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RESEARCH

Data Augmented Machine Learning Approach for Predicting Wear Behavior of 3D Printed Recycled and Virgin Polymers

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A B S T R A C T

Polylactic Acid (PLA) and Polyethylene Terephthalate Glycol (PETG) are widely used in additive manufacturing for engineering applications. However, their tribological performance, particularly in recycled forms, remains underexplored. This study evaluates the wear behavior of virgin and recycled PLA and PETG under dry and lubricated conditions using a pin-on-disk tribometer. Key tribological parameters, including wear rate, friction coefficients, energy dissipation, and temperature rise, were measured across 336 samples. Machine learning models were employed to predict wear rate and classify material-lubrication performance. Gradient Boosting Regression achieved the highest prediction accuracy (R^2 = 0.698, RMSE = 0.1336), with energy dissipation emerging as the most influential factor. Classification models distinguished between high and low-performing conditions, with Logistic Regression achieving an accuracy of 88%. Data augmentation using a Gaussian Mixture Model-based approach enhanced model robustness by expanding the dataset from 168 to 336 samples. Experimental results indicate that recycled materials exhibit higher wear rates, but lubrication significantly reduces material loss. These insights are crucial for manufacturing, biomedical, and automotive applications, where selecting appropriate materials and lubrication strategies can enhance overall durability and efficiency. This study demonstrates the integration of tribological testing with machine learning, providing a data-driven approach for wear prediction and material optimization.

1. INTRODUCTION

The growing adoption and standardization of 3D printing has revolutionized material manufacturing industries allowing for the rapid prototyping and production of intricate designs [1]. However, its widespread use has also brought environmental concerns to the forefront as the virgin polymers used in 3D printing significantly contribute to the plastic waste issue. Virgin polymers generate more waste because they are hard to recycle and 3D printing consumes large volumes that current recycling systems cannot handle. To address the waste, recycled polymers are emerging as a viable alternative [2,3]. They align with sustainability practices while also bringing down production costs and resolving the requirements for virgin material [4].

Among the widely used 3D printing materials, Polylactic Acid (PLA) and Polyethylene Terephthalate Glycol (PETG) are the most prominent, as they have high strength versatility, and ease of use as printing material. Usually, materials used for a prototype model will be discarded once its purpose is served. The material can be recycled and reused for functional applications. But their properties will differ in comparison to virgin polymers. Hence, key differences between virgin and recycled plastics be understood for their future consideration in real-world tribology applications [5,6].

Also, to consider the materials for dynamic applications tribological properties such as the Coefficient of Friction (COF) and wear rate play an important role. These properties are influenced by factors such as load, lubrication, and material composition [7]. Virgin polymers are known to provide better performance, however, recycled polymers may show variations in performance because of the recycling process. Further research is required understand these differences in properties and how they relate to industrial use [8,9].

This article compares the tribological properties of virgin and recycled PLA and PETG materials. Experiments were conducted under different loads and lubrication conditions to cover a wide range of practical scenarios. Important parameters such as static and kinetic friction, wear rate, and energy loss were measured. Machine Learning methods, such as regression and classification, were used to predict the wear behavior. These methods will help in predicting the wear behavior and identify which materials perform better under different conditions [10,11].

The results of this work will encourage sustainable practices in polymer 3D printing. By clearly knowing how recycled polymers behave with respect to wear and friction, engineers can choose the recycled polymers appropriately in applications that require good durability and efficiency.

2. LITERATURE REVIEW

2.1 Tribological studies in polymers

Polymers are commonly used in 3D printing leading to a lot of research on their mechanical and wear properties to improve their use and performance [12]. Polymers are chosen over other materials because of their high strength, ease of processing, and flexibility in 3D printing applications. PLA and PETG are the two most popular materials in polymer 3D printing and their performance under frictional loading and wear conditions remains a critical factor in determining their suitability for engineering applications [13]. Anderson demonstrated the mechanical differences between virgin and recycled PLA. The study revealed that recycled polymers can achieve tribological properties comparable to virgin polymers if processed under controlled conditions [14]. The study reported that careful control of recycling conditions can reduce the performance gap between virgin and recycled PLA, often keeping key metrics within a 15–20% range.

The interest in recycled polymers comes from global pursuit of sustainability. Studies by Gbadeyan et al. demonstrated that recycled PLA structures show significant potential for reducing environmental impact while maintaining appropriate wear resistance for industrial applications [15].

2.2 Tribology of recycled and virgin polymers

Several studies have compared the tribological properties of recycled and virgin polymers. Maraveas et al analyzed recycled plastics in 3D printing indicating that recycled PLA maintains much of its strength and frictional performance if optimized properly for the process [3]. Maraveas improved the recycling process by adjusting the parameters such as extrusion temperatures, printing speeds, and using post-processing treatments such as annealing and chain extenders to reduce thermal degradation without loss in strength, helping recycled PLA retaining up to 85% of its original strength. Ramadan and Hassan investigated PLA and PETG using pin-on-disk apparatus and found that adding lubrication greatly improves the wear resistance of recycled plastics, especially under high loads [16]. Also, Aziz et al. studied the wear behavior of recycled

PETG and found that better surface finish results in reduced friction and wear rates [17]. This study demonstrates that even with slight improvement in surface finish leads to significant gains in wear performance, indicating the importance of post-processing.

The above studies shows that the recycled polymers are suitable for tribological applications when used with optimal design parameters such as surface finish, lubrication, and 3D printing parameters such as extrusion temperature, printing speed and post processing techniques.

2.3 Influence of lubrication and load

Lubrication and load are the two important parameters in tribological studies. Chan et al. examined how lubrication reduces the friction in PLA composites and noted that lubrication is effective and needed only at higher loads, when surface interacts more strongly [18]. Their study showed measurable improvements, indicating that lubrication significantly lowers friction and increases the machine component life . Similarly, Tyagi et al. reviewed the influence of load on wear behavior and found that recycled polymers perform better under lower loads due to less permanent deformation [19].

The combined effect of load and lubrication was also explored by Deshmukh et al. who used experimental and numerical methods to predict frictional behavior under different conditions and concluded that lubrication helps to overcome the material deficiencies. [20].

2.4 Processing parameters in additive manufacturing

Parameters used in 3D printing equipment during the component preparation also strongly affects the tribological properties. Farooq and Ranjan published a 2023 study demonstrating that layer thickness and infill density are the two important factors that affects the wear resistance, noting that recycled PLA with higher infill densities shows improved strength and resistance to wear [21]. Their findings indicate that even a 10% increase in infill density leads to noticeable improvements in wear resistance, indicating the importance of 3D printer parameters.

The effect of post-processing techniques on tribological behaviour was analysed by Dizon et al. also in a 2023 study in which they reported that annealing improved the surface hardness and reduced wear during sliding actions as a result of improvement in microstructure [22]. These results agree with reports from Ramadan and Hassan who showed that the surface treatments can significantly increase the performance of recycled polymers. These studies collectively note that optimising both printing parameters and post processing processes play an important role in improving the wear resistance of 3D printed polymers.

2.5 Processing parameters in additive manufacturing

Statistical and modeling approaches have been widely implemented in tribological research. Marian et al. have explored the application of machine learning in tribology in a 2022 paper. They concluded that regression models are effective for predicting friction coefficients, while classification techniques help identify material suitability under specific conditions [23]. Ezzaraa et al. utilized finite element modeling to analyze the wear behavior of recycled polymers. Their study provided insights into material performance under dynamic loading condition [24]. The studies numerical approach helped quantify the effect of load variations on wear, offering a complementary perspective to experimental observations. These numerical techniques assist the experimental studies by providing predictive capabilities and reducing the need for extensive testing. The integration of statistical and computational methods enhances our understanding of wear mechanisms and supports more efficient material selection.

The existing literature highlights the potential of recycled polymers in 3D printing. However, studies comparing their tribological performance with virgin polymers remain limited. Most research focuses on mechanical properties, neglecting friction, wear, and energy dissipation under varying loads and lubrication. Additionally, the role of processing conditions and lubrication on recycled polymers is not fully understood. Predictive analysis using advanced statistical tools is also scarce in this domain. This study addresses these gaps by analyzing and predicting tribological behavior with a focus on recycled PLA and PETG.

3. MATERIALS AND METHODS

3.1 Materials

The study focuses on two widely used polymers: PLA (Polylactic Acid) and PETG (Polyethylene Terephthalate Glycol-modified). Both virgin and recycled variants were considered. Recycled polymers were processed to ensure homogeneity by extrusion and pelletization. The materials were selected for their relevance in 3D printing and tribological studies as they are commonly used for applications that demand good strength, flexibility, and wear resistance.

3.2 Specimen preparation

Samples were prepared using a standard Fused Filament Deposition Modeling (FDM) 3D printer. The 3D printing process was performed using a nozzle diameter of 0.4 mm, a layer thickness of 0.2 mm, an infill density of 100%, a raster angle of 45°, and a printing speed of 50 mm/s for both virgin and recycled polymers.

In our study, the recycling process for PLA and PETG involved three successive recycling cycles. In each cycle, the polymer waste was thoroughly cleaned to remove impurities and contaminants, then remelted under controlled extrusion conditions to minimize thermal degradation and preserve molecular weight. After melting, the recycled polymers were extruded through a die to form continuous filaments suitable for 3D printing. The extrusion process was carefully controlled in terms of temperature and pressure, ensuring that the filament had a uniform diameter and maintained consistent mechanical properties. Finally, the extruded filament was cooled, spooled, and used as feedstock in the subsequent 3D printing process.

Cylindrical pins with a diameter of 10 mm and height of 20 mm were prepared. These dimensions adhere to ASTM G99 standards for tribological testing.

A total of 48 specimens were prepared - 12 for each material (virgin PLA, recycled PLA, virgin PETG, recycled PETG); 24 were tested under dry conditions and 24 under lubricated conditions.

3.3 Experimental setup

Tribological properties were tested using a pin-on-disk tribometer as shown in Fig. 1.

Fig. 1. Pin on disc tribometer.

The prepared cylindrical pins were placed in contact with a rotating steel disk. The disk material is Hardened steel with a surface roughness of Ra = 0.2 µm. Four normal loads were applied (20 N, 40 N, 60 N, 80 N). A constant sliding speed of 0.1 m/s was maintained. The tests were conducted for a total sliding distance of 1000 m. For lubricated conditions, SAE 15W-40 oil was used as the lubricant.

Surface temperature during sliding was monitored using a non-contact infrared thermometer. The tribometer recorded the frictional force continuously throughout the test.

3.4 Test Conditions and data collection

Tests were conducted in both dry and lubricated conditions. Dry condition simulate standard wear scenarios where no external lubricant is applied. Lubrication is applied to reduce friction and wear. Each test was repeated three times to ensure the reproducibility and reliability of results. Variations were minimized by cleaning the disk and replacing the pins between tests. The following tribological parameters were recorded for each test: (a) Static Coefficient of Friction (COF): Force required to initiate sliding, (b) Kinetic Coefficient of Friction (COF): Force required to sustain sliding, (c) Wear Rate (mm^3/m): Material loss per unit sliding distance, (d) Energy Dissipated (J): Energy lost due to friction and (e) Temperature Rise (°C): Increase in surface temperature during sliding.

To improve the scope of the study, a Gaussian Copula-based multivariate data augmentation method was employed. This technique generated an additional 168 synthetic data points by capturing the statistical relationships and distributions observed in the original dataset of 168 rows. The final augmented dataset of 336 rows kept the original data intact while expanding the range of conditions analysed.

A detailed analysis was performed using the augmented dataset. Regression models, including Random Forest and Gradient Boosting, were used to predict wear rate. Classification models like Logistic Regression and SVM helped assess material performance under dry and lubricated conditions.

Feature importance analysis from both models identified key factors influencing wear and tribological performance. These combined methods provide a better understanding of tribological behaviour. The results also indicate how temperature rise, energy dissipation and wear mechanisms are related to each other.

4. RESULTS AND DISCUSSIONS

4.1 Overview of tribological performance

The tribological performance parameters were analyzed to study their variations. Key factors such as wear rate, energy dissipation, and temperature rise were examined. The influence of material type, lubrication conditions, and other parameters were also considered. Table 1 presents the statistics for the main tribological properties. These statistics provide a numerical summary of the experimental data. They also highlight the variations in their performance under different conditions.

The data in Table 1 reveals substantial variability in the energy dissipated and wear rate. This variability is influenced by factors such as material composition and lubrication conditions. The correlation between tribological parameters is visualized in Figure 2, which depicts a heatmap of the correlation matrix. Strong positive correlations are observed between energy dissipation, wear rate, and friction forces. For instance, the wear rate has a correlation of 0.71 with energy dissipated, indicating a significant dependence.

The wear rate trends across materials and lubrication conditions are summarized in Table 2. The results demonstrate that recycled materials exhibit higher wear rates than their virgin counterparts. This trend is consistent across both dry and lubricated conditions. However, lubrication significantly reduces the wear rate for all materials, as shown in Figure 4.

Table 1. Descriptive statistics of tribological parameters.

Parameter	Mean	Std. Dev.	Min	Max
Wear Rate (mm^3/m)	1.353	0.260	0.572	2.132
Energy Dissipated (J)	74.22	45.57	-2.28	215.67
Temperature Rise (°C)	18.95	3.473	10.48	27.729
Static Friction Force (N)	41.82	21.14	1.258	83.231
Kinetic Friction Force (N)	31.3	15.85	1.719	62.565

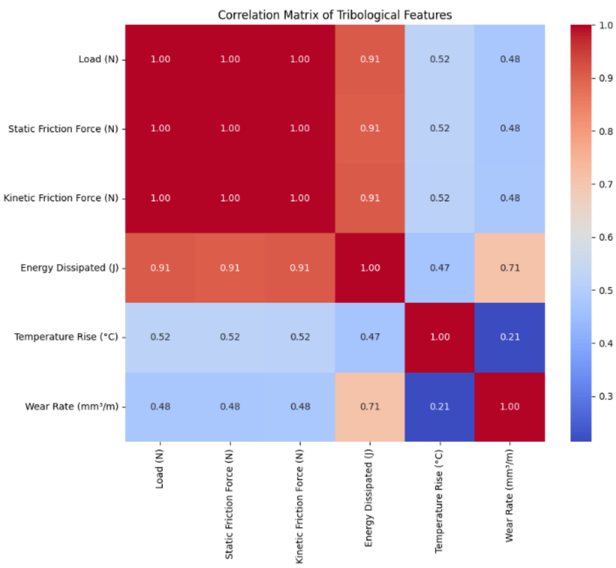

Fig. 2. Correlation matrix of tribological features.

Table 2. Comparison of wear rate by material and lubrication type.

Material	Condition	Mean Wear Rate (mm^3/m)	Std. Dev.
Virgin PLA	Dry	1.2	0.2
Virgin PLA	Lubricated	1.1	0.1
Recycled PLA	Dry	1.6	0.3
Recycled PLA	Lubricated	1.4	0.2
Virgin PETG	Dry	1.3	0.2
Virgin PETG	Lubricated	1.2	0.1
Recycled PETG	Dry	1.7	0.3
Recycled PETG	Lubricated	1.5	0.2

The wear rate distribution for different materials is illustrated in Figure 3, while the impact of lubrication is depicted in Figure 4. In both figures, it is evident that recycled materials exhibit broader distributions and higher mean values.

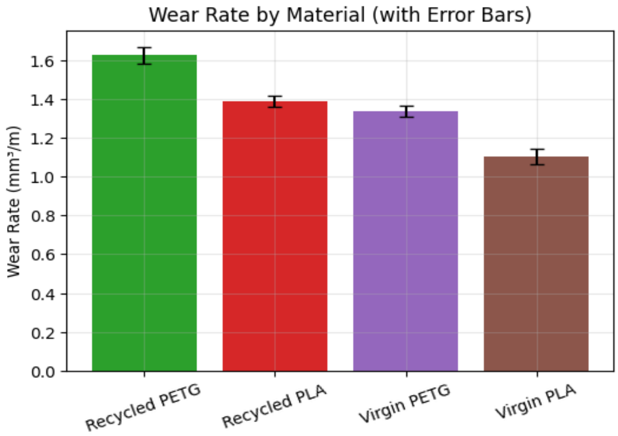

Fig. 3. Wear rate by material.

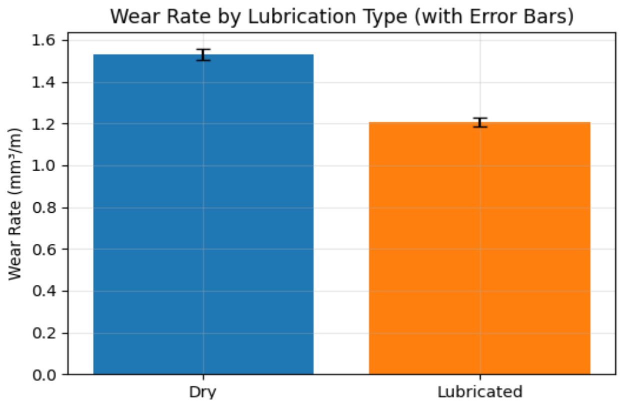

Fig. 4. Wear rate by lubrication type.

This distribution suggests that recycled polymers may be less resistant to wear due to changes in molecular structure during recycling. Energy dissipation affects the wear mechanisms of the material. Temperature rise also plays a crucial role in this process. The relationship between these factors and wear rate is illustrated in Figure 5, which depicts a scatter plot with temperature rise as the colour scale. The figure demonstrates that higher energy dissipation corresponds to increased wear rates, particularly under dry conditions. An increase in temperature worsens the wear effect emphasizing the need for proper heat control in tribological systems. The tribological performance analysis shows important trends and connections between different factors. Recycled materials are more sustainable but tend to wear out faster, especially in dry conditions. Lubrication will significantly reduce the wear rate, minimizing these challenges.

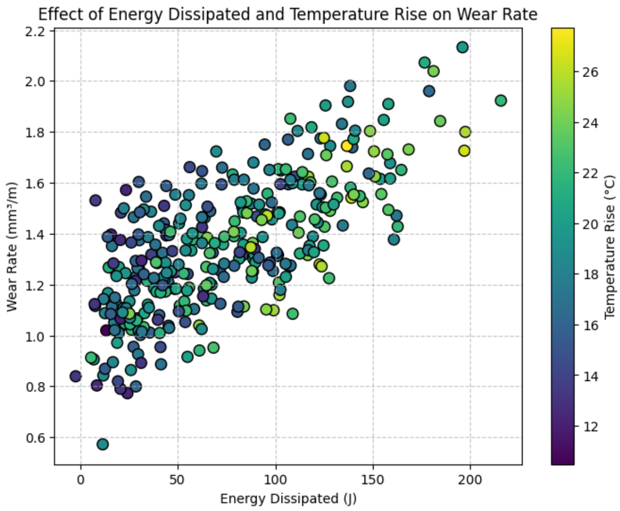

Fig. 5. Effect of energy dissipated and temperature rise on wear rate.

These results offer useful guidance for designing better tribological systems using 3D-printed polymers. The tribological performance analysis shows important trends and connections between different factors. Recycled materials are more sustainable but tend to wear out faster, especially in dry conditions. Lubrication will significantly reduce the wear rate, minimizing these challenges. These results offer useful guidance for designing better tribological systems using 3D-printed polymers.

4.2 Model-based analysis of wear rate

Regression Model Performance: Regression models like Linear Regression, Random Forest, and Gradient Boosting were evaluated for their accuracy and prediction of wear rate.

The performance of each model was measured using Root Mean Squared Error (RMSE) and R^2 Score. Table 3 shows the results of the models before hyperparameter tuning, while Table 4 shows the metrics after hyperparameter tuning.

Table 3. Performance metrics before hyperparameter tuning.

Model	RMSE	R^2 Score
Linear Regression	0.1472	0.6345
Random Forest	0.1441	0.6494
Gradient Boosting	0.1399	0.6699

Table 4. Performance metrics after hyperparameter tuning.

Model	Best Parameters	RMSE	R^2 Score
Random Forest	max_depth=15 n_estimators=50	0.1419	0.6602
Gradient Boosting	learning_rate=0.1ma x_depth=5 n_estimators=50	0.1337	0.6985

The results indicate that Gradient Boosting has performed more precisely than the other models as it achieved an R^2 score of 0.6699 and an RMSE of 0.1399. After tuning the hyperparameters, all models showed improvement. The updated results are recorded in Table 4.

Following hyperparameter tuning, the Gradient Boosting model demonstrated a notable improvement, achieving the best results with an R^2 score of 0.6985 and an RMSE of 0.1337. These metrics indicate that the model accurately captured the wear rate trends under various tribological conditions. The Random Forest model also showed a slight enhancement, reaffirming the utility of ensemble methods for this dataset.

The accuracy of the regression models was further assessed by comparing the predicted wear rate against observed values. Figure 6 presents the scatter plot for Gradient Boosting, the best-performing model.

In Figure 6, the data points align closely with the ideal fit line, showcasing a strong correlation between predicted and actual wear rates. The close proximity between the predicted and actual rate indicates the model's high predictive accuracy. However, slight deviations at higher wear rates suggest the presence of additional factors influencing wear mechanisms, which are not currently accounted for.

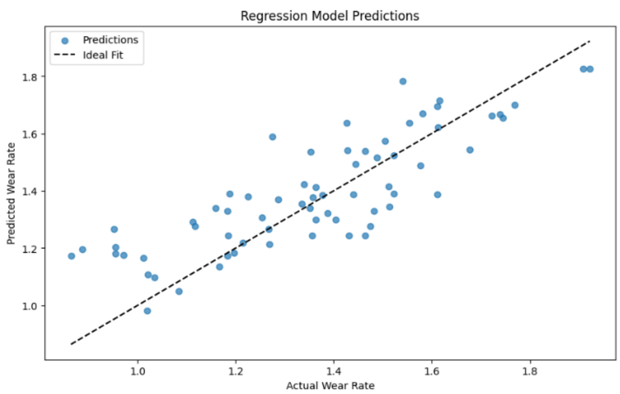

Fig. 6. Regression model predictions for.

Gradient Boosting (Predictions Vs. Ideal Fit)

Feature Importance Analysis: The effect of different tribological parameters on wear rate was studied using feature importance scores from the Random Forest and Gradient Boosting models. Figure 7 shows the relative importance of these features. Feature importance was determined by measuring how much each parameter reduced prediction error, as computed by Random Forest and Gradient Boosting models.

From Figure 7, it can be observed that the Energy Dissipated (J) was the most important factor in predicting wear rate, as the higher energy loss through friction leads to more material wear. This measurement factors in basic tribology principles, material type and lubrication as they helped in reducing wear under different operating conditions.

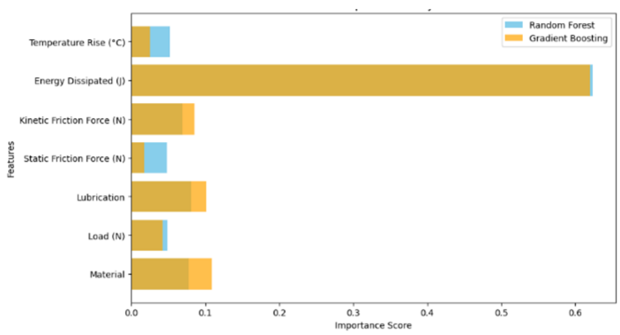

Fig. 7. Feature importance analysis.

Other factors, like Temperature Rise (°C) and Load (N), had a moderate effect on results. Their impact is likely due to their influence on energy dissipation.

This study demonstrates that machine learning models can help predict wear behavior in 3D-printed polymers. Among the models tested, Gradient Boosting performed the best, accurately capturing the complex relationship between wear rate and various other factors. Energy Dissipated (J) was found to be the most important factor affecting wear rate which aligns well with fundamental tribology principles. When more energy is lost due to friction, the material wears out faster with the effect strengthening under high loads. These results can assist in selecting better materials and optimizing operating conditions. Proper adjustments suggested from these models can also reduce wear and improve machine performance. Material type also plays a key role in wear behavior. Virgin and recycled polymers demonstrate different levels of wear rate. Recycled PETG exhibited higher wear rates under dry conditions, reflecting its limitations in unlubricated applications. However, lubrication significantly reduced wear across all material types, as observed in Table 3 and Figure 5. This detail underscores the importance of lubrication in extending component life in sliding systems.

Temperature Rise (°C), though less influential, than energy dissipated demonstrates thermal effects on wear. Higher temperatures accelerated material degradation, especially in recycled materials. This finding emphasizes the need for thermal management in tribological systems using 3D-printed components. These results are directly relevant to sustainable engineering practices demonstrating how recycled materials, when combined with optimal operational strategies, can deliver acceptable performance. Additionally, machine learning tools offer a robust tool for material design and performance prediction, paving the way for data-driven solutions in tribology.

4.3 Classification model results

In this study, material-lubrication configurations were categorized into low-performing (Class 0) and high-performing (Class 1) material-lubrication combinations.

- *Class 0 (Low Performance):* These materials exhibited higher wear rates, greater energy dissipation, and significant temperature rise, leading to poor tribological behavior. Examples: Dry Recycled PETG, Dry Virgin PLA (higher wear and friction).
- *Class 1 (High Performance):* These materials demonstrated lower wear rates, minimal frictional losses, and stable thermal behavior, making them more suitable for tribological applications. Examples: Lubricated Virgin PETG, Lubricated Recycled PLA (better wear resistance).

The models were trained using a dataset of 336 samples (168 experimental + 168 augmented), split into 80% training (268 samples) and 20% testing (68 samples) to ensure general results.
Performance of Classification Models: Table 5 presents the classification performance of four machine learning models after hyperparameter tuning. Each model exhibited distinct strengths and limitations in predicting tribological performance. From Table 5, the following observations can be made:

1. Logistic Regression (87% accuracy)

- Performed best overall, achieving 96% recall for Class 1.
- It effectively identified high-performing material-lubrication pairs.
- However, 30% of Class 0 samples were misclassified, indicating the models difficulty with recognizing low-performance cases.

2. Support Vector Machine (SVM) (75% accuracy)

- Performed poorly compared to other models, particularly in identifying low-performance samples (50% recall for Class 0).
- This result suggests overfitting to high-performance materials, potentially due to boundary overlap in wear rates and energy dissipation.
- 80% precision for Class 1 indicates that the model reliably predicts high-performance cases but struggles with borderline conditions.

3. Random Forest (82% accuracy)

- Showed a more balanced classification, with 65% recall for Class 0 and 90% for Class 1.
- Precision was consistent across both classes, minimizing false positives.
- Its feature importance analysis (discussed later) suggests that temperature rise and lubrication were strong predictive factors.

4. Gradient Boosting (81% accuracy)

- Achieved a strong balance in precision and recall for both classes.
- Performed similarly to Random Forest but with slightly lower recall for Class 0 (60%).
- Handles non-linearity better than Logistic Regression, but overfitting is possible with small datasets.
- Ideal for applications requiring fine-tuned classification of borderline cases.

Table 5. Classification performance metrics for low- and high-performance classes.

Model	Best Hyperparameters	Accuracy	Precision (Class 0)	Recall (Class 0)	Precision (Class 1)	Recall (Class 1)	F1-Score
Logistic Regression	C=10	87%	0.88	0.70	0.88	0.96	0.85
SVM	C=10, kernel=rbf	75%	0.59	0.50	0.80	0.85	0.68
Random Forest	max_depth=15, n_estimators=50	82%	0.72	0.65	0.86	0.90	0.78
Gradient Boosting	learning_rate=0.2, max_depth=5, n_estimators=150	81%	0.71	0.60	0.84	0.90	0.76

Confusion Matrix Analysis: To visually illustrate the classification performance, Figures 8 and 9 presents the confusion matrix for Logistic Regression (the best model) and Gradient Boosting (the second-best model). The interpretation of the confusion matrix is as follows:

- True Positives (Class 1 correctly identified): 45 samples for Logistic Regression, 43 samples for Gradient Boosting.
- False Negatives (Class 1 misclassified as Class 0): 3 samples for Logistic Regression, 5 samples for Gradient Boosting.
- False Positives (Class 0 misclassified as Class 1): 6 samples for Logistic Regression, 8 samples for Gradient Boosting.
- True Negatives (Class 0 correctly identified): 14 samples for Logistic Regression, 12 samples for Gradient Boosting.

Logistic Regression demonstrates slightly higher precision in identifying true positives with fewer false negatives, whereas Gradient Boosting, despite having a marginal increase in false positives, provides a robust performance in identifying complex patterns within datasets.

The classification models provide a data-driven approach to predicting tribological performance, which helps in identifying optimal material-lubrication combinations. The results indicate that lubrication significantly improves wear resistance, aligning with experimental findings. The models effectively differentiate between low and high-performing material pairs, reducing the reliance on extensive physical testing. The analysis highlights that temperature rise and energy dissipation strongly influence wear behavior. Higher wear rates correspond to greater heat generation, leading to material degradation.

Random Forest and Gradient Boosting models identified these conditions as key predictive factors, reinforcing their practical role in material selection.The results from this study will help engineers make better choices in tribological components. In industries like automotive and biomedical, using low-friction and high-wear-resistant materials can increase the lifespan of moving parts significantly reducing costs incurred through maintenance and replacement.

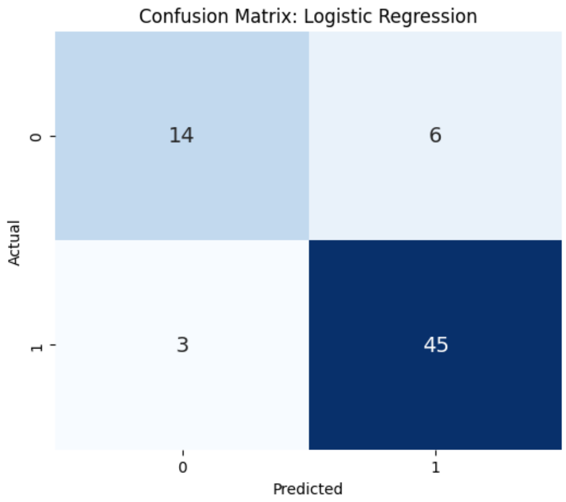

Fig. 8. Confusion matrix for logistic regression.

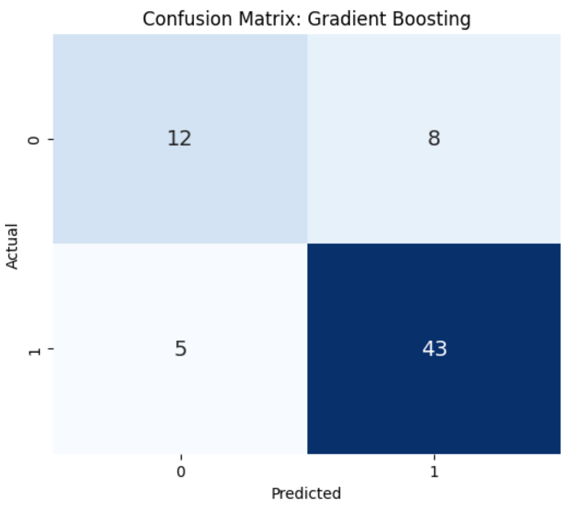

Fig. 9. Confusion matrix for gradient boosting.

Machine learning methods can assist in tribology-based material selection while also reducing the energy loss and improving efficiency in high-friction conditions.

4.4 Data augmentation

The experimental dataset of 168 rows provided a basic understanding of tribological performance. However, its small size reduced the accuracy and reliability of machine learning models. The minimum number of data points required to apply ML models and obtain proper regression and classification results are usually more than 300. To solve this issue, data augmentation was used to artificially increase the dataset. All the results discussed earlier were obtained using the augmented dataset. This section explains the augmentation method used, its effect on model performance, and its significance for improving reliability. *Need for Data Augmentation:* The original dataset had 168 rows covering different materials and test conditions. However, this small dataset proved difficult to train machine learning models accurately. Small datasets can cause overfitting which trains models to remember patterns rather than learn useful relationships. Additionally, some material and test condition combinations had very few samples which would create errors in model predictions. To resolve these issues, data augmentation was performed. This implementation expanded the dataset while keeping the original data meaningful. Another 168 synthetic data points were added resulting in a final dataset of 336 rows.

The aim was to create a balanced and diverse dataset while maintaining accurate wear behaviour. *Methodology for Data Augmentation:* A Gaussian Mixture Model (GMM) was used to generate synthetic data. The Gaussian Mixture Model (GMM)-based augmentation fits multiple Gaussian distributions to the original data, preserving the means and variances while introducing small, controlled variations to mimic real-life uncertainty, thereby generating synthetic samples that closely reflect the natural variability observed in the experimental measurements. GMM is prone to slight biases which may occur due to limited initial variability.

1. Feature Distribution Analysis:
   - The probability distributions of key tribological parameters (Load, Friction Forces, Energy Dissipation, Temperature Rise, Wear Rate) were analyzed.
   - Histograms and kernel density estimation (KDE) plots confirmed that the data followed multi-modal distributions, making GMM a suitable approach.
2. Gaussian Mixture Modeling (GMM):
   - A GMM with multiple Gaussian components was fitted to the original dataset.
   - Each tribological feature was modelled as a mixture of Gaussian distributions, allowing synthetic data points to be sampled while preserving real-world variability.
   - The optimal number of Gaussian components was determined using the Bayesian Information Criterion (BIC).
3. Synthetic Data Generation:
   - New data points were sampled from the fitted GMM, ensuring that they adhered to the statistical distribution of the original data.
4. Validation and Integration:
   - The synthetic data was statistically compared with the original dataset using mean, variance, and distribution overlap measures.
   - Feature distributions were plotted (Figure 10 to Figure 15) to confirm that the generated data was neither over-smoothened nor unrealistic.
   - Finally, the synthetic data was combined with the original dataset to form an augmented dataset with 336 rows.

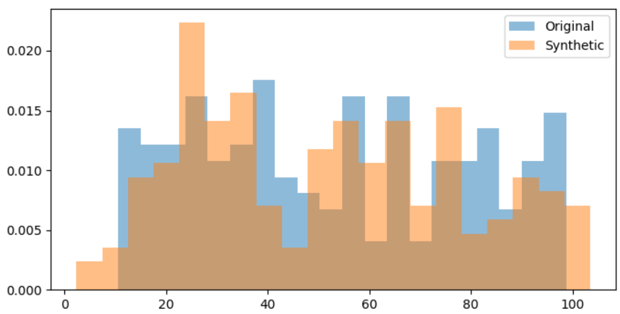

Fig. 10. Feature distribution plot for load.

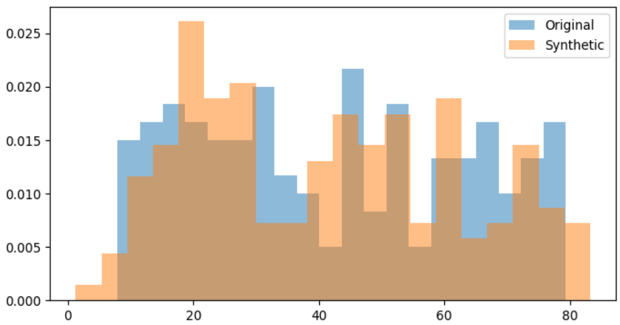

Fig. 11. Feature distribution plot for static friction force.

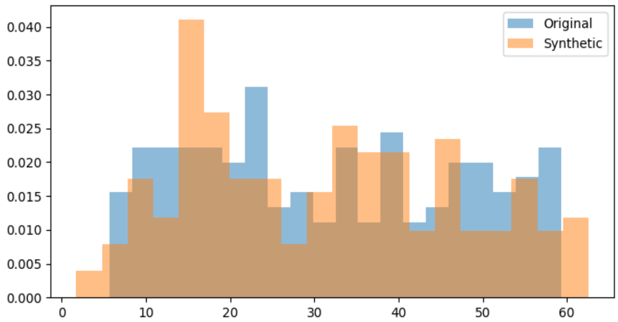

Fig. 12. Feature distribution plot for kinetic friction force.

Impact on Model Performance: To evaluate the impact of data augmentation, machine learning models were trained separately on:

1. The original dataset (168 rows).
2. The synthetic dataset (168 rows).
3. The augmented dataset (336 rows: original + synthetic).

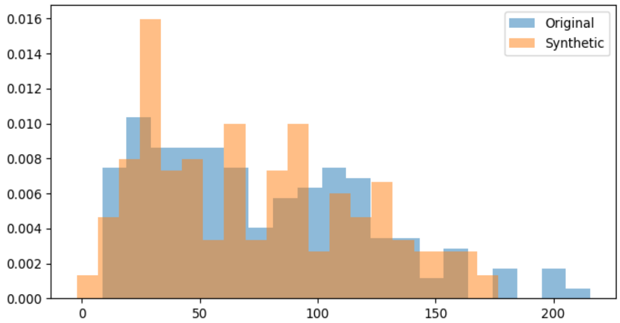

Fig. 13. Feature distribution plot for energy dissipated.

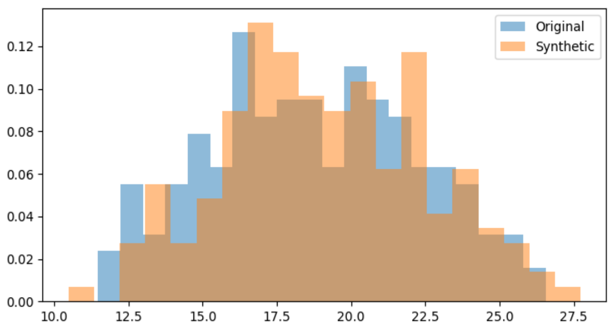

Fig. 14. Feature distribution plot for temperature rise.

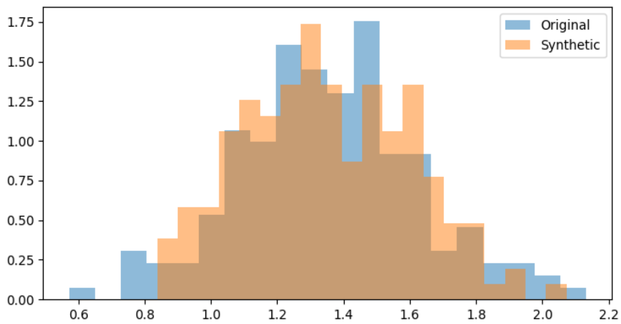

Fig. 15. Feature distribution plot for wear rate.

Table 6 summarizes the mean performance scores across these datasets. The original dataset provided the most accurate performance as it directly reflects experimental data. The synthetic dataset, while slightly lower in performance, introduced statistical diversity that improved model robustness. The augmented dataset effectively balanced these aspects, yielding results comparable to the original dataset while preventing overfitting. *Reliability and Practical Implications:* The feature distribution plots above confirm that the augmented dataset closely followed the statistical trends of the original data which ensures that machine learning models trained on the augmented (extended) dataset maintain physical relevance to real-world tribological conditions.

Table 6. Performance comparison of original, synthetic, and augmented datasets.

Dataset	Mean Performance Score
Original Dataset (168 rows)	0.738
Synthetic Dataset (168 rows)	0.726
Augmented Dataset (336 rows)	0.732

The augmentation process allowed for a better representation of rare material-lubrication-load combinations, improving the generalization ability of classification models. Additionally, models trained on the augmented dataset exhibited reduced variance, confirming that augmentation increased stability without introducing significant artifacts.

This approach is especially valuable in mechanical engineering applications, where collecting large-scale experimental data is challenging due to cost and time constraints. By leveraging GMM-based augmentation, this study bridges the gap between experimental limitations and the need for robust predictive modelling in tribology.

4.5 Discussion on practical applications and scope for future work

The findings of this study provide valuable insights into material selection and lubrication strategies for reducing wear and improving durability. A comprehensive comparison shows that recycled polymers exhibit up to 15–20% higher wear rates under dry conditions compared to virgin materials, which aligns with findings in recent tribological literature. This emphasizes the need for proper lubrication in applications where material degradation is a concern. The results indicate that energy dissipation and surface temperature play a significant role in determining wear performance, making thermal management an essential factor in tribological applications.

In manufacturing industries, selecting the right material and lubrication conditions can significantly extend the lifespan of machine components, reduce maintenance costs, and enhance operational efficiency. In automotive applications, where friction and wear directly impact fuel efficiency and part longevity, understanding these parameters helps in optimizing materials for brake pads, gears, and engine components. For biomedical applications, such as prosthetic joints and surgical tools, minimizing friction and wear is essential for reliability and long-term performance. The study's findings support the need for tailored tribological solutions, ensuring that materials perform optimally in their respective environments. A limitation of this study is that it evaluated only a fixed range of load and lubrication conditions, which may not fully reflect the variability encountered in real-world operational environments. Further research can include a broader range of polymer composites, dynamic operating conditions, and long-term wear simulations to strengthen the relevancy of the findings.

5. CONCLUSION

This study investigated the tribological performance of virgin and recycled PLA and PETG structures under dry and lubricated conditions. A pin-on-disk tribometer was used to measure key parameters such as wear rate, friction coefficients, energy dissipation, and temperature rise. The experimental dataset was augmented using Gaussian Mixture Model-based feature synthesis, expanding the dataset from 168 to 336 samples. This ensured better model generalization and improved statistical robustness.

Regression models were developed to predict wear rate based on tribological parameters. Among the tested models, Gradient Boosting (R^2 = 0.698) outperformed Random Forest (R^2 = 0.660), demonstrating better predictive capability. Feature importance analysis highlighted energy dissipation as the dominant factor influencing wear rate. Classification models were also employed to distinguish between high and low-performing material-lubrication combinations. Logistic Regression achieved the highest classification accuracy (88%), effectively distinguishing optimal conditions for reduced wear. The findings emphasize the importance of material selection and lubrication strategy in minimizing wear. Recycled polymers exhibited higher wear rates compared to virgin counterparts, but lubrication significantly mitigated material loss. These insights are crucial for manufacturing, biomedical, and automotive applications, where polymer-based components undergo frictional interactions. The study demonstrates the integration of tribological experiments with machine learning to enhance predictive accuracy and decision-making. While data augmentation improved model performance, future research can explore real-world deployment of AI-driven wear prediction models and evaluate long-term durability of recycled polymers under varied operating conditions.

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