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AI-Driven Optimization of Drilling Parameters for Minimizing Delamination and Improving Surface Quality in Hybrid Polymer Composites

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Abstract: Hybrid polymer composites are growingly adopted in industrial applications due to their exceptional strength-to-weight ratio, and excellent durability to corrosion and wear. Drilling, a crucial machining operation in these composites is influenced by various parameters, leading to challenges like delamination, micro-cracks, thermal damage, and excessive thrust force can lead to inefficiencies and material damage. This research aims to develop an Artificial intelligence (AI) model using Support Vector Machine (SVM) to optimize machining parameters (spindle speed, feed rate, point angle) during the drilling of hybrid polymer composites. The focus is on predicting delamination, thrust force, and Surface roughness to enhance drilling efficiency. The SVM model achieves impressive performance metrics: for thrust force, an MSE of 0.63569, RMSE of 0.821569, NRMSE of 0.015246, and MAPE of 1.32548; for delamination, an MSE of 0.008952, RMSE of 0.09652, NRMSE of 1.45263, and MAPE of 6.49852; for Surface roughness, an MSE of 0.67852, RMSE of 0.82356, NRMSE of 0.15365, and MAPE of 13.025. The findings will advance the machining of hybrid polymer composites, providing industries with improved drilling processes, minimizing delamination, thrust force, and Surface roughness, and enhancing manufacturing processes, product quality, and industrial competitiveness.

Keyword: *Support Vector Machine, composite material, drilling, machining parameters, thrust force, delamination, and surface roughness*.

Introduction:

Hybrid polymer composites are progressively substituting traditional materials across a range of commercial uses, such as in aerospace, and ocean industries, various industrial sectors, military, and transportation [1, 2]. These composites provide benefits such as reduced weight, enhanced strength, superior corrosion resistance and wear, making them versatile substitutes for many traditional engineering materials [3, 4]. Drilling is a pivotal machining operation in polymer composites, and the quality of drilled holes is intricately tied to drilling parameters and conditions [5].

Drilling hybrid polymer composites presents several challenges owing to the anisotropic characteristics of these materials [6, 7], the positioning of reinforcement; the types of fillers, tool wear characteristics, and tool geometry. Common challenges faced during the drilling process incorporate defects caused by machining processes such as delamination, Fiber detachment, and the shape irregularity of drilled holes [8]. Therefore, there is a need for a comprehensive and efficient approach to optimize drilling parameters for enhanced performance in hybrid polymer composites [9]. This research aims to design an AI model that can predict to optimize machining parameters [10], namely spindle speed, feed rate, and Point angle, during the drilling of hybrid polymeric composites [11, 12]. Specifically, the focus will be on predicting delamination, thrust force, and Surface quality in drilling [13]. The goal is to improve the overall drilling process efficiency by reducing delamination, thrust force, and surface roughness [14].

This study employs a structured methodology to design and assess SVM models for forecasting the response parameters in hybrid polymer composites [15, 16]. Initially, experimental data on drilling hybrid polymer composites under various conditions will be collected. Key drilling parameters such as spindle speed, feed rate, and point angle [17] will be varied to understand their effects on performance, specifically predicting delamination, thrust force, and Surface roughness [18]. This data will then be used to train and validate the SVM algorithm. SVMs are especially effective in high-dimensional spaces and exhibit strong efficiency, particularly when the number of dimensions exceeds the number of samples [19]. They are robust to overfitting, especially in high-dimensional space, and provide good generalization performance. The study aims to determine the optimized process parameters to minimize delamination, Surface roughness, and thrust force [20]. In addition, the SVM model will be compared with existing models such as k-Nearest Neighbors (KNN) [21], General

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Regression Neural Network (GRNN) [22], and Artificial Neural Network (ANN) for performance evaluation [23].

These findings contribute to the advancement of machining hybrid polymeric composites, benefiting industries seeking improved drilling processes, minimizing delamination, thrust force, and Surface roughness in advanced materials. The research's significance lies in its potential to provide valuable knowledge, tools, and guidelines that address the dynamic demands of industries utilizing hybrid polymer composites, driving advancements in manufacturing processes, product quality, and overall industrial competitiveness.

The paper is structured as follows in the remaining sections: Section 2 presents a review of the literature, while Section 3 provides a detailed explanation of the research methodology. Section 4 deliberates on the results and their interpretation. Subsequently, the research culminates with a dedicated conclusion section, succeeded by the references.

2 Literature review:

This literature review provides valuable insights into cutting-edge research in machining behavior analysis in filled hybrid composites. The highlighted studies showcase various experimental methodologies and optimization techniques aimed at improving drilling performance, enhancing hole quality, and minimizing the need for time-consuming and costly experiments.

In 2021, Shanmugam et al [24] underscored the importance of understanding machining behaviors in fiber composites for structural applications. Their study focused on a hybrid composite made with red mud filler and sisal fiber reinforcement in a polyester matrix. Using Taguchi L27 orthogonal array experiments, they investigated the impact of drill tool point angle, cutting speed, and feed rate on thrust force, delamination, and surface roughness. Their findings provided valuable insights into drilling sisal fiber/polyester composites with red mud filler, identifying spindle speed and feed rate as critical factors affecting thrust force and delamination.

In 2023, Bukhari et al [25]. continued exploration in 2023 by examining hybrid composites incorporating various fiber types within a single matrix. Their research concentrated on drilling processes, emphasizing the significant influence of twist drill geometry and drilling parameters on hole quality. Utilizing Taguchi-based experiments with different drill bits, they highlighted the importance of optimal helix and point angles for achieving high-quality holes.

In 2023 Chaiprabha et al [26] presented a cyber-physical drilling machine integrating technologies from the Fourth Industrial Revolution. The machine learning algorithm can detect if it hits or breaks through a workpiece using only a position sensor, enabling it to adjust and modify controllers for position, velocity, and force according to the drilling environment. The machine can detect and switch controls for HIT and breakthrough events within 0.1 and 0.5 seconds, respectively. The design optimized for high visibility aids in classifying workpiece materials. Using a SVM on thrust force and feed rate, the machine achieved 92.86% accuracy in classifying materials such as medium-density fiberboard (MDF), acrylic, and glass.

In 2020 Sharma et al [27] examined the impact of filler aspect ratios on the fracture toughness of glass-filled epoxy composites subjected to impact loading. They used three filler types with volume fractions of 5%, 10%, and 15%. The Stress Intensity Factor results were obtained using a gas gun setup combined with a high-speed camera, followed by detailed analysis via Scanning Electron Microscope fractographs. The study also investigated the use of an ANN with a Multi-Layer Perceptron feed-forward network to predict the effect of filler shape on fracture behavior. The ANN achieved a prediction accuracy of 91% when compared to experimental results.

In 2023 Chai et al [28] proposed the use of KNN and ANN meta-models to create predictive surrogate models that establish input-output correlations in the mold-filling process, aiding in mold design. The input variables encompass resin injection positioning and resin viscosity, while The resulting parameters are the required number of vents and the maximum injection pressure. Both meta-models showed promising prediction accuracies, with KNN exhibiting prediction errors ranging from 5.0% to 15.7%, and ANN ranging from 6.7% to 17.5%.

These investigations underscore the ongoing progress in AI-based models for predicting thrust force, delamination, and surface roughness, demonstrating enhanced hole quality. Findings from this literature review are instrumental in shaping the development of the proposed AI-based prediction model in this study, thereby enriching the continual evolution of this field.

3 Materials and Methods:

The HGFRP are indispensable in various industries, necessitating precise drilling processes. Drilling, a pivotal operation for polymer composites heavily depends on optimal parameters and conditions to ensure impeccably crafted holes. Achieving superior drilling performance in hybrid composites requires overcoming challenges like micro-cracks, thermal damage, delamination, excessive thrust force, and surface roughness. Traditional methods for determining these factors are often cumbersome and expensive, highlighting the demand for advanced predictive models. This study introduces an AI model employing SVM algorithm to predict thrust force, delamination, and surface roughness.

Sisal fibers treated with 2% triethoxy (ethyl) silane solution were combined with 20wt% red mud and 40wt% fiber reinforcements to form a hybrid structural composite. Polyester resin, chosen for its strong natural fiber adhesion, was used with cobalt naphthalate as the curing agent. A compression molding process produced a 300 mm × 127 mm × 6 mm composite plank. The composite's drilling properties were evaluated and compared with untreated fiber composites.

Dataset Description

In this study, dataset acquisition relied on existing literature. The drilling trials were performed on a JV 55 vertical drilling machine with numerical control, achieving up to 6000 rpm spindle speed and 10 m/min cutting feed rate. The L27 orthogonal array was used to control spindle speed, feed rate, and tool point angle during the drilling process. An 8 mm diameter high-speed steel tool was employed for drilling operations. The thrust force was recorded using the IEICOS drill dynamometer model 600A. Delamination was inspected using a Motic optical microscope equipped with a Moticam 2500 camera and analyzed with Image-J software. Surface quality was evaluated using a Mitutoyo SJ410 surface roughness tester, with a 4 mm cut length [24]. The controls variables, including tool point angle, spindle speed, and feed rate, are presented in Table 1.

Table 1: Overview of Process Variables and Their Corresponding Levels.

Symbol	Process Variables	Levels		
		I	II	III
A	Point angle (◦)	90	118	135
B	Spindle Speed (rpm)	1000	1500	2000
C	Feed rate (mm/min)	100	150	200

SVM-based model:

An SVM is a supervised machine learning technique widely employed for classification problems and can be integrated with an SVM network for enhanced performance [29]. The SVM prediction leverages a diverse set of features that encompass various levels of language description. The algorithm functions by determining a hyperplane that separates the dataset into two distinct categories. More specifically, SVMs focus on the "data points nearest to the hyperplane," which are crucial for determining the optimal position of the separating hyperplane. Consequently, in a given dataset, these support vectors are integral to the model's decision-making process. One of the key advantages of SVMs is their ability to make highly accurate predictions while working with smaller, more concise datasets. Additionally, SVMs are recognized for their efficient memory usage and their capability to manage high-dimensional spaces effectively. Figure 1 presents the basic architecture of the SVM.

Let i be the training instances $\{x_i, y_i\}$, i=1,..l where each sample comprises an input x_i and corresponding category $y_i \in \{-1,1\}$. Every hyperplane is characterized by bias b and weight vector w, which can be determined using the following equation (1).

$$wx + b = 0 \qquad \text{…(1)}$$

The decision boundary that separates the training and testing data can be defined by the following equation (2),

$$f(x) = \text{sgn}(wx + b) \qquad \text{…(2)}$$

The previous function can be expressed as an equation when utilizing the kernel function (3),

$$f(x) = \text{sgn}\left(\sum_{i=1}^{N} \alpha_i y_i k(x_i, x) + b\right) \qquad \text{…(3)}$$

Here, b represents the bias, x_i signifies the input of a training instance, N denotes the total number of training examples, and y_i corresponds to the associated label. The kernel function $K(x_i,x)$ is utilized to transform the input vectors into a higher-dimensional feature space. The coefficients α_i are obtained under two constraints, which are defined in Eqs. (4) and (5).

$$0 \le \alpha_i, i = 1, \ldots, N, \qquad \text{…(4)}$$

$$\sum_{i=1}^{N} \alpha_i y_i = 0 \qquad \text{…(5)}$$

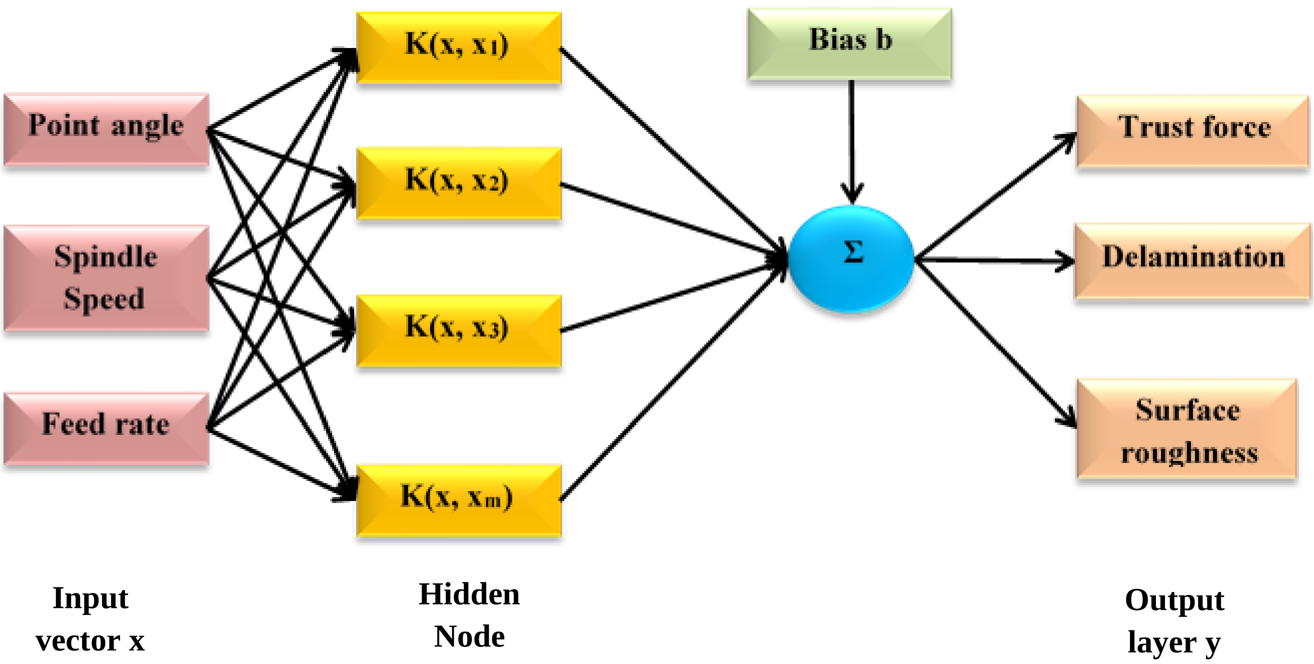

Fig 1 Basic architecture of the SVM

Result and discussion:

The present study focuses on optimizing multiple responses for the input parameters involved in the drilling of HGFRP nanocomposites. The study focuses on minimizing thrust force, Surface roughness, and delamination to achieve high-quality holes in GFRP nanocomposites. The study assesses the effect of drilling parameters, namely spindle speed, feed rate, and drill diameter, on the corresponding response characteristics. Figures 2 to 4 present graphical representations that clarify the most influential parameters affecting these responses.

The figure 2 presented showcases the comparison of different machine learning models in predicting thrust force values. The thrust force, which is crucial in various engineering and mechanical applications, is measured in units. The experiment measured thrust force values are provided alongside the predictions made by various models, including different ANN architectures LM, KNN, GRNN, and SVM.

This figure 2 shows the predicted thrust force values using the ANN (LM) training algorithm. The predictions are 58.08514, 36.5236, 27.1524, 83.4521, and 110.782. This case of higher thrust force values. The KNN model predictions values are 58.0052, 36.4215, 27.1035, 83.658, and 110.7624. KNN also shows predictions close to the experiment values, with slight differences. The GRNN model predictions values are 58.05874, 36.4012, 27.0124, 83.6258, and 110.714. The SVM model's predictions the values are 58.09388597, 36.54803534, 27.17668668, 83.20979596, and 110.6602838. SVM predictions also align closely with the experiment values, although, similar to the other models, there are small deviations.

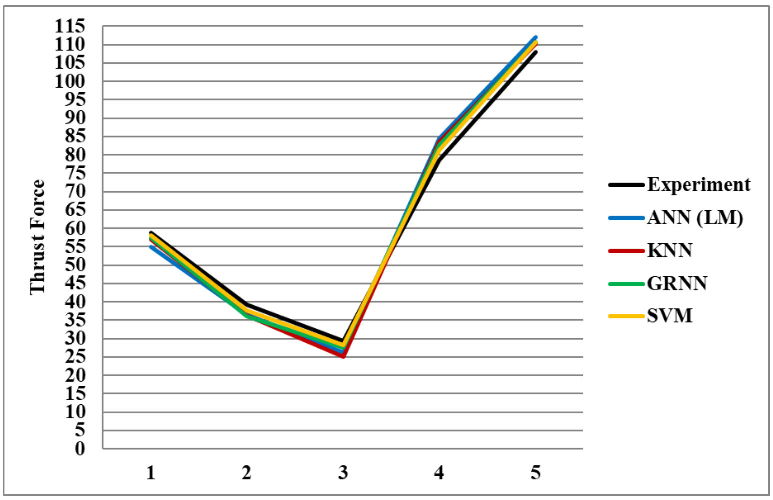

Fig 2 Thrust Force performace of SVM vs Experiment

The figure 3 provides a comparison of delamination factor predictions using different machine learning models: ANN (LM), KNN, GRNN, and SVM. Each figure corresponds to a different experiment delamination factor value and the predicted values from each model. The delamination factor predicted by an ANN (LM). The values shown (0.88658, 1.9521, 1.9582, 1.3256, 1.4215) are the ANN's predictions for each corresponding experiment value. The numbers (0.8145, 2.4521, 2.0231, 1.4421, 1.5362) indicate the predictions made by the KNN model. The values (0.8365, 2.0325, 2.0031, 1.4251, 1.5023) represent the predictions from the GRNN model. The predictions (0.90254, 1.7524, 1.7695, 1.22458, 1.385) are given by the SVM model.

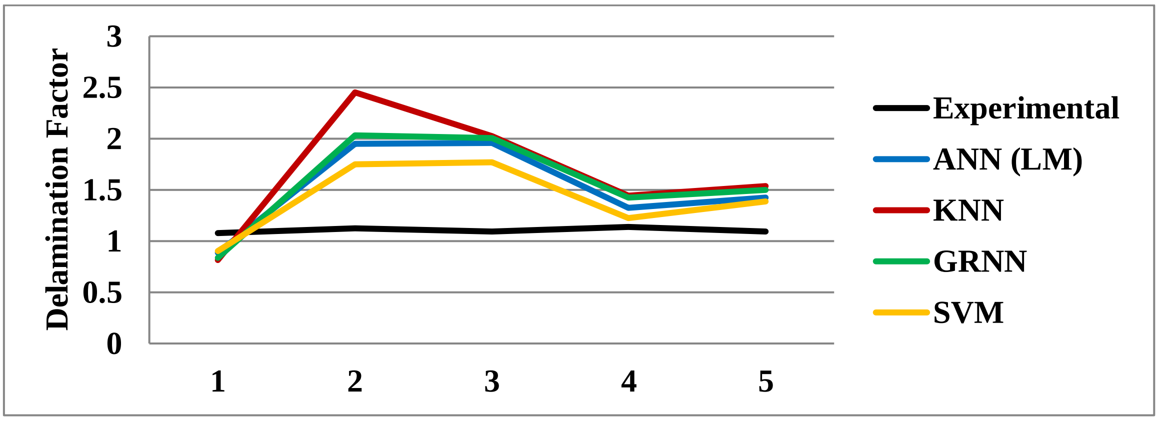

Fig 3 Delamination Factor performace

The figure 4 provides a comparison of experiment Surface roughness values with predictions made by various machine learning models: ANN (LM), KNN, GRNN, and SVM. The ANN (LM) predicted values are 6.76589, 7.385, 0.3524, 5.0252, and 5.852 for the corresponding rows. The KNN model predictions are 6.5682, 7.2632, 0.3012, 7.9921, and 5.7854. The GRNN model values given are 6.6852, 7.023, 0.31254, 7.9905, and 5.8201. Finally, the SVM model Surface roughness predictions values are 6.780855638, 7.431483902, 0.444006233, 5.057685537, and 6.071963767.

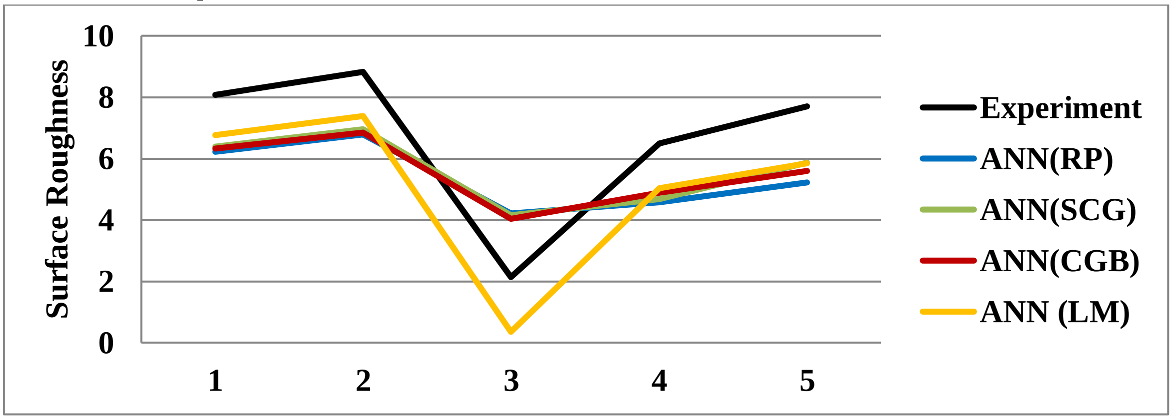

Fig 4 Surface roughness performace

Error value prediction:

The impact of machining parameters can be analyzed by reviewing the error values presented in Table 2. This analysis helps identify the optimal parameter levels by focusing on drilling parameters that significantly affect machining performance. Table 2 provides a comparative evaluation of various machine learning techniques ANN(LM), KNN, GRNN, and SVM—based on their performance in predicting Trust Force and Delamination, using MSE, RMSE, NRMSE, and MAPE as performance metrics.

Trust force of ANN (LM) exhibits an MSE of 0.64895, RMSE of 0.83621, NRMSE of 0.016854, and MAPE of 1.4123. ANN (LM) has an MSE of 0.010234, RMSE of 0.11233, NRMSE of 1.59851, and MAPE of 6.6568. This suggests good performance but with some error in delamination prediction. Thrust force of KNN exhibits higher errors with an MSE of 0.67895, RMSE of 0.86621, NRMSE of 0.028854, and MAPE of 1.6826, suggesting lower accuracy compared to ANN (LM). KNN Displays higher error rates with an MSE of 0.01265, RMSE of 0.13254, NRMSE of 1.61235, and MAPE of 6.8457, indicating it is less accurate than ANN(LM) in predicting delamination. GRNN has an MSE of 0.6524, RMSE of 0.84521, NRMSE of 0.017581, and MAPE of 1.49824. It performs similarly to ANN(LM) but with slightly higher error rates. Delamination of GRNN shows an MSE of

0.01125, RMSE of 0.12562, NRMSE of 1.59985, and MAPE of 6.6785, performing comparably to ANN(LM) but with slightly higher errors. SVM achieves the lowest error rates in Trust Force prediction with an MSE of 0.63569, RMSE of 0.821569, NRMSE of 0.015246, and MAPE of 1.32548, demonstrating the highest accuracy among the techniques. SVM outperforms the other techniques with the lowest error rates in delamination prediction: an MSE of 0.008952, RMSE of 0.09652, NRMSE of 1.45263, and MAPE of 6.49852, demonstrating highest accuracy. Overall, SVM stands out as the most accurate technique for predicting both Trust Force and Delamination, exhibiting the lowest error rates across all performance metrics.

Table 2: Error values of Trust Force and Delamination

Techniques	Trust Force				Delamination			
	MSE	**RMSE**	**NRMSE**	**MAPE**	**MSE**	**RMSE**	**NRMSE**	**MAPE**
ANN (LM)	0.64895	0.83621	0.016854	1.4123	0.010234	0.11233	1.59851	6.6568
KNN	0.67895	0.86621	0.028854	1.6826	0.01265	0.13254	1.61235	6.8457
GRNN	0.6524	0.84521	0.017581	1.49824	0.01125	0.12562	1.59985	6.6785
SVM	0.63569	0.821569	0.015246	1.32548	0.008952	0.09652	1.45263	6.49852

In this table 3, the ANN (LM) model has an MSE of 0.6895, KNN has 0.70245, GRNN has 0.69854, and SVM has the lowest MSE of 0.67852, suggesting SVM performs slightly better in minimizing prediction errors compared to other models. Here, the RMSE values for ANN (LM), KNN, GRNN, and SVM are 0.84521, 0.86451, 0.8566, and 0.82356 respectively, again showing SVM with the lowest error magnitude. The NRMSE values for ANN (LM), KNN, GRNN, and SVM are 0.17548, 0.18842, 0.18142, and 0.15365 respectively. A lower NRMSE indicates better relative accuracy, and here, SVM again shows the lowest NRMSE among the models. MAPE measures the average absolute percentage difference between predicted and experiment Surface roughness values.

Table 3: Error values of Surface roughness

	MSE	**RMSE**	**NRMSE**	**MAPE**
ANN (LM)	0.6895	0.84521	0.17548	13.315
KNN	0.70245	0.86451	0.18842	13.6214
GRNN	0.69854	0.8566	0.18142	13.5624
SVM	0.67852	0.82356	0.15365	13.025

Conclusion:

The significance of this study lies in developing an SVM-based model, which effectively predicted thrust force, delamination, and surface roughness with high accuracy. The predictive model demonstrated its capability to closely approximate the experimental values, thus reducing the reliance on time and cost-intensive experimentation. The SVM outperformed other traditional predictive model such as GRNN, KNN, ANN (LM) and RF with regard to MSE, RMSE, NRMSE and MAPE.

The results of the study contribute significantly to the understanding of the machining behaviour of filled hybrid composites, providing valuable insights for structural applications. By employing the SVM -based model, manufacturers and engineers can efficiently assess the drilling performance and quality of holes in the composite materials without the need for extensive experimental trials. Overall, this research offers a novel and resource-efficient approach for analyzing the drilling behavior of filled hybrid composites. The combination of observational data and the SVM model acts as an effective tool for predicting thrust force, delamination, and surface roughness. The results validate the efficacy of the proposed methodology in achieving accurate predictions, promoting resource conservation, and enhancing the understanding of machining behavior in critical structural applications.

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