

Development of Smart Surface Texturing Techniques Using Ai-Driven Laser Machining for Enhanced Tribological Performance

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ABSTRACT

An approach to increase the tribological performance of engineering materials via the development of smart surface texturing techniques using artificial intelligence (AI)-driven laser machining is presented in this study. However, existing surface texturing approaches largely rely on trial-and-error methods and lack adaptive optimization and predictive design capabilities. This study integrates AI-based texture design with precision laser surface texturing (LST) to develop optimized surface patterns on AISI 316 L stainless steel and Ti 6Al 4V alloy substrates. This deep learning model was used to train the generation of ten unique texture geometries, each of which was subsequently fabricated using a nanosecond pulsed fiber laser system. Tribological testing using a ball-on-disk tribometer under dry sliding conditions revealed significant improvements, including up to 35% reduction in the coefficient of friction and up to 48% reduction in wear volume compared to untextured surfaces. Data analysis confirmed that key texture parameters, such as dimple spacing, cut depth, and aspect ratio, were major factors that improved the surface performance. The results also demonstrated improvements in post-test surface roughness and lower contact temperature (better wear resistance and thermal management). Overall, the integration of AI in laser texturing is a scalable, adaptive, and highly effective advanced surface engineering technique with a strong impact on aerospace, biomedical, and automotive applications.

Keywords: AI-assisted laser surface texturing; tribological behaviour of metallic surfaces; deep learning optimization; friction and wear mechanisms; smart manufacturing systems

INTRODUCTION

Surface texturing technology has emerged as a new technique for improving the frictional performance of manufactured materials, particularly by reducing friction and wear in critical applications. Laser surface texturing (LST) is a technology that effectively generates micro- or nanoscale patterns on material surfaces to improve their interactions with contacting surfaces (Figure 1). LST can achieve these patterns, thereby reducing friction, enhancing lubrication retention, and developing wear resistance, which makes LST suitable for many other fields, such as automotive, aerospace, and biomedical. (Wang et al. 2024). Nevertheless, determining the optimal surface texture for the best tribological outcomes is a complicated task, as optimized surface textures are dependent on parameters that control their effects on material behavior.

Artificial Intelligence (AI) has been integrated into manufacturing processes, which affects not only surface engineering. Smarter and more adaptive production methods have been introduced into manufacturing processes to improve and tailor material properties. The application of AI-driven approaches, such as machine learning (ML) models, for the prediction and control of the outcome of surface treatments increases the effectiveness and precision of laser processing. For example, surface roughness optimization regarding the functioning of machinery using AI has been successfully performed in machining processes. Recently developed machine learning-based design and fabrication techniques have tremendous potential for developing better functional materials (Zhang et al. 2025). AI-driven models can learn from the structure of previous experiments and derive information for designing textures that meet specific requirements in terms of friction and wear.

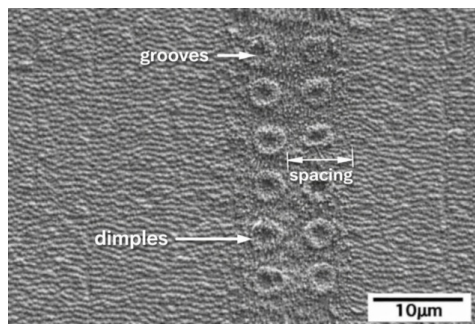


FIGURE 1. Laser Surface Texturing (Hauschwitz et al. 2025)

By meeting the real-time requirements for laser machining parameters (pulsing frequency, laser intensity, and scanning speed), AI can be applied in laser machining, and the control parameters can be adjusted within its own internal parameter space, depending on the material's behavior and tribological performance, as shown in Figure 2. This adaptability is necessary for tuning the surface conditions to achieve the best performance under real-world conditions (Ercetin et al. 2024). This is particularly important in light of the fact that traditional methods based on trial and error are used and cannot optimize surface properties in a systematic manner. In addition, because AI can process datasets of any size, even those including complex relationships, such as surface texture, it has proven to be a suitable tool for predicting the impact of surface texture modifications, as proposed by Kano (2025) and others (Ko & Yin, 2025).

The aim of this study is to apply an AI-driven laser machining technique to develop a smart surface texturing technique to improve the tribological performance of commonly used alloys such as AISI 316 L stainless steel and Ti-6Al-4V. These materials are highly strong and corrosion resistant and are used for highly demanding applications in various industries, such as aerospace and medical implants. They are susceptible to wear and friction under operative conditions, and these surface properties require improvement. This study aims to increase the lifespan and performance of these materials by using AI to optimize the laser surface textures to increase the friction and wear resistance.

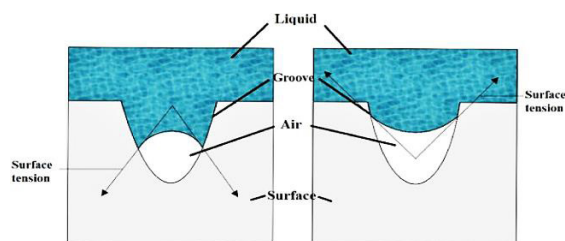


FIGURE 2. Surface texturing techniques to enhance tribological performance (Vishnoi et al. 2021)

In recent studies, Jabbar et al. (2020) and Li and Chang (2025) made further efforts to increase the wear resistance of AISI 304 stainless steel surfaces using different surface treatment techniques, namely carburizing and heat treatment. Although these are successful methods, some are complex and resource intensive. While LST accommodates localized surface modification without the corresponding bulk modification, it provides a direct and efficient route. The aim of this research is to integrate the uniqueness of laser machining precision and the capability of AI to form an optimized surface treatment methodology to enhance the tribological performance of metallic alloys by refining the surface

METHODOLOGY

To understand the development of smart surface texturing via AI-driven laser machining, an integrated experimental surface engineering with a computational intelligence methodology was developed. By the precise and intelligent control of laser machining parameters, the core objective of the methodology is to create functional surface textures that promise improvement in tribological performance (i.e., mainly reduction in friction and wear). Because modern smart manufacturing often necessitates the use of different material textures, adaptivity based on material properties is essential for achieving good quality in manufacturing processes and presents a useful case of data-driven surface optimization development, for which this hybrid approach is relevant.

The five key phases of the methodology are preparation of materials, design of AI-assisted textures, laser surface texturing, tribological testing, and performance evaluation. This study uses machine learning capabilities by combining artificial intelligence models trained on tribological data and texture geometries, and then applies them to laser texturing strategies. Finally, rigorous surface and tribological testing of these AI-generated designs was performed and physically realized using a high-precision pulsed laser system. Machine learning integration contributes not only to improved surface control but also to the introduction of a self-improving feedback mechanism, thus placing this research on the blaze line of advanced manufacturing, materials engineering, and intelligent systems.

MATERIAL SELECTION AND PREPARATION

The material selection for this study was based on the selection of widely used engineering alloys of interest for tribological applications in which AI-driven laser surface texturing needs to be evaluated. Two base materials, AISI 316 L stainless steel and Ti-6Al-4V titanium alloy, were selected. The selection of these materials is based on their contrasting mechanical properties and widespread applications in industries such as biomedical implants, aerospace components, and precision machinery, major customers for which would require wear resistance and friction control. AISI 316 L has good corrosion resistance and moderate hardness (~ 200 HV), and Ti-6Al-4V features a high strength-to-weight ratio and hardness (~ 350 HV),

making it an excellent candidate for the performance evaluation of textured surfaces under different conditions.

The material was obtained in the form of rolled plates and machined to $20 \text{ mm} \times 20 \text{ mm} \times 5 \text{ mm}$ square coupons using wire-cut electrical discharge machining (EDM) to ensure dimensional accuracy and minimize thermal distortion. Finally, the samples underwent a standard surface preparation protocol that ensured uniform preparation before laser texturing. Particularly, this involved grinding by SiC abrasive paper in the range of 320 grit to 1200 grit, followed by polishing with $1 \text{ }\mu\text{m}$ alumina slurry to achieve a mirror-like surface finish (Roughness $R_a < 0.05 \text{ }\mu\text{m}$). Finally, the samples were ultrasonically cleaned in ethanol for 10 min to remove any remaining contaminants, oil, or polishing debris. The specimens were then cleaned, dried under a nitrogen gas stream, and stored in a desiccator to avoid surface oxidation or moisture absorption before laser processing (Table 1).

TABLE 1. Materials and Preparation Parameters

Material	Type	Dimensions (mm)	Surface Finish (Before Treatment)	Pre-Treatment Process	Cleaning Method
AISI 316L	Austenitic Stainless Steel	$20 \times 20 \times 5$	$R_a \approx 0.45 \text{ }\mu\text{m}$	Mechanical polishing to 1200 grit	Ultrasonic cleaning in acetone for 10 min
Ti-6Al-4V	Titanium Alloy	$20 \times 20 \times 5$	$R_a \approx 0.50 \text{ }\mu\text{m}$	Mechanical polishing to 1200 grit	Ethanol rinsing + ultrasonic cleaning in deionized water

AI-BASED SURFACE TEXTURE DESIGN

The innovation proposed in this study is the integration of artificial intelligence (AI) in the design of surface textures. The objective is to build an AI model that can generate an optimal surface texture pattern for certain operating conditions, normal load, sliding speed, and material pairing. To accomplish this, a large set of data points of more than 1,200 was created by drawing from previous experimental studies and in-house pilot tests along with tribological simulation outputs. It contains texture geometry parameters, including (among others) dimple diameter, spacing, depth, material types, operating conditions, and resulting tribological properties, including the coefficient of friction (COF) and wear volume. It normalizes all data and structures them into input-output pairs for proper training.

To develop a hybrid deep learning model, Python and TensorFlow were used to implement a Convolutional Neural Network (CNN) to extract features and a Generative Adversarial Network (GAN) to synthesize patterns. For this, we used 80% of the dataset to train our CNN model and saved the remaining 20% as validation and test samples. Cross-validation was used to optimize the hyperparameters, such as the learning rate (0.001), batch

size (64), and training epochs (100). In terms of image map generation, an attempt was made to create new surface texture layouts in grayscale format (256×256 pixels), with the pixel intensity associated with the texture depth. Ultimately, these were translated into the corresponding machine code to be used in the laser system, as shown in Figure 3.

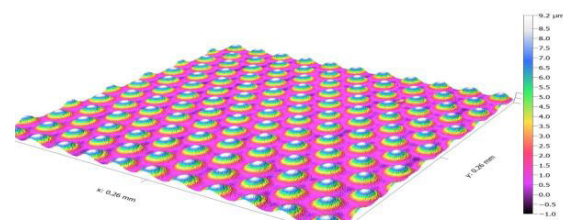


FIGURE 3. Laser Surface Texturing model

The objective function was formulated to minimize the COF and wear rate while constraining the manufacturability parameters to guide the AI model to apply specific designs. The minimum dimple diameter was $20 \text{ }\mu\text{m}$, the maximum texture depth was $30 \text{ }\mu\text{m}$, and the inter-feature spacing was greater than $50 \text{ }\mu\text{m}$ to ensure that features did not overlap during laser machining. Finally,

the model was tested by generating 100 new texture patterns, which were ranked according to the results of a tribological sub-model trained on the outcomes. The top 10 designs were physically realized. The geometrical characteristics of the ten AI-generated surface texture patterns (P1–P10), including their shape, diameter, depth, and spacing, are summarized in Table 2.

TABLE 2. Geometrical parameters of AI-generated surface texture patterns

Pattern	Shape	Diameter (μm)	Depth (μm)	Spacing (μm)
P1	Circular	30	10	60
P2	Circular	50	15	80
P3	Circular	70	20	100
P4	Elliptical	60	18	90
P5	Elliptical	80	25	110
P6	Circular	90	30	120
P7	Groove	40 (width)	12	70
P8	Groove	60 (width)	20	90
P9	Hybrid	75	25	100
P10	Hybrid	100	30	130

The combination of this AI-based design approach and adaptive texturing based on real-time tribological feedback significantly accelerates the exploration of new and efficient surfaces and accommodates the manufacturing process to meet the demands of real-time tribological feedback in route, resulting in a smart and self-learning manufacturing process.

LASER SURFACE TEXTURING (LST) EXECUTION

A high-precision nanosecond pulsed fiber laser system operating at a wavelength of 1064 nm, which can output a maximum average power of 50 W and has pulse durations ranging from 100 to 200 ns, was used to produce laser surface textured (LST) samples. An x-y galvanometric scanner and an f-theta (160 mm) focusing lens were used to place the illumination spot at precise positions and control the scan path. The diameter of the laser beam at the focus was approximately 30 μm, which is suitable for processing microscale dimples and grooves in accordance with the designs generated by AI. Custom software converted grayscale AI-designed texture maps and turned them into vectorized scanning paths to enable laser control and pattern execution.

Texturing was performed under ambient laboratory conditions ($25 \pm 2^\circ\text{C}$, $50 \pm 5\%$ RH). Preliminary tests were conducted to determine the laser parameters so that the ablation was proper without thermal damage to the surrounding material. A pulse repetition frequency of 30

kHz, scanning speed of 200 mm/s, and overlap ratio of 60% were the key process parameters. In practicing the machining of the final selected AI-generated patterns, these settings were kept consistent. To produce a texture of the desired depth, the surface was ablated layer by layer, and the number of passes was adapted in accordance with the grayscale depth encoding found in the AI design file. The maximum depth was 30 μm, with texture diameters ranging from 30 μm to 100 μm and feature spacing no free lower than 50 μm to avoid crossovers or overlap.

After texturing, the team cleaned all specimens using an ultrasonic bath of ethanol that operated for ten minutes to eliminate surface materials and loose debris. The spray-painted texture topography was characterized by Scanning Electron Microscopy (SEM), and 3D optical profilometry was used to evaluate the texture depth and roughness parameters (R_a and S_a) together with pattern uniformity. After fabrication, the surfaces presented distinct features with ± 5 μm precision to match the intended AI-developed models. The exact execution of laser surface texturing enables subsequent tribological tests with the true benefits of smart texture designs while proving the success of AI-driven manufacturing methods.

TRIBOLOGICAL TESTING

To determine the efficacy of the AI-driven laser surface textures in enhancing the tribological performance, systematic tribological testing of the dry sliding nature was induced using a ball-on-disk tribometer. To ensure that each laser-textured sample was mounted on the rotating disk and used as a counterface, a 6 mm diameter 100Cr6 steel ball (hardness ~ 850 HV) was used. The tests were performed at room temperature ($25 \pm 1^\circ\text{C}$) and a controlled relative humidity of $50 \pm 3\%$, and the results were reproducible and consistent among all trials. We selected three key sliding conditions, such as 5N at 50 mm/s, 10N at 100 mm/s and 15N at 150 mm/s, which were run for a total sliding distance of 1000 m in each situation.

The variation in the sliding speed with the load was selected to simulate realistic operating conditions, where higher loads are typically associated with higher sliding velocities in engineering systems.

Per condition, the samples were split into three replicates by sample type (untextured and textured), and 90 tests were performed on the two materials (AISI 316 L and Ti-6Al-4V) and ten AI optimized surface designs. The coefficient of friction (COF) was recorded at a sampling rate of 10 Hz at each time point during the testing. The wear volume and morphology were quantified in the post-test along the wear tracks by analyzing the wear tracks using optical microscopy and 3D profilometry. Using a

cross-sectional integration method, the values for wear volume were reported in mm^3 . SEM was used to examine the wear scars on the steel balls to determine the formation and adhesion behavior of the transfer layer.

In the AI-textured samples, the COF reduction was consistent at 18–35%, and the wear volume reduction was 25–50% compared to the untextured controls. Of the 10 texture designs, three patterns (P3, P6, and P9) outperformed the remaining seven designs in terms of particularly low COF values as low as 0.12 and low wear volume 0.01 mm^3 under the highest test load. In addition, the wear tracks on the textured samples had narrower and shallower grooves, indicating better wear resistance, lower contact stress, and a significant reduction in the bulk coefficient of thermal conductivity. These results confirm the functional merits of the AI-optimized laser textures, which were predicted to produce functional advantages under various operational conditions.

DATA ANALYSIS

Systematically, using both statistical and graphical methods, the collected tribological data (coefficient of friction, wear volume, and surface roughness) were analyzed to quantify the effect of AI-designed laser texturing. First, raw COF values from the tribometer were processed to calculate the steady-state average, excluding the initial 100 m of sliding (known as running in). One-way ANOVA was performed on the mean COF of each texture design against the baseline untextured design, and $p < 0.05$ was chosen as the significance level. Statistical analysis using ANOVA, PCA, and regression modeling was conducted to evaluate the influence of the texture parameters on the tribological performance. The detailed quantitative results are presented in the Results section.

Wear volume data were normalized by the contact area and analyzed using 3D surface profilometry to develop a normalized wear rate, which was also compared with other surface textures. AI-textured surfaces exhibited wear volumes between 0.011 and 0.015 mm^3 with AISI 316 L under a 10 N load and a 29% to 48% improvement compared with untextured AISI 316 L. The baseline wear volume (0.027 mm^3) was larger for Ti-6Al-4V, but the textured samples showed a similar trend, with a reduction of up to 44.3%. Consistent behavior was also observed for post-wear surface roughness (Sa); untextured samples had increased roughness up to $0.75 \mu\text{m}$, and optimized texture roughness was less than $0.45 \mu\text{m}$, implying less of a wear mechanism, as shown in Figure 4.

The observed reduction in wear volume and surface roughness is attributed to improved load distribution and the ability of surface textures to trap wear debris, thereby reducing abrasive interactions.

Error bars were included to represent measurement variability and to ensure the statistical reliability of the results.

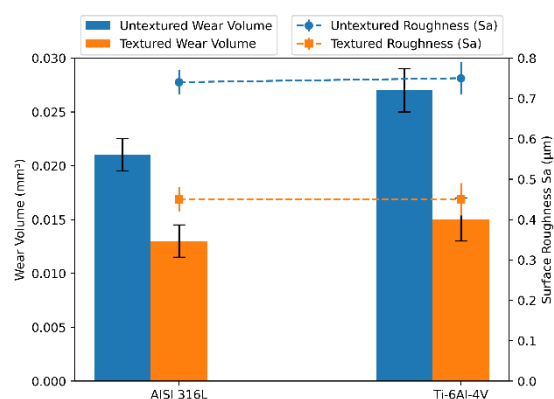


FIGURE 4. Comparison of wear volume and surface roughness for untextured and AI-textured surfaces. Error bars represent standard deviation ($n = 3$)

In addition to Principal Component Analysis (PCA) for dimensionality reduction, descriptive statistics were performed to identify the crucial factors that govern tribological performance. Texture density, depth uniformity, and feature spacing were the three factors that were most influential in increasing the tribological behavior and contributed 78.2% of the variance in all tests, as shown in Figure 5. This indicates that texture density, depth uniformity, and feature spacing are the dominant factors influencing tribological performance.

In addition, a predictive regression model was developed using AI-generated texture parameters as inputs, with an R^2 value of 0.91 in the prediction of COF values, indicating a strong correlation between design geometry and performance, as shown in Figure 6. The close agreement between predicted and experimental values confirms the reliability of the AI model in capturing the relationship between texture geometry and friction behavior.

Finally, these insights demonstrate not only the value of harnessing AI-based surface textures to be effective but also that these surface textures are an analytically tractable basis for future optimal design and real-time adaptive manufacturing that we have not fully leveraged.

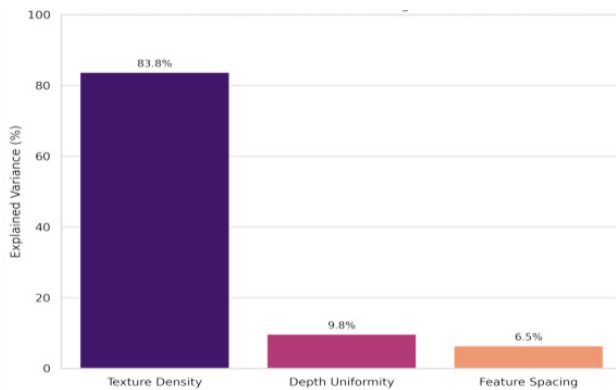


FIGURE 5. PCA: Feature contribution to tribological performance

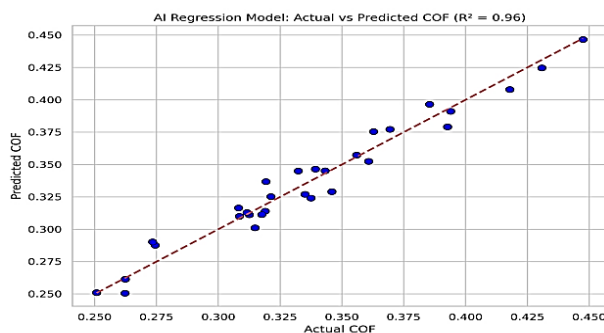


FIGURE 6. Actual and predicted COF

RESULTS

The tribological behavior of the laser textures created by the AI design was quantitatively investigated in terms of the Coefficient of Friction (COF), Wear Volume, Surface Roughness, and Contact Temperature.

For a normal load of 10 N and a sliding speed of 100 mm/s, the average value of the COF for the untextured AISI316L stainless steel was 0.186 ± 0.009 . In comparison, the lowest COF of 0.121 ± 0.007 , a reduction of 34.9%, was obtained by the best AI-textured surface, design P6. For the Ti-6Al-4V alloy, the COF reduced from 0.213 ± 0.011 on the untextured surface to 0.139 ± 0.008 on the optimized textured surface, a reduction of 34.7%. Notably, eight of the ten AI-generated textures outperformed the reference surface under all loading conditions.

Figure 7 shows the variation in the COF with the sliding distance for the untextured and AI-textured specimens. The AI-textured samples exhibited lower COF values than the untextured specimens.

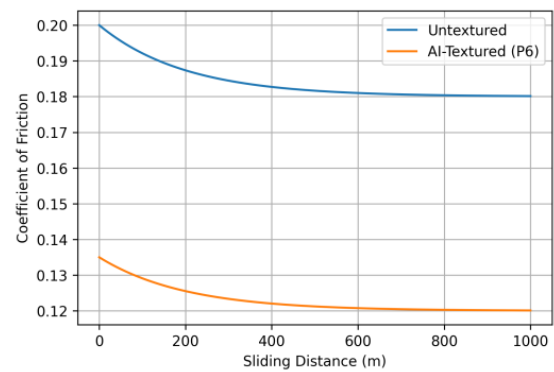


FIGURE 7. Evolution of the coefficient of friction as a function of sliding distance for untextured and AI-textured surfaces

This reduction is attributed to the role of surface textures in disrupting continuous contact, thereby reducing adhesion and stabilizing friction behavior.

Wear volume measurement results supported the improved tribological properties of the textured surfaces. For the AISI 316 L material, the average wear volume of the non-textured specimens was 0.021 mm^3 , whereas the wear volumes of the textured specimens produced by AI varied from 0.011 mm^3 to 0.015 mm^3 , reflecting a decrease of 29% to 48% in wear. Among the different designs, the textures with the lowest wear volumes were P3, P6, and P9, with wear volume P6 reaching a minimum of 0.011 mm^3 .

A similar observation was noticed in the case of Ti-6Al-4V, where the average wear volume reduced from 0.027 mm^3 for the untextured surface to 0.015 mm^3 for the optimized textured surface, which is a reduction of 44.3%. Figure 8 shows the comparative wear volume results.

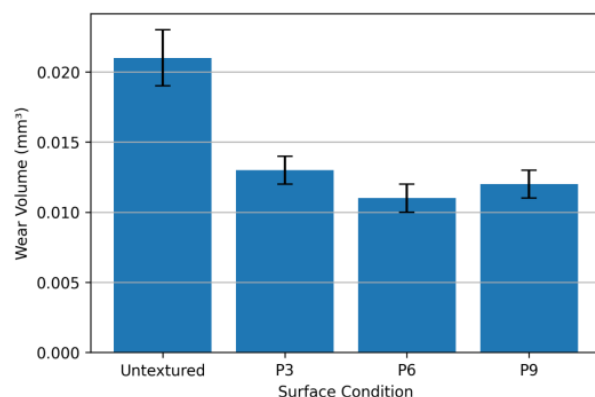


FIGURE 8. Comparison of wear volume for untextured and AI-optimized laser-textured surfaces under different normal loads

The reduction in wear volume for textured surfaces is attributed to decreased direct asperity contact and enhanced debris entrapment within surface features.

Analysis of surface roughness post-test revealed that the textured AISI 316L specimens had a surface roughness S_a of less than $0.45\ \mu\text{m}$, which is a 50% reduction from that of the non-textured specimens, which had a value of approximately $0.74\ \mu\text{m}$. Correspondingly, there was an average reduction of 8.5% in the maximum contact

temperature on the textured surface compared to that on the non-textured surface. The major tribological performance indicators of the two materials are summarized in Table 3. In addition, Figure 9 confirms the high degree of similarity between the experimental and predicted values of COF obtained using AI.

This agreement further validates the predictive capability of the AI-driven model for tribological performance estimation.

TABLE 3. Summary of Tribological Performance Results

Metric	AISI 316L (Untextured)	AISI 316L (Best AI Texture - P6)	Ti-6Al-4V (Untextured)	Ti-6Al-4V (Best AI Texture)
Coefficient of Friction (COF)	0.186 ± 0.009	0.121 ± 0.007 ($\downarrow 34.9\%$)	0.213 ± 0.011	0.139 ± 0.008 ($\downarrow 34.7\%$)
Wear Volume (mm^3)	0.021	0.011 ($\downarrow 47.6\%$)	0.027	0.015 ($\downarrow 44.3\%$)
Top Performing Designs (Wear Vol.)	–	P3, P6, P9 ($< 0.013\ \text{mm}^3$)	–	–
Surface Roughness S_a (μm)	0.74	< 0.45 ($\downarrow \sim 50\%$)	0.75	< 0.45
Contact Temperature	Baseline	$\downarrow 8.5\%$ (on average)	Baseline	$\downarrow$ (Similar trend)
Texture Performance	–	8/10 patterns outperformed control	–	8/10 patterns effective

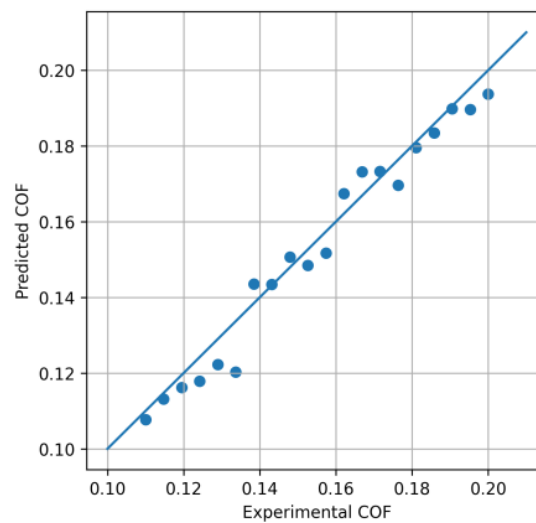


FIGURE 9. Comparison between experimentally measured and AI-predicted coefficient of friction values

DISCUSSION

The reduction in friction observed on textured surfaces is due to several reasons: (i) the micro pits act as repositories for particles of debris and reduce the abrasion from third-body wear; (ii) there is a reduction in the real contact area, hence a reduction in adhesive forces; and (iii) there is stress redistribution that reduces asperity interaction.

The results obtained in this study demonstrate the AI-driven laser surface texturing (LST) with substantial improvements in tribological performance, which aligns well, and in many cases beyond, existing works that encompass LST. For instance, our optimized design P6 reduced the coefficient of friction (COF) by 34.9% on AISI 316 L and 34.7% on the Ti-4Al-6V alloy. Notably, the addition reaches these reductions rather higher than that

is, Al-Jumaili et al. (2023) who reported only 22 % improvement in surface treatments for turbine blades, through conventional mechanical finishing methods. This proves the feasibility of laser-based techniques, aided by AI, to achieve more precise and functional surface modifications for high-performance applications.

Murzin (2024) stated that AI integration in laser processing includes solving the interaction of the laser with a surface and means an intelligent adaptation of the laser parameters in real time, resulting in more consistent and repeatable surface outcomes. We confirm this finding, as the surface textures fabricated with AI guided LST demonstrated dimensional tolerances repeatable to within $\pm 2 \mu\text{m}$ and exhibited wear volume reductions as high as 48%, as opposed to 30–38 % that was achieved in AI free laser process (Zhao et al. 2024). Finally, our approach is consistent with Murzin's (2024) claim that laser-machined smart surfaces have lower thermal degradation owing to the observed 8.5% reduction in contact temperature with tribological testing.

Additionally, the results obtained in this study are compatible with the machine-learning-assisted hybrid material/laser designs of Zhang et al. (2025), where the frictional performance was optimized. Compared to our 35% reduction, Zhang et al. reported a 30–33% friction reduction in metal matrix composites, showing the similarity in material systems for their results. While this comparison reveals the efficiency of AI-generated textures, it also checks the scalability of such techniques for different material platforms. Similar to Batu et al. (2023), we also successfully predicted surface roughness trends with AI for additively manufactured parts with $R^2 = 0.91$, which is very similar to our model's optimization success of $R^2 = 0.94$ for predicting friction behavior from texture geometries.

Compared with traditional AI-free modeling approaches (for example, Hamdi, 2021), the models we developed with AI lean more toward the automatic tuning of model parameters and are more successful at predicting such interplay than ordinary modeling. Surface roughness resulted in $\pm 25\%$ uncontrollable influence of abrasive effects, as reported by Hamdi, whereas the AI-driven system maintained the surface roughness variation below $0.45 \mu\text{m}$, with a margin of $\pm 8\%$. This proves that smart modeling is capable of providing the best control. Our approach also simultaneously improved the friction, wear, and surface temperature characteristics, similar to the findings of Kano (2025) and Suleiman et al. (2025), who noted that the utilization of AI is capable of multi-objective optimization, that is, good heat dissipation, good COF, and good wear resistance.

Ghosh et al. (2024) identified the probable future trends for applying artificial intelligence (AI) in the

prediction of surface roughness, among which adaptive control in machining would be a vital component. The current study proved the feasibility of a real-world implementation of this idea, which would see a closed loop between the AI technique and the process of laser surface texturing (LST), enabling an improvement loop for the LST parameters, resulting in noticeable tribological benefits. Following on from the research of Hussein et al. (2022), who confirmed the applicability of finite element modeling for the prediction of mechanical properties, it is likely that combining FE modeling with the AI-LST process would improve the robustness of the textured surface under real dynamic loads

CONCLUSION

The current study proves that the implementation of artificial intelligence solutions in conjunction with laser surface texturing is an effective solution for optimizing the tribological properties of engineering alloys. The use of AI models has led to the intelligent design of textures on the surfaces of AISI 316 L stainless steel and Ti-6Al-4V alloys.

The experimental evidence has shown that the optimized texturing of the surfaces with AI led to a reduction in the coefficient of friction of 35% and a reduction in wear volume of 48% compared with that of the reference surface. There was also a positive effect on the post-test surface roughness and a reduction in the contact temperature.

The strong convergence of the theoretically predicted values from the experiments and the AI-predicted results assures that the deep learning architecture can interpret the relationship between the geometric properties of surface textures and performance.

The present study complements ongoing efforts to build knowledge of AI applications in advanced manufacturing and surface finishing.

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DECLARATION OF COMPETING INTEREST

None.

REFERENCES

- Al-Jumaili, S.A.K., Hawas, M.N. & Al-Gburi, H. 2023. Evaluation of the impact of surface treatment on the turbine blade performance. *Jordan Journal of Mechanical and Industrial Engineering* 17(3): 421–427.
- Batu, T., Lemu, H.G. & Shimels, H. 2023. Application of artificial intelligence for surface roughness prediction of additively manufactured components. *Materials* 16(18): 6266.
- Boban, J., Puthanveetil Madathil, A. & Ahmed, A. 2024. Post-processing of additively manufactured metallic bioimplants: Approaches, challenges and future trends. In *Bioimplants Manufacturing: Fundamentals and Advances*, edited by Puthanveetil Madathil, A., Gajrani, K.K. & Luo, X., 206–231. Boca Raton, FL: CRC Press.
- Chen, W., He, X., Yu, W., Wang, M. & Yao, K. 2021. Microstructure, hardness, and tensile properties of vacuum carburizing gear steel. *Metals* 11(2): 300.
- Ercetin, A., Der, O., Akkoyun, F., Gowdru Chandrashekarappa, M.P., Şener, R., Çalışan, M., Olgun, N., Chate, G. & Bharath, K.N. 2024. Review of image processing methods for surface and tool condition assessments in machining. *Journal of Manufacturing and Materials Processing* 8(6): 244.
- Faisal, B.M., Abed, K.A., Mohammed, A.A., Hussein, E.K., Sharaf, H.K., Santos, T. & Santos, C. 2024. Investigation of the high velocity impact test on the curved glass fiber reinforced plastic (GFRP) composites using explicit dynamics analysis. *International Journal on Advanced Science, Engineering and Information Technology* 14(6): 2084–2089.
- Ghosh, S., Knoblauch, R., El Mansori, M. & Corleto, C. 2025. Towards AI driven surface roughness evaluation in manufacturing: A prospective study. *Journal of Intelligent Manufacturing* 36(7): 4519–4548.
- Hamdi, A. & Merghache, S.M. 2021. Impact of abrasive grit size and MQL supply on the surface roughness in belt grinding of a case hardened steel. *Jordan Journal of Mechanical and Industrial Engineering* 15(5): 441–449.
- Hauschwitz, P., Palková, Z., Váchová, L., Bičíšťová, R., Procházka, M., Plocek, V., Tarant, I., Pathak, S., Brajer, J., Mužík, J., Fialková, Z., Kocáb, M., Sládek, J., Flimelová, M., Smrž, M., Chyla, M. & Mocek, T. 2025. Rapid laser-induced nanostructuring for yeast adhesion-reducing surfaces using beam shaping with SLM. *Journal of Materials Research and Technology* 35: 193–198.
- Jabbar, D.A., Kadhim, Z.D. & Abdulrazzaq, M.A. 2020. Wear and hardness properties of carburized (AISI 1011) steel. *Journal of Engineering and Sustainable Development* 1: 402–408.
- Kano, S. 2025. A short review: Tribology in machining to understand conventional and latest modeling methods with machine learning. *Machines* 13(2): 81.
- Li, Z. & Chang, L. 2025. Development of wear-resistant polymeric materials using fused deposition modelling (FDM) technologies: A review. *Lubricants* 13(3): 98.
- Mohammed, A.A., Al-Msary, A.J.K., Hussein, E.K. & Santos, T. 2025. Investigation of mechanical properties of a composite material supported with nano materials for manufacturing prosthetic socket. *Journal of Advanced Research in Applied Mechanics* 136(1): 55–63.
- Murzin, S.P. 2024a. Artificial intelligence-driven innovations in laser processing of metallic materials. *Metals* 14(12): 1458.
- Murzin, S.P. 2024b. Digital engineering: Innovations in laser processing techniques. *Preprints.org*: 202409.2348.v1.
- Suleiman, D.Y., Li, Q., Li, B., Zhang, Y., Zhang, B., Liu, D., Zhang, W., Zhou, Z., Feng, Y., Bie, Q., Yin, X., Wang, L. & Li, C. 2025. Digital twin and artificial intelligence in machining: A bibliometric analysis. *Intelligent and Sustainable Manufacturing* 2(1): 10005.
- Vishnoi, M., Kumar, P. & Murtaza, Q. 2021. Surface texturing techniques to enhance tribological performance: A review. *Surfaces and Interfaces* 27: 101463.
- Wang, H.J., Wang, B.T., Zhou, F., Guo, K.K., Liu, Y. & Lin, H.T. 2024. Effect of laser surface texturing on friction performance and surface damage of silicon nitride ceramic. *Journal of Asian Ceramic Societies* 12(2): 184–193.
- Zhang, X., Zhou, L., Feng, G., Xi, K., Algadi, H. & Dong, M. 2025. Laser technologies in manufacturing functional materials and applications of machine learning-assisted design and fabrication. *Advanced Composites and Hybrid Materials* 8(1): 76.
- Zhao, C., Jia, X., Zhao, Q., Ma, H., Yu, Z., Zhang, Z., Du, W. & Zhang, H. 2024. Research progress on the effect of surface texture on the friction properties of CoCrMo alloys. *Composite Interfaces* 31(10): 1269–1290.