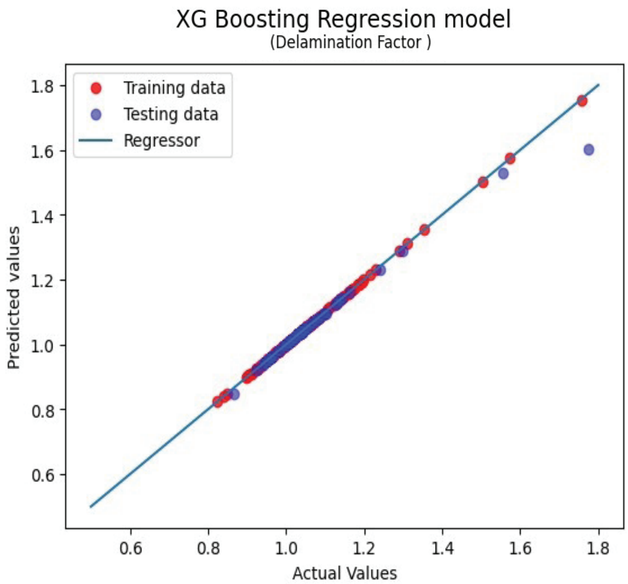


Figure 9. Actual vs predicted delamination-XGB.

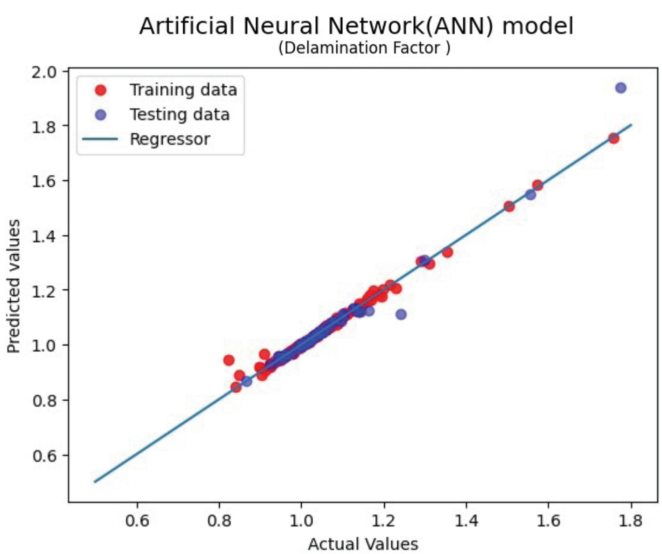


Figure 10. Actual vs predicted delamination-XGB.

The ANN model explains about 98.42 % of the variance in training data, indicating a good fit to the observed data points, according to the training R2 value close to 1. Almost 97.18 % of variation in testing dataset shown in Fig. 10.

5. CONCLUSIONS

This research focused on surface treated CFRP drilling with variable cutting parameters to find optimum delamination which is impossible to eliminate. Taguchi's L9 orthogonal array experiments were designed and investigated after machining using digital microscope, these inspected values are compared with ML algorithms and are as follows:

- Surface treatment of CFRP resulted best inter laminar bonding found in FESEM analysis which impacted in mechanical properties, including ILSS, flexural and tensile strength
- Experimental investigation revealed minimum delamination observed at 1000 rpm cutting speed,15 feed and 85^0-point angle from which showed least effect compared
- High torque leads to tool wear, especially for coated and carbide tools that are frequently used in CFRP drilling. This is because high torque and the abrasive properties of carbon fibers increase friction.
- It is concluded penetration of drill bit into the laminate made the significant impact as particularly at the laminate's entry or exit sites, excessive torque can cause the drill to twist the fibers, resulting in interlaminar delamination
- The comparative analysis of ML is at its best within acceptable range but still. Random Forest has shown 99.61 % accurate for training data and 98.81 % accurate for testing values as the computation time is high for all other algorithms. RF is considered to be the optimum predictive technique.

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CONTRIBUTORS

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In the current study he carried out both the experimentation and investigation and prepared the final draft.

Dr Nayani Kishore Nath is working as a Scientist 'G' at DRDO-ASL, Hyderabad.
In the current study he identified the problem statement and guided the research right from beginning till its completion.

Dr P. Ramesh Babu obtained his PhD from IIT, Kharagpur and working as a Senior Professor at Osmania University Hyderabad. His contribution involves the selection of the material for novel fabrication and application of the concepts of Machine learning algorithms.