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Machine Learning Model for Friction Prediction on Textured Surface

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Abstract: Friction significantly affects the efficiency, wear and durability of mechanical systems. Surface texturing has been widely adopted to control frictional characteristics by modifying contact interactions. However predicting friction behaviour based on texture parameters remains challenging due to nonlinear dependencies among operating conditions, material properties and surface geometry. This paper presents a comprehensive study on the application of machine learning (ML) techniques for predicting friction on textured surfaces. Various ML models, including linear regression, support vector machines, decision trees and artificial neural networks are explored. The results demonstrate that ML models effectively capture complex relationships and provide accurate predictions, enabling optimization of surface textures for enhanced tribological performance.
Keywords: Friction prediction, Machine learning, Surface texturing, Tribology, Artificial neural networks.

I. INTRODUCTION

Friction is a fundamental phenomenon in mechanical systems, influencing energy consumption and wear characteristics. It is estimated that a substantial portion of global energy losses in industrial systems is due to frictional interactions. Reducing friction can therefore improve system efficiency and longevity. Surface texturing, which involves introducing micro-scale patterns such as dimples or grooves has emerged as an effective technique for controlling friction. These textures can enhance lubrication, reduce contact area and trap wear debris. However determining the optimal texture configuration is complex due to the nonlinear interplay between various parameters such as load, speed and lubrication regime. Traditional approaches to friction prediction rely on empirical models and experimental studies which are often time consuming and costly. Machine learning offers a promising alternative by enabling data driven modelling of complex systems.

II. LITERATURE REVIEW

A. Recent advancements in machine learning have significantly impacted tribological research. Several studies have explored ML based approaches for friction prediction:
Regression based ML models have been used to predict friction in textured seals using geometric parameters such as dimple size and density.[7] [11]
Artificial neural networks (ANNs) have demonstrated high accuracy in predicting friction coefficients due to their ability to model nonlinear relationships. [4] [9]
Support vector machines (SVMs) have been effective for small datasets with nonlinear characteristics. [6] [12]
Hybrid models combining ML algorithms with optimization techniques such as particle swarm optimization (PSO) have improved prediction performance. [13] [10]
Deep learning approaches, including convolutional neural networks (CNNs) have been applied to analyse surface images and generate optimized textures. [2] [3]
These studies confirm that ML techniques outperform conventional methods in terms of accuracy and efficiency. [8] [9]

III.PROBLEM STATEMENT

Despite advancements in surface engineering, predicting friction behaviour remains challenging due to:
Complex non-linear relationships between variables.
High dimensional parameter space.
Variability in operating conditions.
The objective of this study is to develop machine learning models capable of accurately predicting the coefficient of friction (COF) based on surface texture parameters and operating condition

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IV. METHODOLOGY

A. Data Collection Data for this study can be obtained from experimental measurements, numerical simulations or published datasets.

The dataset typically includes:
Simple diameter.
Texture depth.
Spacing.
Area density.
Applied load.
Sliding velocity.
Temperature.
Lubrication condition.
Output Parameter: Coefficient of friction (COF).

B. Data Preprocessing

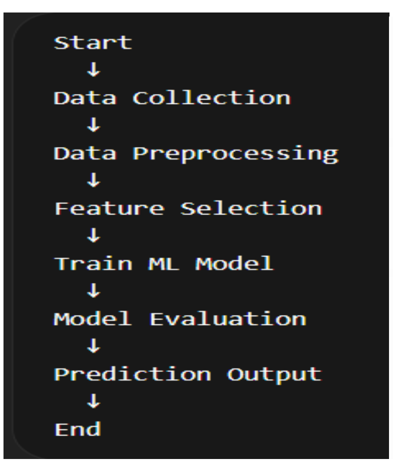
Data preprocessing steps include
Handling missing values.
Normalization or standardization.
Feature selection.
Splitting data into training and testing sets.

C. Machine Learning Models

Linear Regression Serves as a baseline model but is limited in capturing nonlinear relationships.
Support Vector Machine (SVM): Uses kernel functions to model nonlinear relationships and performs well on smaller datasets.
Decision Tree and Ensemble Methods: Includes Random Forest and Gradient Boosting techniques that effectively capture feature interactions.
Artificial Neural Network (ANN): ANNs are highly effective for modelling complex nonlinear systems and have shown superior performance in friction prediction tasks.
Convolutional Neural Network (CNN): CNNs are used when surface texture images are available, enabling automatic feature extraction.

D. Model Training Models are trained using supervised learning techniques.

The training process involves minimizing a loss function such as Mean Squared Error (MSE) using optimization algorithms like gradient descent.



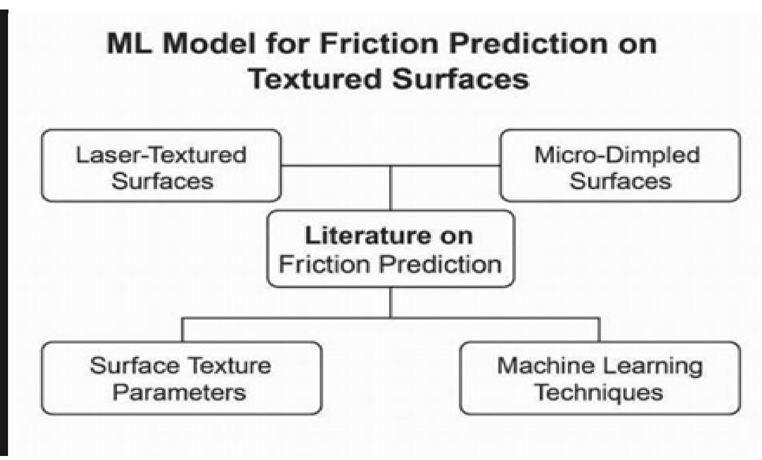


Fig. 1. Methods for traning model Fig. 2. Friction Prediction

Mathematical Modeling of the coefficient of friction is expressed as = f(d,h,s,L,V,T) Where: d: Simple diameter, h: Texture depth, s: Spacing, L: Load, V: Velocity, T: Temperature.

E. Evaluation Metrics Performance is evaluated using:

Mean Absolute Error (MAE).
Root Mean Square Error (RMSE).
Coefficient of Determination (R^2).

F. Algorithm (Pseudocode) Friction Prediction using ML

Input: Dataset D
Output: Predicted COF
Load dataset D.
Preprocess data (normalize, clean).
Split data into training and testing sets.
Select ML model (ANN/SVM).

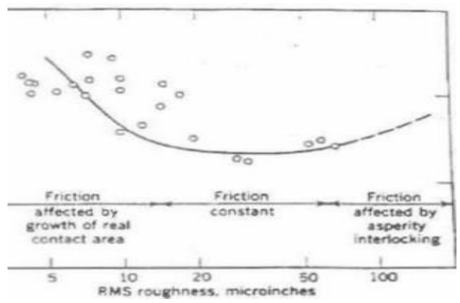


Fig. 3. R.M.S. roughness microinches

Train model on training data.
Predict COF on test data.
Compute error (MSE, RMSE).
If error acceptable: Output predictions Else: Tune model parameters and Repeat.
End.

G. Results and Discussion

Machine learning models demonstrate strong predictive capability for friction behaviour. Key observations include:
ANN models achieve the highest accuracy due to their ability to capture nonlinear relationships.
Ensemble methods such as Random Forest and Gradient Boosting provide robust and interpretable results.
SVM performs well for limited datasets but may struggle with scalability.
The results indicate that texture parameters such as depth and density significantly influence friction. Additionally, operating conditions such as load and lubrication regime play a critical role in determining frictional performance.
Model Training Results: The collected experimental dataset consisting of surface texture parameters (Ra, Rq, depth, spacing) operating conditions (normal load, sliding speed, lubrication state) and material properties was used to train multiple supervised machine learning models. The dataset was divided into 80testing data to ensure proper generalization. The following regression models were implemented and evaluated:
Linear Regression (baseline model)
Support Vector Regression (SVR)
Random Forest Regression
Gradient Boosting Regression

Model performance was evaluated using standard regression metrics:
Root Mean Square Error (RMSE)
Mean Absolute Error (MAE)
Coefficient of Determination (R^2)

Feature Importance Analysis Feature importance analysis using Random Forest revealed that:
Normal Load highest influence on friction
Surface Roughness (Ra, Rq)
Texture Geometry (Depth, Spacing)
Sliding Speed
Lubrication Condition
This confirms tribological theory that friction is governed by both contact mechanics and surface texture geometry, validating the physical relevance of the ML models.

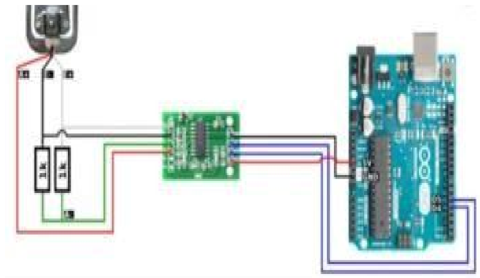


Fig. 4. Proposed setup

H. Applications

ML based friction prediction framework has applications:
Automotive components (engine parts, seals, piston rings).
Bearings and gear systems.
Biomedical implants.
Microelectromechanical systems (MEMS).
Robotics and automation systems.

Advantages and Challenges
Advantages;
Accurate prediction of complex systems.
Reduction in experimental costs.
Faster design optimization.
Ability to handle large datasets.

Challenges:
Requirement for high quality data.
Risk of overfitting, interpretability of complex models.
Generalization across different materials and conditions.

V. EXPECTED OUTCOMES

By studying different aspects of the project till date following outcomes were made:
Conclusion Present final model with best prediction accuracy.
Reduction in Experimental Costs.
Enhanced Surface Design Optimization.
Scalability: Scalability is the property of a system to handle a growing amount of work.
One definition for software systems specifies that this may be done by adding resources to the system. In computing, scalability is a characteristic of computers, networks, algorithms, networking protocols, programs and applications. An example is a search engine which must support increasing numbers of users and the number of topics it indexes. Web scale is a computer architectural approach that have actually brings the capabilities of largescale cloud computing companies into enterprise data.

VI. CONCLUSION AND FUTURE WORK REFERENCES

This paper presents a comprehensive study on machine learning based friction prediction for textured surfaces. The findings demonstrate that ML models, particularly neural networks, significantly outperform traditional approaches in capturing complex relationships. The integration of ML into tribological design processes can lead to improved efficiency, reduced wear and optimized surface performance.

Future Roadmap: Although the present work successfully establishes a machine learning framework for predicting the coefficient of friction on textured surfaces, several extensions can be pursued to further enhance the robustness, applicability and industrial relevance of the proposed approach.

Expansion of Experimental Dataset: Future work will focus on generating a larger and more diverse experimental dataset by including additional material pairs such as ceramics, composites and coated surfaces. Extending the operating range of load, speed, temperature and lubrication conditions will improve model generalization and reliability across real world applications.

Incorporation of Transient and Dynamic Friction Behaviour: The current study primarily addresses steady state friction. Future research can include transient friction phenomena such as running in behaviour, stick slip motion and wear evolution over time. Time series machine learning models (e.g., LSTM or GRU networks) can be explored for this purpose.

Integration of Real Time , Low Cost Sensor Data: The framework can be extended by incorporating real time sensor inputs such as vibration, acoustic emission or MEMS- based force sensors. This will enable online friction prediction and condition monitoring, making the system suitable for practical industrial deployment.

Advanced Image-Based and Multi-Modal Learning: Future work may involve deeper convolutional neural networks trained on high resolution surface topography, SEM images or 3D surface scans. Combining image based features with numerical texture parameters in a multi modal learning frame- work is expected to further improve prediction accuracy.

Physics Informed and Hybrid ML Models: The hybridization of machine learning models with established tribological theories (contact mechanics, lubrication regimes and Stribeck behaviour) can be strengthened. Physics informed neural networks (PINNs) can help enforce physical consistency and reduce data dependency.

Uncertainty Quantification and Model Explainability: Future studies can incorporate uncertainty quantification techniques such as Bayesian machine learning to assess confidence in predictions. Explainable AI methods can also be used to better understand the influence of surface texture parameters on friction behaviour.

Optimization and Automated Surface Design: The trained ML models can be integrated with optimization algorithms (genetic algorithms, particle swarm optimization) to automatically suggest optimal surface texture designs for minimum friction.

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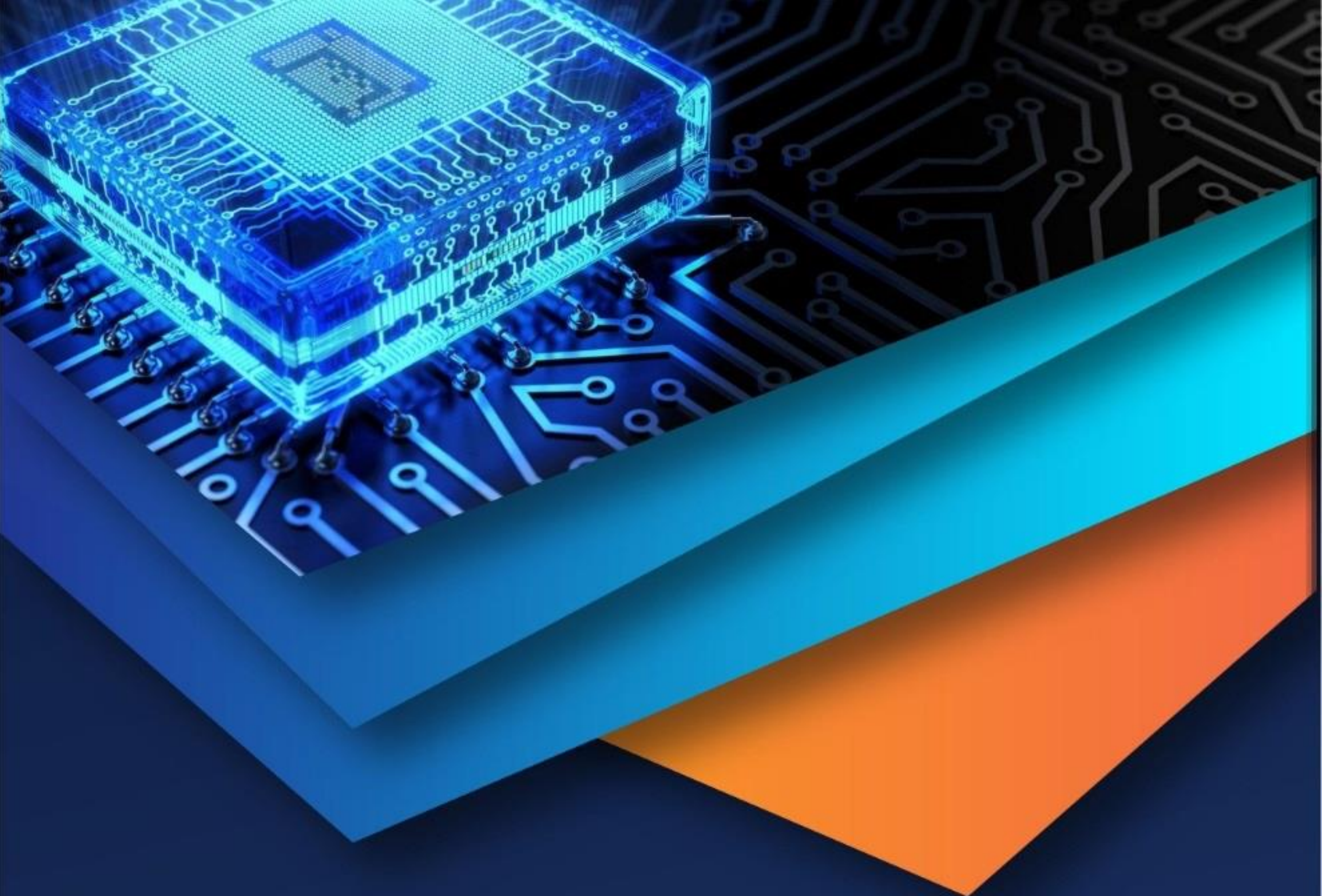

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