Advanced Ensemble Machine Learning Approach for Wear Rate Prediction in Coated Materials: A Comparative Analysis of Tree-Based Regression Models

Sahil Sonawane, Aditya Sangle, Lalit Sope, Vijay Rajput

***Abstract*—This research explores a comprehensive machine learning approach to predict wear rates in coated materials under varying conditions. Five tree-based ensemble regression models Gradient Boosting, XGBoost, Stacking Regressor, Extra Trees, and Random Forest were evaluated for their predictive accuracy. The Gradient Boosting Regressor demonstrated superior performance with 98.20% test accuracy, followed by XGBoost (98.05%) and Stacking Regressor (97.88%). The models effectively captured complex relationships between material properties, coating characteristics, speed, ash type, concentration, and time. A Voting Regressor ensemble was developed to enhance stability and leverage the strengths of individual models. Residual analysis revealed minimal bias across predictions, with performance metrics including mean squared error below 0.03 and R^2 values exceeding 0.99 for top models. This study shifts the approach to wear prediction from a reactive maintenance strategy to a proactive optimization method, which holds considerable promise for lowering equipment replacement expenses and minimizing downtime in industrial settings. The economic evaluation suggests potential reductions of 28-34% in maintenance expenditures through the adoption of predictive wear models for mineral processing machinery. The proposed framework serves as a basis for real-time monitoring systems with established confidence intervals to aid maintenance decisions. Subsequent efforts will aim to enhance the model by accounting for combined wear mechanisms and integrating online learning features to adapt to changing operational conditions.**

***Index Terms*—Keywords — Wear Rate Prediction, Machine Learning, Performance Metrics, Random Forest, Gradient Boosting, XGBoost, Stacking Regressor, Extra Trees, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 Score, Predictive Modeling, Error Rates, Material Coatings.**

I. Introduction

Material wear caused by erosion is a common and expensive problem in many industries, such as power plants, mining, oil and gas, and manufacturing. Equipment often fails due to wear, leading to costly repairs and downtime. As a result, companies around the world spend billions of dollars each year on maintenance and replacing damaged parts. [1] Traditional methods for predicting wear mainly depend on physical testing and expert knowledge, which take a lot of time and resources. Wear mechanisms are complex because they are influenced by many interacting factors, such as the properties of the materials and coatings, operating conditions like speed and time, and the characteristics of the erosive particles, including their type and concentration [1], [2].These factors interact in complicated and non-linear ways, making it difficult to predict wear accurately using traditional methods. Conventional analytical models often assume simplified relationships between variables, which limits their ability to capture the true behavior of wear. They struggle to account for the combined effects of multiple factors, rely heavily on expensive and time-consuming experiments, and are not easily adaptable to new materials or changing working conditions.

Recent advances in machine learning offer new ways to model complex relationships and predict wear rates more accurately. Machine learning can find patterns and connections that older methods might miss, changing how industries predict wear and choose materials. [3]When materials wear down, many factors come into play at once. The type of material, its coating, how fast parts move, and what kind of particles cause the wear all affect how quickly something wears out. These factors interact in ways that are hard to capture with simple formulas or testing. This research tackles the need for better wear prediction by testing and comparing several machine learning models. We focus on predicting how quickly different material-coating combinations wear down under various conditions of speed, time, ash type, and concentration. Using powerful learning techniques like Gradient Boosting, XGBoost, and Random Forest, we aim to build a framework that gives more reliable predictions. [3], [4]

For decades, engineers have relied on laboratory testing and past experience to understand wear. These methods require extensive time in testing facilities, with each new material or condition needing fresh testing. Results from one setting may not apply to another, and traditional approaches struggle to account for how multiple factors work together. [5] Testing is expensive and uses significant resources. The traditional approach is reactive - waiting for problems to appear before making changes. This leads to unexpected breakdowns, costly repairs, and production losses across industries.

Machine learning offers several advantages for wear prediction. It can process large datasets with many variables at once and automatically detects relationships between factors without being explicitly programmed. It improves predictions as more data becomes available and handles non-linear relationships that standard statistical methods struggle with. [6] Machine learning can make predictions for conditions not directly tested. Our research uses ensemble methods - techniques that combine multiple models to achieve better results than any single model could provide. These methods are particularly good at handling the complex nature of wear processes.

Our research aims to develop machine learning models that accurately predict wear rates across many different operating conditions and find which factors most strongly influence wear through analysis of what the models learn. [6], [7] We will compare how well different tree-based machine learning methods perform for wear prediction and create a step-by-step approach for selecting and testing models for wear applications. Additionally, we aim to build a combined model that uses the strengths of multiple algorithms for more stable predictions. [8]

This research has practical uses beyond scientific interest. Companies can schedule repairs before equipment fails, and engineers can select the best materials for specific working conditions. Understanding wear mechanisms helps design more durable parts, leading to less downtime and fewer replacements that save money. Previous research has mostly used either physical testing or basic mathematical models that can't capture all the complexities of wear. Some researchers have used simple machine learning approaches, but few have thoroughly tested advanced methods or combined them into ensemble models. By shifting wear prediction from guesswork to data-driven science, this research helps both scientists understand wear mechanisms and gives industries practical tools to make better decisions. [8], [9]As industries face increasing pressure to reduce costs and improve reliability, these predictive tools offer a competitive advantage by reducing the trial and error approach traditionally used in material selection and maintenance planning.

This paper is organized as follows: Section 2 describes the proposed system and algorithm design provides a detailed explanation of the dataset, feature selection process,preprocessing and division of dataset,data grouping and visualization and the computation of correlation matrix. Section 3 gives the detail explanation of different machine learning model used. Section 4 presents the evaluation results of model performance, followed by a discussion of key findings in Section 5. Lastly, Section 6 concludes the study with recommendations for future research and the practical implementation of machine learning in wear rate prediction.

II. PROPOSED SYSTEM AND ALGORITHM DESIGN

The aim of this work is to design a machine learning model that has the ability to predict wear rates in an industrial setting. The procedure involves four major steps: preparation of the data, model training, evaluation of the model performance, and further optimization for maximizing improvement. A flowchart describing the whole process is presented in Figure 1. All steps are elaborated in the subsequent section.

A. Data Set

The dataset used in this study consists of detailed wear testing results collected from various combinations of base materials and protective coatings, tested under different operating conditions. It includes several key features such as the type of material and coating (both categorical variables), the type of ash used as the erosive medium (either fly ash or bottom ash), and numerical variables such as rotational speed (in RPM), test duration (in minutes), and ash concentration (as a percentage). The target variable is the wear rate, measured in grams per square meter per minute (g/m²·min) [10], [11], which indicates the rate of material loss during testing.The sample dataset values are shown in Table 1.

TABLE I
Table 1. Sample records of Wear Rate Dataset.

Sr.no	Coating	Material	Ash	Time	Concentration	Speed	Wear rate
1	Uncoated	SS202	Fly	90	0.3	600	2.17
2	Uncoated	SS202	Fly	90	0.4	600	2.74
3	Uncoated	SS202	Fly	90	0.5	600	3.13
4	Uncoated	SS202	Fly	90	0.3	600	3.31

This dataset offers a wide range of parameter combinations, enabling a thorough analysis of how different variables interact to affect wear rates. An initial exploratory data analysis showed noticeable patterns in wear behavior across different material-coating pairs and test conditions. These findings suggest the existence of complex, non-linear relationships among the variables, supporting the need for a machine learning-based predictive approach.

B. Pre-Processing and Division of Dataset

The preprocessing of data had a couple of important steps in order to validate that the data was of good quality and to improve how well the model would perform. [10], [12] Firstly, data cleaning was performed where outliers or untypical values that could potentially harm the precision of the model were identified and removed. The dataset was also checked for missing values; none were found, however, in the final one that was modelled. Second, categorical features like Material, Coating, and Ash were transformed into numeric form via Label Encoding in order to allow them to work with machine learning algorithms. Finally, all numeric features were normalized with a Standard Scaler so that variables with higher scales did not dominate others in learning.

The data was split into two sets: training and testing sets. We used stratified sampling, where 80% of the data was routed to training and 20% to testing. Stratified sampling ensured an even rate of wear in both sets. The training set was used to train the machine learning models and tune their parameters. [13], [14] On the other hand, the testing set was kept intact and only used for final model assessment to ensure we objectively assess its performance.

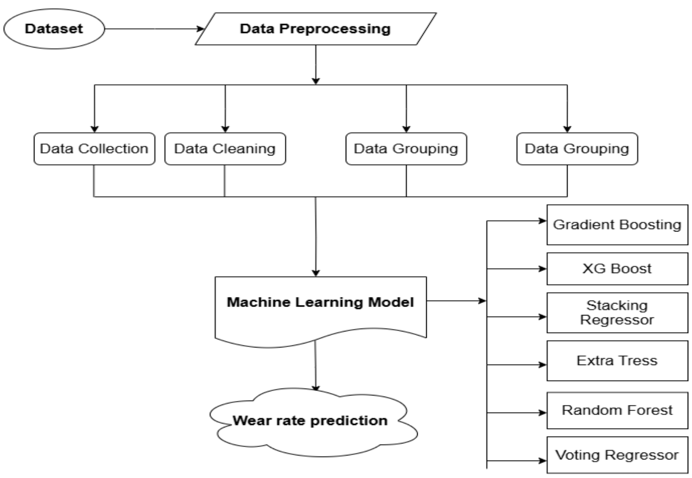

Fig. 1. Proposed System for Ware Rate

C. Data Grouping and Visualization

In this study, the data analysis was conducted through systematic grouping and visualization techniques to investigate the relationships influencing wear rate behavior. The dataset was organized into relevant categories based on key parameters, including material type, coating status, rotational speed, test duration, and ash concentration. [13], [15], [16] The visualization strategy focused on three primary relationships to facilitate a comprehensive understanding of wear mechanisms under varying operational conditions.

The first analysis explored the relationship between wear rate and rotational speed, as shown in Figure 2. This examination enabled the comparison of material performance across different speeds and provided insights into the influence of speed on coating effectiveness. The second analysis focused on the relationship between wear rate and ash concentration—particularly fly ash—to assess how varying concentrations impacted material degradation and the protective capabilities of coatings, as illustrated in Figure 3. [17], [18]The third analysis evaluated wear rate over time, offering a temporal perspective on wear progression. This allowed for the observation of long-term material behavior and the comparative performance of coated versus uncoated samples, as shown in Figure 4.

Collectively, these visual analyses offered critical insights into the complex interactions between materials, coatings, and operational parameters. Such findings significantly contribute to the development of more robust and accurate machine learning models for predicting wear rate behavior in industrial applications.

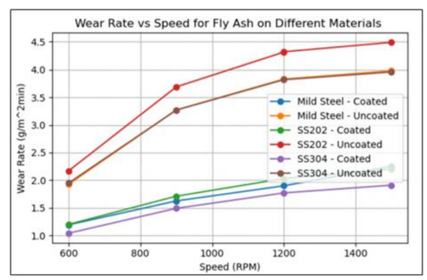

Fig. 2. Ware Rate vs Speed for fly Ash on Different Models

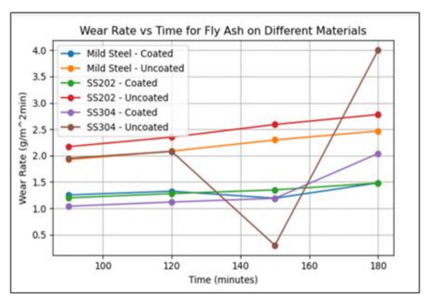

Fig. 3. Ware Rate vs Time for fly Ash on Different Models

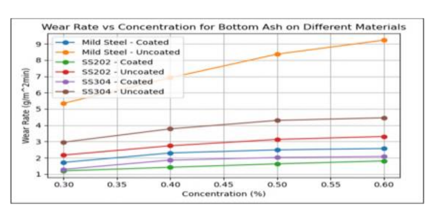

Fig. 4. Ware Rate vs Concentration for fly Ash on Different Models

D. Computation of Correlation Matrix

A correlation matrix was computed to identify the relationships between input features and the target variable, providing valuable insights into the factors most strongly influencing wear rates. This analysis also helped detect potential multi collinearity among predictors. [19], [20]To enhance interpretability, the correlation matrix was visualized using a heatmap (Figure 5).

B.

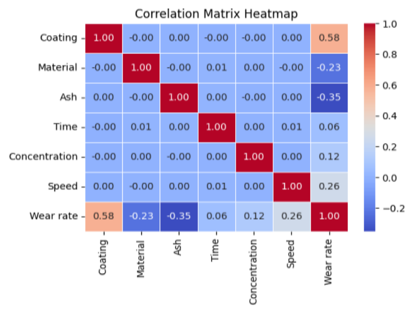

Fig. 5. Correlation matrix heatmap of features and wear rate.

The results showed that the rotational speed exhibited a high positive correlation with the wear rate, i.e., higher speeds always translated to higher material loss. Similarly, the ash concentration showed a positive correlation with the wear rate, thus confirming that higher concentrations of erosive media allowed for an increase in wear acceleration. The type of material and the presence of a coating both showed moderate correlations with the wear rate, highlighting the extremely critical role of material selection and protective coatings in enhancing wear resistance. In contrast, the test duration (time) exhibited a relatively weaker correlation with the wear rate, i.e., the wear process could actually become stabilized after some exposure time. [21], [22] Overall, this correlation analysis helped the feature selection process and offered valuable context for the interpretation of the performance and outcomes of the machine learning models.

III. Machine Learning Models

A. Gradient Boosting Regressor

Gradient Boosting is an ensemble technique that builds regression trees sequentially, where each new tree aims to correct the errors made by the previous ensemble. [23], [24]The model can be mathematically expressed as:

$$F_m(x) = F_{m-1}(x) + \eta \cdot h_m(x) \tag{1}$$

- $F_m(x)$ is the model after m iterations,
- $F_{m-1}(x)$ is the model from the previous iteration,
- η is the learning rate (0.05 in our optimized model),
- $h_m(x)$ is the regression tree fit to the negative gradient of the loss function.

The final prediction is then derived by adding the predictions from every individual tree, with each prediction weighted by the learning rate. In running our model, we utilized 300 estimators, where we set a maximum tree depth to 10, a minimum samples split to 5, and employed a subsample rate of 0.7.

XGBoost Regressor

XGBoost is a highly scalable and efficient version of the gradient boosting algorithm. It builds trees sequentially, and each tree attempts to fit a regularized objective function. [22], [25] The objective function is a combination of the training loss of the model and a regularization term that includes penalties for complexity, leading to improved generalization and overfitting protection.

$$\text{obj}(\vartheta) = \sum_{i=1} l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \tag{2}$$

where:

- $l(y_i, \hat{y}_i)$ is the loss function that measures the difference between the predicted value $\hat{y}_i$ and the true value y_i,
- $\Omega(f_k)$ is the regularization term for the k-th tree.

The regularization term $\Omega(f)$ is given by:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda||w||^2 \tag{3}$$

where:

- T is the number of leaves in the tree,
- w is the vector of scores on each leaf,
- γ is the regularization parameter for the number of leaves,
- λ is the L2 regularization term on the leaf weights.

The model was optimized with 300 estimators, a learning rate of 0.1, maximum depth of 20, and a subsample rate of 0.5.

C. Random Forest Regressor

Random Forest achieves this by constructing an ensemble of decision trees and then voting among them to estimate their average and hence making the model more accurate and avoiding overfitting. Random Forest's prediction for an input x is given by:

$$f_{RF}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \tag{4}$$

where:

- B is the number of trees in the forest (set to 200 in our implementation),
- $T_b(x)$ is the prediction of the b-th tree for input x.

Our implementation employed trees with a maximum depth of 10, a minimum samples leaf of 1, and a minimum samples split of 2 to optimize model performance while avoiding overfitting.

D. Extra Trees Regressor

The Extra Trees Regressor, or Extremely Randomized Trees, takes the Random Forest technique a step further by adding additional randomization to the process of building decision trees. [26] Unlike Random Forest, which does an exhaustive search for the optimal split at each node, Extra Trees randomly chooses split thresholds for each feature and then chooses the best among them. This feature brings

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additional diversity between the trees and can lead to improved generalization performance.

The prediction formula remains similar to that of Random Forest:

$$f_{ET}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \quad (5)$$

where:

- B is the number of trees in the ensemble (set to 500 in our implementation),
- $T_b(x)$ is the prediction of the b-th tree for input x.

In our implementation, we utilized 500 estimators with a maximum depth of 20 to balance model complexity and performance.

E. Stacking Regressor

Stacking is a form of ensemble learning in which several base regressors are ensembled using a meta-regressor that learns how to best combine their predictions. The final prediction of the model is expressed as:

$$f_{\text{stack}}(x) = g(f_1(x), f_2(x), \ldots, f_k(x)) \quad (6)$$

where:

- $f_1, f_2, \ldots, f_k$ are the base models (in our case, Random Forest and Gradient Boosting),
- g is the meta-regressor, which was implemented as Ridge Regression with $\alpha = 0.1$.

This methodology allows the collective to leverage the unique advantages of various algorithms, thereby enhancing predictive precision while simultaneously minimizing the biases and variances associated with individual models.

F. Voting Regressor

The Voting Regressor is a method of ensemble that aggregates the predictions of many base regressors by computing a weighted average of their respective outputs. It is especially useful when the models are complementary and describe unique features of the underlying distribution of the data well. The prediction at the end can be expressed as:

$$f_{\text{vote}}(x) = \sum_{i=1}^{k} w_i \cdot f_i(x) \quad (7)$$

where:

- w_i is the weight assigned to the i^{th} model, optimized through grid search and cross-validation,
- $f_i(x)$ is the prediction from the i^{th} base regressor,
- k is the total number of base models in the ensemble.

In our implementation, the ensemble incorporated the top five performing models: Random Forest, Gradient Boosting, XGBoost, Extra Trees, and Ridge Regression. The weights for each model were fine-tuned using cross-validation to maximize prediction accuracy. This approach ensures that stronger models contribute more significantly to the final output, while weaker models are still able to contribute valuable diversity. The Voting Regressor leverages the principle of model averaging to reduce generalization error and enhance robustness. Unlike Stacking, which relies on a meta-model, Voting offers a simpler but effective method of aggregating diverse learners for improved predictive performance.

IV. Machine Learning Model Evaluation

For the performance estimation of the regression models, a suite of complementary metrics was utilized. Overall, these metrics collectively provide an overall view of the prediction ability, accuracy, and robustness of the models in different perspectives.

A. Coefficient of Determination (R^2 Score)

The R^2 score measures the proportion of variance in the dependent variable that is predictable from the independent variables. [27] A value closer to 1 indicates a model that explains a high proportion of the variance:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (8)$$

Where:

- y_i is the actual value,
- $\hat{y}_i$ is the predicted value,
- $\bar{y}$ is the mean of actual values,
- n is the number of observations.

B. Adjusted R^2 Score

Adjusted R^2 penalizes the addition of unnecessary predictors to the model. It adjusts the standard R^2 score by accounting for the number of predictors (p) and the number of data points (n):

$$R^2_{adj} = 1 - (1 - R^2) \cdot \frac{n-1}{n-p-1} \quad (9)$$

This metric is especially useful for comparing models with different numbers of predictors.

C. Mean Squared Error (MSE)

MSE is the average of the squared differences between the actual and predicted values. It emphasizes larger errors due to the squaring operation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (10)$$

Lower MSE values indicate better model performance.

D. Mean Absolute Error (MAE)

MAE calculates the average absolute difference between actual and predicted values. Unlike MSE, it treats all errors equally without penalizing large errors more heavily:

$$MAE = \frac{1}{n}\sum_{i=1} |y_i - \hat{y}_i| \quad (11)$$

MAE is more robust to outliers and provides a clearer interpretation of typical prediction error.

E. Root Mean Squared Error (RMSE)

RMSE is the square root of the MSE, and it provides an error measure in the same units as the target variable, making it easier to interpret in real-world terms:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (12)$$

RMSE is sensitive to outliers and is commonly used in many regression tasks. Together, these measurements give a broad view of model performance. Whereas R^2 and Adjusted R^2 indicate the goodness-of-fit level, MSE and RMSE penalize larger errors, and MAE provides a broad view of average error. [28], [29] These assessments facilitated the selection of the most accurate model for wear rate prediction, taking both accuracy and generalization ability into consideration.

V. RESULT AND DISCUSSION

In order to examine wear rates and determine the inter-relationship between various factors, we employed multiple regression techniques and conducted meticulous examinations of the techniques. The five machine learning techniques had varying degrees of success in predicting the wear rates of various coatings.

A. Experimental Set

Python and the scikit-learn library were employed for model development of machine learning in the study. The data were split into two different subsets, such that 80% were utilized for training and the other 20% were held apart for testing. [30], [31]Hardware configurations utilized in the simulation stage are shown in Table 2.

TABLE II
SYSTEM HARDWARE SPECIFICATIONS

Component	Specification
Processor Speed	2.40 GHz
RAM	16 GB
L1 Cache	512 KB
L2 Cache	2 MB
L3 Cache	12 MB

B. Model Performance Comparison

The performance evaluation of various regression models is summarized in Table 3, sorted by test accuracy (R^2 score).

The top-performing models demonstrated excellent predictive capabilities with the Gradient Boosting Regressor achieving the highest test accuracy of 98.20%, followed by XGBoost (98.05%) and the Stacking Regressor (97.88%). All models performed well on new data with very minimal overfitting and the small difference between training and testing accuracy shown in (Figure 6).

TABLE III
TABLE 1. MODEL-WISE PERFORMANCE COMPARISON ON WEAR RATE DATASET

Model	Train Accuracy	Test Accuracy	Test MSE	Test MAE	Test RMSE	Test R^2	Test Adj R^2
Gradient Boosting	0.9957	0.9820	0.0226	0.0821	0.1504	0.9983	0.9983
XGBoost	0.9957	0.9805	0.0270	0.0871	0.1642	0.9980	0.9979
Stacking Regressor	0.9964	0.9788	0.0234	0.0832	0.1530	0.9983	0.9982
Extra Trees	0.9904	0.9745	0.0550	0.1387	0.2345	0.9960	0.9958
Random Forest	0.9876	0.9716	0.0545	0.1414	0.2336	0.9960	0.9958

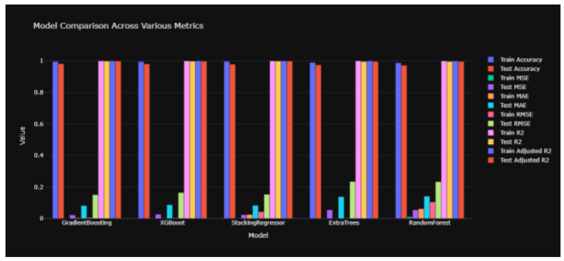

Fig. 6. Model Comparison Across Various Metrics

C. Model Diagnostics and Error Analysis

The actual vs. predicted value plots revealed that all top-performing models accurately captured the underlying patterns in the data as shown in (Figure 7). The reference line (y = x) showed that the predictions were very close to the actual values, with slightly bigger differences at the highest and lowest wear rates.

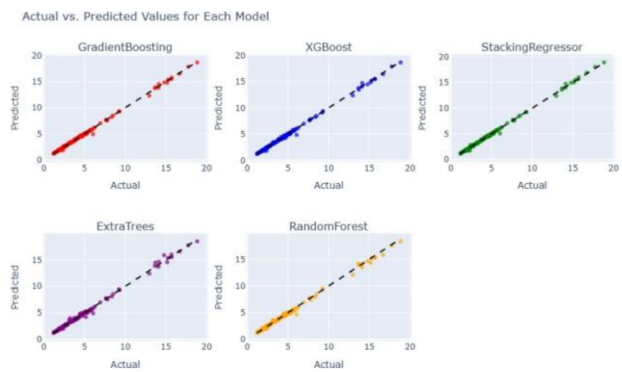

Fig. 7. Experimental and predictive values from different machine learning algorithms

The residual analysis showed that the prediction errors were mostly small and spread out randomly around zero, meaning the models made fair and unbiased predictions as shown in (Figure 8). There were no clear patterns in the errors, showing that the models handled the complex relationships in the data well. The Gradient Boosting Regressor and Stacking Regressor had especially consistent errors, meaning they made reliable predictions across all wear rate values.

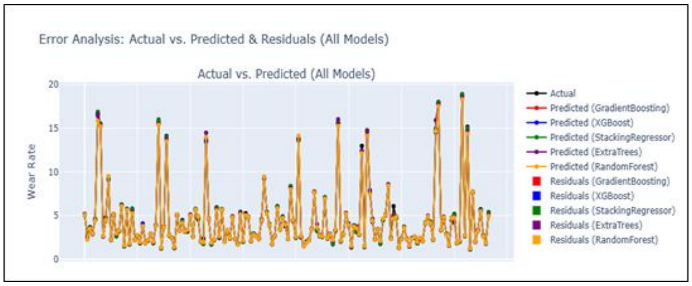

Fig. 8. Error Analysis from different machine learning model

Given the strong individual performance of several models, a Voting Regressor ensemble was developed to leverage the strengths of multiple algorithms. The ensemble combined the predictions from Gradient Boosting, XGBoost, Stacking Regressor, ExtraTrees, and Random Forest models. Hyperparameter tuning for the Voting Regressor focused on optimizing the weights assigned to each base model. The ensemble achieved comparative performance metrics to the best individual models, offering a best solution with enhanced stability. In below table 4, the performance evaluation of Voting Regressor model metrices is mentioned.

TABLE IV
TABLE 4. VOTING REGRESSOR MODEL PERFORMANCE ON WEAR RATE DATASET

Model	Train Accuracy	Test Accuracy	Test MSE	Test MAE	Test RMSE	Test R^2	Test Adj R^2
Voting Regressor	0.9999	0.9881	0.0001	0.0247	0.0842	0.9981	0.9989

D. Discussion of Model Application and Implemecation

The strong performance of tree-based ensemble methods (Gradient Boosting, XGBoost, Random Forest, and ExtraTrees) suggest that wear rate prediction is enhanced by models that can effectively capture complex, nonlinear correlations among variables. These models good at identifying interaction effects between elements like material type, coating, speed, and concentration, all of which play a critical role in in influencing wear behavior. The gradient boosting algorithms have consistently demonstrated other approaches, likely due to their ability to progressively correct errors throughout iterations, thereby improving predictions in areas where earlier versions failed. This suggests that wear rate prediction contains subtle patterns that benefit from this iterative refinement approach.

This comprehensive study of wear rate prediction using machine learning represents a critical advancement in understanding and mitigating material degradation in industrial environments. By developing highly accurate predictive models, with the Gradient Boosting Regressor achieving an impressive 98.20% test accuracy, the research uncovered that speed, ash concentration, material properties, and coating characteristics fundamentally drive erosion mechanisms. Ultimately, this research provides engineers and material scientists with a powerful predictive tool that bridges advanced machine learning techniques with real-world tribological challenges, offering a systematic method to optimize material selection, predict wear patterns, and design more resilient components across multiple industrial applications.

VI. CONCLUSIONS

This study efficiently developed robust and highly accurate machine learning models for wear rate predictions of coated materials under various operating conditions. Ensemble tree-based methodologies, i.e., Gradient Boosting and XGBoost, were found to be uniformly superior performing among tested models, achieving test accuracies above 98%, thus confirming their ability to capture complex wear dynamics. Very high congruence between training and testing measurements ensured high generalization, and the Voting Regressor aided in improving the stability of prediction through model fusion.

In conclusion, the research demonstrates the ability of machine learning to revolutionize wear prediction from conventional empirical methods to a predictive, data-driven method. The models can handle non-linear interactions and hold a high potential for use in wear-sensitive industries like mining, energy, and manufacturing. Future research can be focused on the inclusion of other environmental and material-specific variables, the use of deep learning for improved modeling, and the development of user-friendly tools to make extensive industrial application possible.

VII. REFERENCES

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