Tribological Properties of Polymer-Based Hybrid Nanocomposites for High Performance Gear Using Experimental and Machine Learning Techniques

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***Abstract*—Polymer gears are increasingly preferred in applications that demand lightweight components and low operational noise, yet their use is still restricted by limitations in wear resistance and thermal stability. One effective way to address these shortcomings is through the incorporation of nanoscale fillers that can significantly improve the mechanical and tribological response of base polymers. In this study, hybrid Polyoxymethylene (POM) nanocomposites reinforced with graphene and iron oxide (Fe_2O_3) nanoparticles were synthesized and examined through tensile, flexural, and pin-on-disc wear experiments. The experimental results were compiled into a dataset that served as the foundation for developing a machine learning system capable of predicting wear rate and friction coefficient based on input parameters such as filler content, applied load, sliding speed, and distance. Three regression models—Decision Tree, Random Forest, and XGBoost—were trained and integrated into a Flask-based web application designed to automate model training, evaluation, and real-time prediction. Model accuracy was quantified using the coefficient of determination (R^2) and mean squared error (MSE), and a comparative analysis was conducted to identify the most reliable model for practical use. The combined experimental and computational findings show that ensemble and boosting-based approaches offer reliable and accurate predictions of tribological behaviour, enabling faster assessment of composite materials and supporting the development of high-performance polymer gears.**

***Index Terms*—Tribology, Graphene, XGBoost, Random Forest, Wear Rate Prediction, Friction Coefficient, Machine Learning.**

I. Introduction

Industries are increasingly adopting polymer gears due to their lightweight structure, vibration reduction, and design flexibility. However, their reliability in friction-intensive environments still depends on understanding performance behaviour under different operating conditions. Among the available polymer materials, Polyoxymethylene (POM) is commonly used in precision gear applications because of its dimensional stability and low friction characteristics. Even so, mechanical stresses and continuous sliding can affect its long-term performance, making intelligent evaluation methods essential.

Recent advances in material engineering show that incorporating nanoscale fillers can improve the physical behaviour of polymers. Hybrid reinforcement using graphene and Fe_2O_3 nanoparticles is one of the approaches shown to enhance the stability and frictional behaviour of polymer composites [1]. While these improvements are valuable, experimental tribology alone is time-consuming and cannot efficiently explore large variations in test conditions.

This limitation highlights the growing need for computational intelligence in material evaluation. Machine learning (ML) has shown the capability to analyse nonlinear behaviour of engineering systems by learning from real measurements. In particular, tree-based models are highly effective due to their interpretability and ability to handle small and moderate-sized datasets. In this study, the Decision Tree algorithm is used for its simple rule-based structure, Random Forest is applied to reduce overfitting through ensemble averaging, and XGBoost is selected for its boosting strategy that significantly improves prediction accuracy and generalization [6]. These three algorithms collectively offer a balanced comparison across transparency, robustness, and computational performance.

However, many existing studies apply ML only as offline prediction tools, without integrating them into a practical deployment environment. As a result, there is limited accessibility for engineers and researchers who need real-time feedback for material and design decisions.

To address this gap, the present work develops a complete and automated ML-based prediction system that uses experimentally observed data of hybrid POM nanocomposites. The trained Decision Tree, Random Forest, and XGBoost regression models are compared to evaluate prediction consistency. Additionally, these models are deployed in a Flask-based web application that allows users to input test parameters and instantly obtain predicted wear and friction behaviour.

By combining experimental evidence with a user-friendly computational platform, this study demonstrates an efficient approach for analysing polymer gear performance. The system enhances accessibility to advanced prediction methods and enables faster decision-making for real-world tribology-focused design processes.

II. Related Work

Traditional tribological analysis primarily relies on physical experimentation; however, these methods are often time-consuming and limited in scalability. With the increasing availability of experimental datasets, recent research has shifted towards machine learning (ML) to predict tribological behaviour more efficiently. Studies have shown that ML enables faster evaluation of material performance by learning complex relationships between operating parameters and wear characteristics [6].

Recent developments demonstrate the effectiveness of supervised regression models such as Random Forest, Support Vector Machines, and ensemble boosting algorithms for predicting wear rate and friction coefficient in polymer-based nanocomposites [7]. These approaches improve reliability compared to manual testing methods by minimizing experimental effort while still maintaining strong predictive capability.

Hybrid artificial intelligence techniques combined with optimization strategies have also been explored to enhance predictive accuracy and material selection [8]. In addition, several investigations have demonstrated that neural network-based prediction significantly reduces dependency on iterative laboratory trials, especially for advanced polymer applications requiring high performance in mechanical systems [10].

ML-driven modelling has been successfully applied to a range of polymer systems, including graphene-reinforced and ceramic-filled nanocomposites, where models effectively captured nonlinear behavioural trends under different loading conditions [12]. These studies confirm the suitability of ML algorithms for tribological prediction involving multiple interacting parameters.

Further, recent research emphasizes the role of intelligent prediction frameworks in supporting engineering design decisions. By integrating experimental datasets with computational analytics, ML models can optimize the selection and evaluation of nanocomposite structures used in dynamic applications [15]. However, most existing systems operate in an offline environment and lack real-time deployment capabilities.

Therefore, there remains a need for a unified platform that incorporates dataset management, automated model training, and instant prediction accessibility. Addressing this research gap, the present work proposes an ML-assisted web application capable of real-time prediction and model comparison to support decision-making in the development of hybrid polymer gear materials.

III. Methodology

The proposed methodology integrates supervised machine learning algorithms with a web-based deployment pipeline to enable real-time prediction of tribological behaviour. The workflow includes dataset uploading, automated model training with performance evaluation, algorithm-specific learning, model storage, and prediction visualization (Fig. 4).

A. Dataset Preparation

The experimental dataset consists of four tribological input parameters: reinforcement percentage (wt.%), applied load (N), rotational speed (rpm), and sliding distance (m). The outputs are wear rate and friction coefficient. The dataset was preprocessed to remove any inconsistent values and then converted into CSV format for compatibility with the backend model training pipeline.

B. Model Training Pipeline

Once the dataset is uploaded, three regression models — Decision Tree, Random Forest, and XGBoost — are trained automatically. An 80:20 split (train:test) enables unbiased model evaluation.

Performance evaluation is carried out using the coefficient of determination (R^2) and Mean Squared Error (MSE). These metrics assist in selecting the best model for deployment. The training performance of the three models is displayed in Table I. XGBoost achieves the highest R^2 and lowest MSE for both wear rate and friction coefficient prediction, confirming its superior modelling ability.

TABLE I: Model Performance Comparison for Wear and Friction Predictions

Model	Target	R^2 Score	MSE
Decision Tree	Wear	1.0	0.0
Random Forest	Wear	0.98862	8.313105
XGBoost	Wear	0.998212	1.306232
Decision Tree	Friction	1.0	0.0
Random Forest	Friction	0.85205	0.000767
XGBoost	Friction	0.999508	2.548439

1) Decision Tree Regression in This System: The Decision Tree predicts wear and friction values by applying sequential decision rules based on input parameter thresholds:

$$\text{If Load} > \text{threshold} \Rightarrow \text{go right, else go left}$$

Splits continue on reinforcement %, rotational speed, and sliding distance until a leaf node is reached:

$$\hat{y}(x) = \frac{1}{N_j} \sum_{i \in R_j} y_i$$

This rule-based model is highly interpretable for understanding tribological behaviour. The flow followed in this system is shown in Fig. 1.

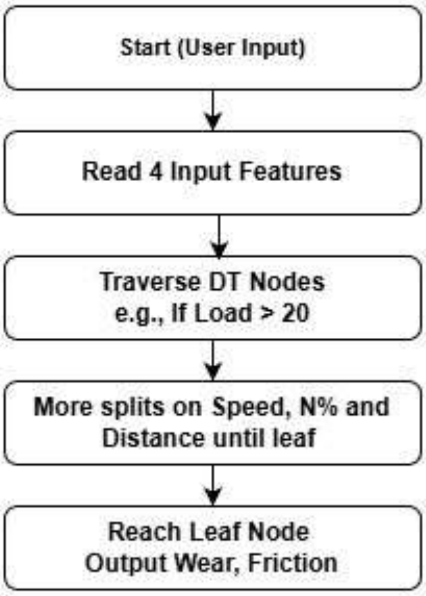

Fig. 1: Decision Tree flow for wear rate and friction coefficient prediction.

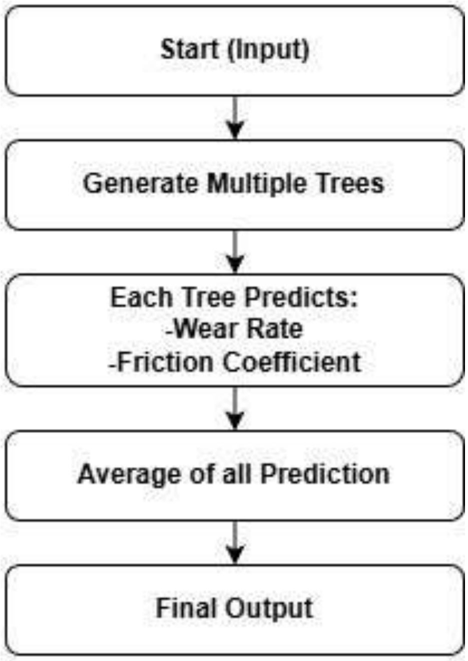

Fig. 2: Random Forest ensemble working process for tribological prediction.

2) Random Forest Regression in This System: Random Forest creates multiple Decision Trees using random samples of data and features. Each tree predicts independently, and the final result is the average output:

$$\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} DT_i(X)$$

This ensemble approach enhances robustness and reduces overfitting. The working flow is shown in Fig. 2.

3) XGBoost Regression in This System: XGBoost improves prediction accuracy using sequential boosting. The model starts with an initial estimate and iteratively trains new trees to correct previous errors:

$$\hat{y}_{new} = \hat{y}_{old} + f_t(x)$$

The final output is obtained by combining all tree corrections. This enables superior nonlinear learning, especially in small datasets. The implemented boosting mechanism is illustrated in Fig. 3.

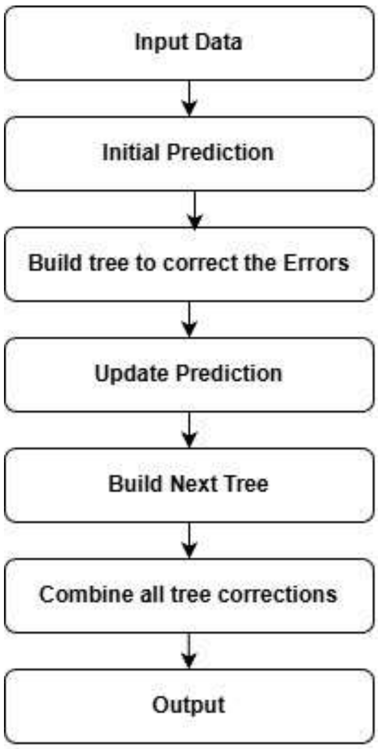

Fig. 3: XGBoost error-correction boosting mechanism.

C. Model Saving and Deployment

Once trained and evaluated, all three models are serialized and stored on the server to avoid retraining for every request. A Flask-based frontend retrieves the saved model files and performs prediction based on user input values.

D. Real-Time Prediction and Comparative Decision

During prediction, all three models produce results simultaneously. The system compares their outputs and highlights the most reliable model by measuring deviation from the ensemble mean. Prediction history is recorded to support system monitoring and performance analysis.

E. *Overall System Workflow*

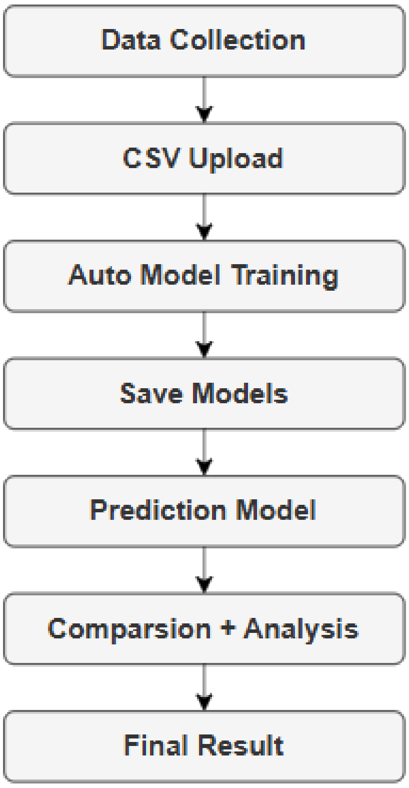

Fig. 4: Overall workflow of the machine-learning-based tribology prediction system.

This integrated system accelerates tribological prediction, reduces experimental cost, and supports informed decision-making in hybrid polymer gear material design.

IV. Results and Discussion

This section presents the real-time prediction outcomes and usage behaviour of the deployed tribological prediction system. The results demonstrate the ability of machine learning algorithms to accurately predict wear rate and friction coefficient for hybrid polymer nanocomposites under varying operating conditions.

A. *Real-Time Prediction Interface*

Fig. 5 shows the real-time prediction interface where users provide input parameters such as reinforcement percentage, load, speed, and sliding distance. The system displays wear and friction predictions from all three models simultaneously. The most reliable model is automatically identified based on prediction deviation from the ensemble mean — in this example, XGBoost is selected as the best model.

B. *Model Selection and Win-Count Analysis*

A model win-count statistics plot (Fig. II) shows how many times each algorithm produced the most accurate prediction. XGBoost achieved the highest count of 13 wins, followed by Decision Tree with 6 wins and Random Forest with 4 wins. This verifies that XGBoost maintains higher reliability across diverse input conditions.

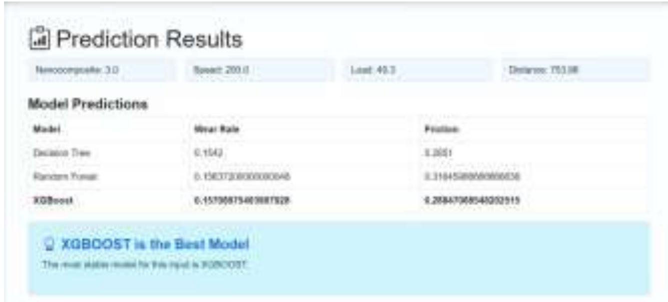

Fig. 5: Sample real-time model prediction results generated by the web application.

TABLE II: Model Win Count

Model	Wins
Decision Tree	6
Random Forest	4
XGBoost	13

C. *Prediction Behaviour Across Input Variations*

Predictions obtained for multiple test scenarios are listed in Table III. As reinforcement percentage increases, the predicted wear rate decreases, confirming improved load distribution and reduced abrasion due to hybrid nanofiller strengthening. Friction behavior remains more stable in hybrid composites, agreeing with the lubricating and thermal stability effects of graphene and Fe_2O_3.

D. *Discussion and Interpretation*

The results confirm that the intelligent prediction system successfully emulates experimental tribological behavior. The integration of ML with a web-based interface allows researchers to:

- Obtain results without repeated physical testing
- Rapidly modify material formulations and operating parameters
- Identify optimal nanofiller content for reduced wear and friction
- Analyze model consistency through automated performance tracking

Overall, the proposed system effectively bridges laboratory tribology and computational modeling, significantly reducing experimental effort and offering a practical decision-support tool for polymer gear design and advanced material development.

V. Conclusion

This study presents a machine learning–assisted framework for predicting the tribological behaviour of hybrid POM

TABLE III: Sample real-time prediction results from the web application.

N%	Load (N)	RPM	Dist. (m)	DT	RF	XGB	Best Model
17.0	49.3	200.0	753.98	0.0970	0.097593	0.096758	Decision Tree
14.0	49.3	200.0	753.98	0.1317	0.129058	0.131932	XGBoost
12.0	49.3	200.0	753.98	0.1455	0.143376	0.146359	Decision Tree
3.0	49.3	200.0	753.98	0.1542	0.156372	0.157090	XGBoost
0.2	49.3	200.0	753.98	0.1642	0.160098	0.162287	XGBoost
5.0	49.3	200.0	753.98	0.1663	0.161016	0.164788	XGBoost
17.0	49.3	200.0	753.98	0.2703	0.268854	0.270259	Decision Tree
14.0	49.3	200.0	753.98	0.2782	0.282639	0.278648	XGBoost
12.0	49.3	200.0	753.98	0.2925	0.286775	0.292220	Decision Tree
3.0	49.3	200.0	753.98	0.2851	0.316460	0.288470	XGBoost
0.2	49.3	200.0	753.98	0.4288	0.413236	0.426899	XGBoost
5.0	49.3	200.0	753.98	0.3353	0.319893	0.333670	XGBoost

nanocomposites reinforced with graphene and Fe_2O_3. Experimental measurements of wear rate and friction coefficient were used to train three regression algorithms—Decision Tree, Random Forest, and XGBoost. Among these, XGBoost demonstrated the highest prediction accuracy by effectively learning nonlinear dependencies between input parameters and output responses.

A Flask-based web application was developed to automate model training, prediction, and visualization, enabling users to obtain real-time performance estimations without additional physical testing. This integrated approach improves accessibility to material behaviour predictions and reduces development time. Overall, the system provides a practical computational decision-support tool for advancing polymer gear design and related tribology-focused engineering applications.

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