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Machine Learning-Based Prediction modelling of EDM application on Ti6Al4V alloy using 3D-Printed SS316L Electrodes

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ABSTRACT

This study explores the application of 3D-printed SS316L electrodes in the Electrical Discharge Machining (EDM) of Ti6Al4V alloy and employs machine learning (ML) models to predict and optimize key performance metrics such as Material Removal Rate (MRR), Tool Wear Rate (TWR), surface roughness, and hardness. EDM experiments were conducted using a Box–Behnken and L27 orthogonal array design, and data-driven models were trained using four regression algorithms. Initial experiments with 27 data points showed limited model accuracy (R^2 = 56.2% for MRR using Random Forest). To enhance prediction capability, the dataset was expanded to 200 samples using polynomial interpolation. After expansion, Random Forest achieved 95.6% R^2 in predicting MRR and TWR, while XGBoost reached 98.6% R^2 for surface roughness and hardness. These findings demonstrate that integrating 3D-printed electrodes with AI-driven modelling and improving the data set significantly improves the predictive control.

1. Introduction

EDM is a thermal erosion process that removes material through controlled electrical discharges between an electrode and the workpiece [1]. This technique is particularly suitable for machining hard-to-cut materials like Ti6Al4V, as it eliminates the mechanical stresses associated with traditional machining. The performance of EDM, however, is heavily influenced by the electrode material and design, making the selection and fabrication of electrodes a critical aspect of the process. Among the unconventional machining methods, electric discharge machining (EDM) is arguably the most advanced and effective. EDM operates differently from conventional techniques, which call for direct mechanical labor. Between a tool electrode and a workpiece immersed in dielectric fluid, a sequence of regulated electrical discharges is produced. The workpiece and electrode are submerged in a dielectric liquid. Small pieces of the workpiece are melted and vaporized by the electrical discharges, and they are flushed away by the dielectric fluid. Titanium and nickel are two extremely difficult alloys to work with using conventional manufacturing techniques, however Advanced EDM can handle them thanks to the particular machining technology. [2,3].

The application of titanium alloys, particularly TI6AL4V, in various industries such as aerospace, biomedical, and automotive, is largely attributed to their high strength-to-weight ratio, biocompatibility, and exceptional corrosion resistance. However, TicA14V poses significant machinability challenges because it is known for its high hardness and strength, leading to rapid tool wear during traditional machining processes [4,5]. This difficulty has resulted in the increased adoption of Electric Discharge Machining (EDM) as a preferred method for fabricating TI6AL4V components, primarily because EDM can achieve better surface finish and precision than conventional techniques [6]. To optimize EDM processes for TI6AL4V, it is crucial to fine-tune machining parameters such as discharge current (Ip), voltage (Vg), pulse-on-time (Ton), and pulse-off-time (Toff). Studies have demonstrated that these factors significantly influence the material removal rate (MRR) and tool wear rate (TWR) [7]. For instance, the discharge current is particularly impactful on the MRR, meaning that adjustments in this parameter can lead to substantial improvements in machining efficiency. The response surface methodology (RSM) is frequently employed in this context to model and optimize theses parameters effectively, enabling precision engineering of the machining process. In recent years, the investigation into the use of 3D printed electrode, particularly from materials like stainless steel (SS316L), has emerged as a promising development in EDM technology [8]. SS316L combines excellent strength and corrosion resistance with the capability for complex geometrical shapes, making it well-suited for additive manufacturing application [9]. Initial findings suggest that using 3D printed SS316L electrodes could enhance the machining performance of TI6AL4V significantly across various EDM parameters, including electrode wear rate (EWR) and surface roughness. The preliminary experiments indicate that leveraging this advanced electrode material may improve the efficiency of EDM processes and lead to better overall outcomes than traditional electrode materials. [10].

The integration of machine learning (ML) approaches in Electric Discharge Machining (EDM) research has opened new avenues for advanced process modeling and optimization. ML has demonstrated efficacy in managing intricate and nonlinear interdependencies among various machining parameters and their corresponding EDM responses, offering significant potential for enhancing process performance outcomes [11]. In particular, numerous ML models have been developed to predict Material Removal Rate (MRR) based on a variety of factors, including specimen hardness, surface roughness, machining time, discharge current, voltage, pulse-on-time (Toff) and pulse-off-time (Toff) [12]. The deployment of ML in EDM not only facilitates the prediction of MRR but also extends the utility of these models to forecast other crucial outcomes, such as Tool Wear Rate (TWR) and post-machining surface characteristics, including surface roughness, and hardness [13,14]. These multi-faceted predictions underscore the versatility of ML techniques in the EDM. The effectiveness of different ML algorithms including artificial neural networks (ANN), hybrid models, and genetic algorithms has been thoroughly evaluated to create robust dependency models that accurately estimate EDM features and further optimize machining parameters [15].Overall, the intersection of ML and EDM not only broadens the insight into how various parameters affect machining outcomes but also provides a data-driven basis for forecasting process parameters in real-time, thus positioning EDM as a more efficient and adaptable manufacturing method. Cogun et al. [16] applied machine learning techniques (ANN, ANFIS, SVM) to optimize machining parameters and reduce tool shape degeneration in die-sinking EDM, demonstrating ANN's superior predictive ability compared to other models. Kosarac et al. [17] optimized machining parameters for Ti-6Al-4V milling to minimize surface roughness using Taguchi's method, and employs machine learning, particularly Random Forest, for predictive modeling of surface roughness. Mollik et al. [18] investigated vibration-assisted micro electro-discharge machining (lEDM), showing that vibration reduces short circuits at low discharge energy but becomes less effective at higher discharge energy. Cetin et al. [19] used machine learning algorithms to predict electro-erosion wear in EDM processes with cryogenically treated mold steel electrodes, achieving 99% accuracy and identifying key factors influencing wear patterns. Abbas et al. [20] investigated EDM processing of composites, examining tool material and process parameters using RSM and machine learning techniques (Xgboost, random forest, decision tree) for predicting surface roughness, with TLBO optimization. Surleraux et al. [21] presented a computationally efficient optimization framework using artificial neural networks (ANN) to generate micro EDM tool shapes, reducing simulation costs and achieving less than 6% deviation from full optimization.

Despite the growing use of EDM for machining difficult materials like Ti6Al4V, the application of 3D-printed SS316L electrodes in this context remains limited. Current studies rarely investigate their effect on key responses such as MRR, TWR, and surface roughness. Additionally, while machine learning (ML) has been used to model EDM processes, most models focus on conventional electrodes and predict outputs independently. There is a noticeable lack of integrated ML approaches that can simultaneously forecast multiple machining responses. This study addresses these gaps by evaluating the effect of EDM parameters (Ip, Vg, Ton, Toff) using 3D-printed SS316L electrodes on Ti6Al4V. ML models will be developed to predict MRR, TWR, surface roughness, and hardness, offering a multi-response perspective.

2. Materials And Methods

2.1 Electrical Discharge Machining (EDM) process

Electrical Discharge Machining (EDM) is a non-traditional machining process that removes material through electrical sparks generated between the electrode and the workpiece [22]. It is widely used for machining hard-to-cut materials such as titanium, superalloys, and hardened steels. Unlike conventional machining techniques, EDM does not require direct contact between the tool and the workpiece, reducing mechanical stresses and making it ideal for intricate shapes and delicate materials [23].

The choice of electrode material significantly impacts EDM efficiency. Materials with high thermal and electrical conductivity, wear resistance, and low electrode wear rate are preferred. SS316L, due to its corrosion resistance, mechanical strength, and excellent thermal stability, is a potential candidate for EDM applications. Traditional electrode materials such as copper and graphite have limitations in terms of wear rate and cost, making SS316L a promising alternative, especially when fabricated through advanced 3D printing technologies. In this study SS316L electrodes are fabricated through Direct Metal laser Sintering (DLMS) process which allows precise fabrication of SS316L electrodes with optimized geometries to enhance EDM performance. The DMLS process for the SS316L electrode is shown in Figure 1. These methods enable customization of electrode designs, leading to improved efficiency, reduced material waste, and enhanced control over microstructural properties. The ability to tailor electrode designs through 3D printing provides an opportunity to optimize EDM outcomes and develop next-generation machining solutions.

In this study TI6AL4V with a dimension of 100 mm length, 60 mm width and 5 mm height workpiece has been chosen. TI6AL4V, a titanium alloy, is known for its high strength-to-weight ratio, excellent corrosion resistance, and biocompatibility [24]. These properties make it a preferred material in aerospace, medical, and automotive industries. However, its low thermal conductivity and high chemical reactivity with cutting tools present challenges in conventional machining [25]. EDM provides an alternative approach, minimizing tool wear and thermal damage while maintaining the integrity of the workpiece. The effectiveness of EDM in machining TI6AL4V is highly dependent on electrode performance, making the study of 3D-fabricated SS316L electrodes crucial.

2.2 Importance of Electrode Material in EDM

The choice of electrode material significantly impacts EDM efficiency. Materials with high thermal and electrical conductivity, wear resistance, and low electrode wear rate are preferred. SS316L, due to its corrosion resistance, mechanical strength, and excellent thermal stability, is a potential candidate for EDM applications. Traditional electrode materials such as copper and graphite have limitations in terms of wear rate and cost, making SS316L a promising alternative, especially when fabricated through advanced 3D printing technologies.

2.3 Overview of 3D Fabrication of SS316L Electrodes

3D printing technologies such as Selective Laser Melting (SLM) and Direct Metal Laser Sintering (DMLS) allow precise fabrication of SS316L electrodes with optimized geometries to enhance EDM performance. These methods enable customization of electrode designs, leading to improved efficiency, reduced material waste, and enhanced control over microstructural properties. The ability to tailor electrode designs through 3D printing provides an opportunity to optimize EDM outcomes and develop next-generation machining solutions.

2.4 Ti6Al4V Alloy and its Machining Challenges

Ti6Al4V, a titanium alloy, is known for its high strength-to-weight ratio, excellent corrosion resistance, and biocompatibility. These properties make it a preferred material in aerospace, medical, and automotive industries. However, its low thermal conductivity and high chemical reactivity with cutting tools present challenges in conventional machining. EDM provides an alternative approach, minimizing tool wear and thermal damage while maintaining the integrity of the workpiece. The effectiveness of EDM in machining Ti6Al4V is highly dependent on electrode performance, making the study of 3D-fabricated SS316L electrodes crucial.

2.5 ML based approached in EDM of TI6AL4V

Artificial intelligence (AI) and Machine Learning (ML) techniques help in optimizing EDM parameters by predicting performance metrics and reducing the need for trial-and-error experimentation. Machine learning models can analyze of experimental data to identify optimal machining conditions, leading to increased efficiency, reduced material wastage, and improved accuracy. The integration of AIML in EDM provides significant advantages by enabling real-time monitoring adaptive control, and predictive maintenance of machining processes.

3. Proposed Model

3.1 Experimental Setup

The EDM experiments were conducted using a CNC EDM machine equipped with a dielectric fluid circulation system. The machine was configured to maintain a controlled environment, ensuring stable spark generation. The setup included a power supply unit, pulse generator, and a servo system for electrode movement control.

3. 2 Selection and Fabrication of SS316L Electrode

The SS316L electrode was fabricated using Selective Laser Melting (SLM) technology. The 3D printing process involved laser melting of SS316L powder layer by layer to achieve the desired electrode geometry. After fabrication, the electrode was post-processed through heat treatment and surface finishing to enhance its electrical conductivity and mechanical strength.

3.3 Workpiece Material: Ti6Al4V Specifications

The workpiece material used in this study was Ti6Al4V, a widely used titanium alloy with the following specifications:

- Composition: Titanium (90%), Aluminium (6%), Vanadium (4%)
- Density: 4.43 g/cm^3
- Hardness: 35-40 HRC
- Thermal Conductivity: 6.7 W/m·K

3.4 EDM Machine and Process Parameters

The EDM process was carried out under controlled conditions with the following process parameters:

- Voltage: 80V
- Current: 10-30 A
- Pulse-on Time: 100-300 μs
- Pulse-off Time: 50-150 μs
- Dielectric Fluid: Kerosene
- Flushing Pressure: 0.3 MPa
- Electrode Polarity: Positive

Machine learning models were developed to predict EDM performance metrics such asMRR ,TWR , surface roughness and harness value. The prediction has been made on aBox–Behnken design of experiment followed by a full factorial L27 OA design. Data analysis was performed to find how each parameter are affecting the other parameters. We have used heatmap to check correlation between each and everyparameters. The figure 2 shows the heatmap and from which we found that the parameters like MRR, TWR are highly correlated with other parameters like current, voltage, Ton, Toff from which we can conclude that regression models can be applied to predict the parameters like MRR, TWR, hardness values etc.The detail process for model application are listed below andFigure 3 demonstrated the flow chart of the model architecture followed in this current work.

Step 1-Data Preprocessing: Experimental data was collected and normalized.

Step 2-Feature Selection: Key parameters affecting MRR, TWR, and SR were identified.

Step 3-Model Training: Various ML algorithms (Random Forest, Linear Regression, Polynomial regression and XGBoostRegression) were trained using experimental data.

Step 4-Validation: Model accuracy was tested using Root Mean Square Error (RMSE) and R^2 score.

Step 5-After accuracy was checked the values were very less as data used had only 27 samples. Then the linear and polynomial interpolation method was executed to increase the data to 76 samples initially then 200 samples.

Step 6-Further the Machine learning algorithms were applied and Root Mean Square Error (RMSE) and R^2 score and accuracy of the models improved after increasing the sample data.

The correlation heatmap in Figure 10 reveals the key relationships among EDM process parameters and machining responses. Notably, Material Removal Rate (MRR) shows a strong positive correlation with the current and Tool wear rate, while having a negative correlation with Ton, surface roughness, and hence it indicates that higher MRR is associated with better surface quality . TWR also correlates positively with MRR, current and micro hardness value showing that TWR increases with material removal rate and current. Interestingly, the core EDM input parameters—discharge current (Ip), pulse on-time (Ton), pulse off-time (Toff), and gap voltage (Vg)—exhibit weak linear correlations with output responses, suggesting complex or non-linear dependencies better suited for machine learning models. Surface roughness shows only mild correlation with other variables, indicating it may be influenced by additional factors beyond the scope of these parameters.

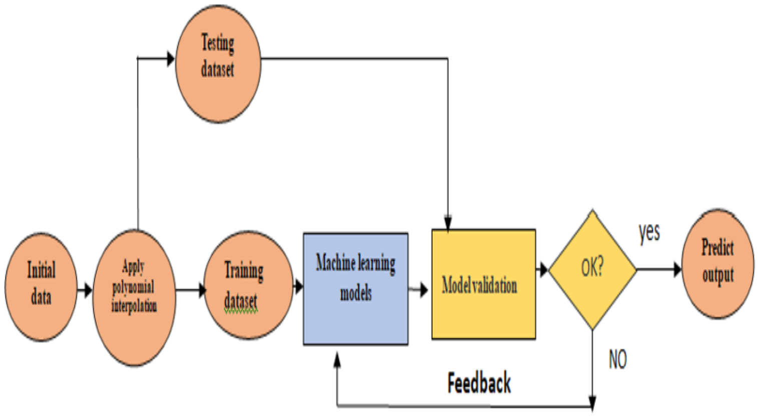

Fig. 1. the machine learning model used for prediction of MRR, TWR, surface roughness and harness values.

The figure 1 shows the flow diagram of the machine learning model used for prediction of MRR, TWR, surface roughness and harness values. Strong methods for producing extra data points between preexisting observations, such as linear and polynomial interpolation, improve datasets for machine learning. Drawing a straight line between two known points and using the method to calculate intermediate values is how linear interpolation estimates new values. The formula used is

$$Y_{new} = (1-\alpha)y_1 + \alpha y_2 \qquad (1)$$

where α controls position between points

Conversely, polynomial interpolation captures intricate, nonlinear trends by fitting a higher-degree polynomial through a number of points. Although techniques like cubic splines and Lagrange interpolation can produce more accurate and smoother data, they run the danger of overfitting if the polynomial degree is too high. Linear interpolation is a technique used to increase the number of data points in a dataset by estimating new values between existing data points, assuming a straight-line relationship between them. It works by taking two known data points and generating intermediate values that lie on the straight line connecting them. For example, if you have measurements at times t1 and t2, linear interpolation can estimate values at time steps between t1 and t2 based on the linear trend between the two. This method is especially useful in machine learning when working with small or sparse datasets, as more data points can improve model performance by providing the algorithm with more information to learn from. However, it's important to note that while linear interpolation can help smooth or densify data, it does not add new information or patterns- it assumes that the trend between points is linear. Therefore, it's best suited for datasets where this assumption holds true, such as in time series or sensor data with gradual changes. Polynomial interpolation is a method used to increase the number of data points in a dataset by fitting a single polynomial function that passes through all the known data points, and then using that function to estimate new intermediate values. Unlike linear interpolation, which assumes straight-line relationships between pairs of points, polynomial interpolation allows for curved, more flexible fits that can capture more complex trends in the data.

In the context of machine learning, polynomial interpolation can be used to densify a sparse dataset, particularly when the underlying relationships between data points are nonlinear. By generating additional synthetic data points along the smooth curve defined by the polynomial, models may have more examples to train on, which can improve learning—especially for algorithms sensitive to data quantity or distribution. However, high-degree polynomials can introduce problems like Runge's phenomenon (wild oscillations between points), leading to unrealistic or unstable interpolations. So, while polynomial interpolation can be powerful, it should be used with caution, ideally with lower-degree polynomials or piecewise approaches (like splines), to balance flexibility with stability and avoid misleading the machine learning model with artificial patterns.

4. Results And Discussion

4.1 AI/ML-Based Prediction of EDM Performance

To predict MRR and TWR value based on current, voltage, Ton, Toff, machining time, surface roughness, hardness value we have used linear regression, polynomial regression, random forest regressor, XGBoostRegressor. Random forest regressor algorithm gave the best accuracy. Multioutput regressor was used to get both the predictions together ie MRR and TWR. Table 1 shows accuracy obtained from predicting MRR and TWR before applying interpolation when we had only 27 data.

Table 1 Evaluation metrics for MRR and TWR modelbefore applying interpolation method

Algorithm	R^2 score	MSE	RMSE	MAE
Linear Regression	28.2%	20521.8	1280.6	210.23
Polynomial Regression	48.6%	10298.2	789.54	102.6
Random Forest Regressor	56.2%	890.33	99.89	20.8
XGBoostRegressor	55.4%	901.3	101.32	21.6

After applying various machine learning algorithm, ensemble methods still accuracy of the model was low. We planned to optimize the model by increasing the sample data as initially the sample data was 27, then we used linear interpolation to make 76 sample data. Table 2 shows results obtained after applying linear interpolation and then the machine learning algorithm.

Table 2 Evaluation metrics for MRR and TWR model before applying linear interpolation method

Algorithm	R^2 score	MSE	RMSE	MAE
Linear Regression	30.4%	18976.9	1018.6	179.9
Polynomial Regression	48.9%	10188.45	779.67	100.88
Random Forest Regressor	60.44%	765.38	69.57	16.66
XGBoostRegressor	59.2%	782.45	78.3	17.25

From table 2 it was noted that the accuracy did not increase much and error were not much optimized. Further we planned to use polynomial interpolation by which we increased the data to 200 samples and then applied machine learning algorithms. Table 3 shows the accuracy and MSE, MAE and RMSE values obtained after applying polynomial interpolation and machine learning algorithms.

Table 3 Evaluation metrics for predicting MRR and TWR modelafter applying polynomial interpolation method

Algorithm	R2 score	MSE	RMSE	MAE
Linear Regression	65.7%	707.31	58.7	15.26
Polynomial Regression	78.6%	578.48	39.9	12.44
Random Forest Regressor	95.6%	205.36	18.2	5.3
XGBoostRegressor	94.2%	217.2	19.11	6.8

From the table 3 results it can be concluded that random forest regressor gave the best result as compared to other machine learning algorithms. Further we have used backward propagation method also to predict surface roughness and hardness value based on MRR, TWR, current , voltage, Ton, Toff, machining time we have used linear regression, polynomial regression, random forest regressor and boosting algorithm. XGB boost algorithm gave the best accuracy. Multioutput regressor was used to get both the parameters prediction together ie surface roughness and hardness value.The table 4 shows the accuracy, mean squared error (MSE), Root mean squared error (RMSE) and Mean absolute error(MAE) before applying interpolation on the data set where the accuracy values were low. In order to increase accuracy of the model the dataset which had initially 27 samples need to be increased for which we have used linear interpolation and increased the data to 76 samples. Table 5 shows the results obtained after applying linear interpolation and then applying machine learning algorithms to the new generated dataset.

Table 4 Evaluation metrics for predicting surface roughness and hardness value before applying interpolation

Algorithm	R^2 score	MSE	RMSE	MAE
Linear Regression	32.8%	17976.9	998.6	155.9
Polynomial Regression	48.9%	10188.45	779.67	100.88
Random Forest Regressor	60.4%	762.18	68.57	16.01
XGBoostRegressor	68.6%	678.22	51.9	15.31

Table 5 Evaluation metrics for predicting surface roughness and hardness value after applying linear interpolation

Algorithm	R^2 score	MSE	RMSE	MAE
Linear Regression	42.5%	12287.4	801.2	125.8
Polynomial Regression	49.9%	9998.7	679.6	98.82
Random Forest Regressor	59.2%	799.28	74.57	18.05
XGBoostRegressor	69.3%	612.33	47.9	14.7

Further polynomial interpolation was applied on the dataset and achieved 200 samples and then applied machine learning algorithm after which the accuracy of the model increased as well as the error were minimized. From Table 6 it can be concluded that XGBoostregressor generated the best resultsi.e. 98.6% accuracy making it most efficient algorithm.

Table 6 Evaluation metrics for predicting surface roughness and hardness value after applying polynomial interpolation

Algorithm	R^2 score	MSE	RMSE	MAE
Linear Regression	52.8%	6798.7	210.6	34.8
Polynomial Regression	78.9%	575.97	38.9	11.76
Random Forest Regressor	90.4%	301.9	25.11	9.99
XGBoostRegressor	98.6%	102.36	15.2	3.1

These models will help user further to know the parameter setting of EDM machine to get a desired surface roughness value. In traditional methods only the experienced person will be able to achieve desired mechanical properties from the EDM process but our proposed model can help anyone to get a desired mechanical property as the ML model can predict the required EDM setting parameters for achieving a particular surface roughness and hardness value. Also if a particular surface roughness value is known we can predict MRR and TWR using our ML model which can be really helpful for the new users of the machine.

Further to check the accuracy of the models, actual versus predicted surface roughness and hardness value plot was done as shown in figure 2 and 3. As we can see the actual values and predicted values are near to each other and this result is obtained from the best algorithm as shown in table 6 ie.XGBoostregressor model which gave the best results

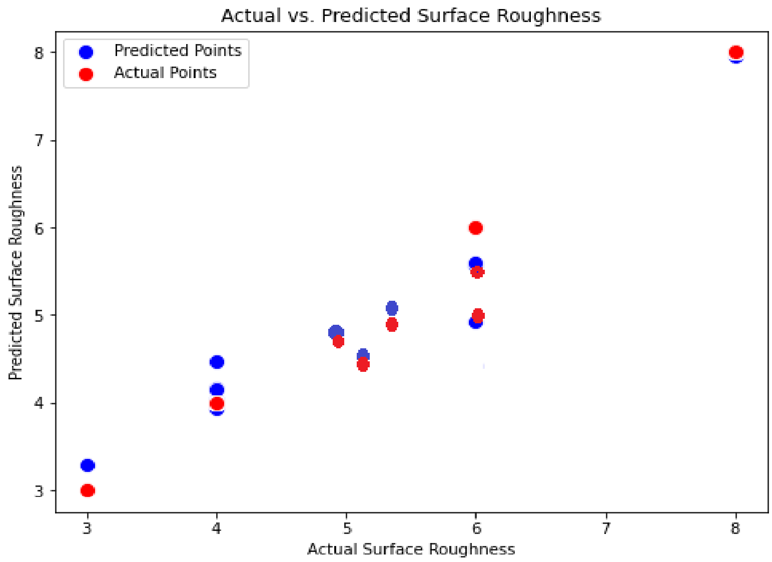

Fig. 2. Actual vs predicted value of surface rougness from XGBoost algorithm

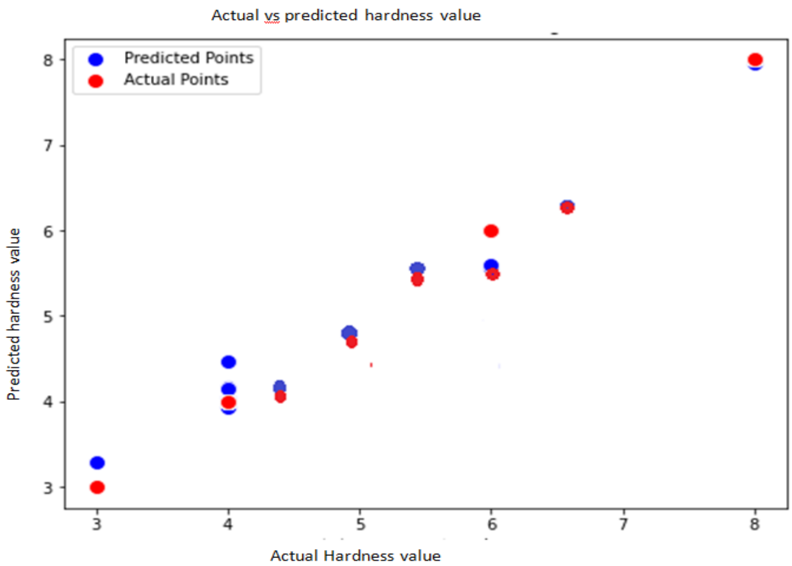

Fig. 3. Actual vs predicted value of hardness from XGBoost algorithm

The figure 4 and 5 shows the actual and predicted value obtained from the best algorithm as shown in table 3 for predicting the MRR and TWR values. We can conclude from the below mentioned graph that actual values are near to predicted values. For conducting the prediction of MRR and TWR as well as for predicting of surface roughness and hardness value we have used multioutput regressor.To improve overall performance and resilience, the multi-regressor output technique combines the predictive capabilities of several regression models. Multiple regression algorithms, including Linear Regression, Random Forest, Polynomial Regression, and others, are trained on the same dataset rather than depending on a single model. The target variable is individually predicted by each model, and the results are then combined using methods like as stacking, voting regressors, or weighted or unweighted averaging to generate a final prediction. By utilizing the distinct benefits of each individual regressor, this ensemble technique helps lower variance and bias, increases accuracy, and guarantees the model runs well under a variety of input situations.

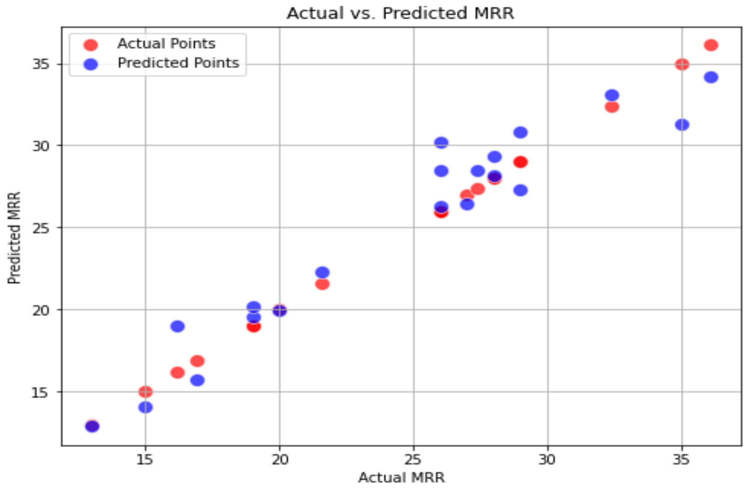

Fig. 4. Actual vs predicted value of MRR from Random forest algorithm

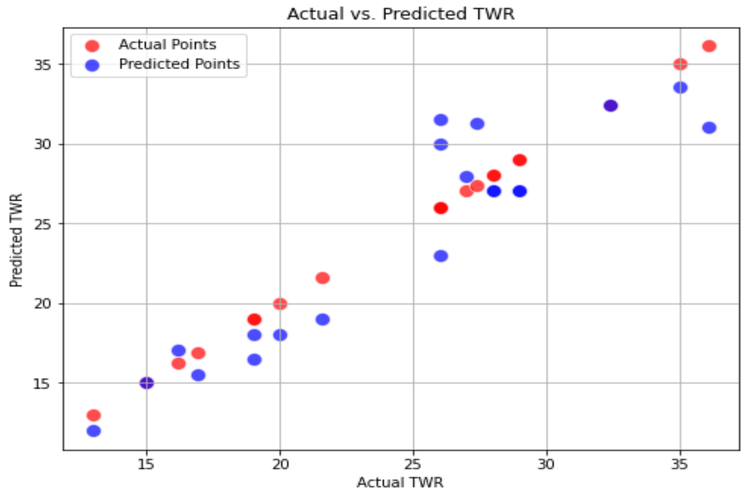

Fig. 5. Actual vs predicted value of TWRRandom forest algorithm

The normal probability plot (also known as a Q-Q plot) is a graphical tool used in regression analysis to assess whether the residuals (errors) of a model follow a normal distribution—a key assumption in linear regression. In this plot, the residuals are plotted against a theoretical normal distribution in such a way that if the residuals are normally distributed, the points will form an approximately straight diagonal line. Deviations from this line indicate departures from normality, such as skewness, kurtosis, or the presence of outliers. This visual test is simple yet effective in identifying whether the regression assumptions hold, which is critical for accurate confidence intervals and hypothesis testing.Thesignificance of the normal probability plot lies in validating the statistical integrity of the regression model. When residuals are normally distributed, it confirms that the model's estimators are unbiased and efficient, and that inferences such as p-values and confidence intervals are reliable. However, if the plot shows systematic deviations from normality, it could signal problems such as omitted variables, incorrect model specification, or non-linearity in the data. Detecting these issues early allows analysts to make informed adjustments to the model, such as applying transformations, using robust regression methods, or switching to non-parametric techniques.

An essential presumption in linear regression is that the residuals, or the discrepancies between observed and predicted values, follow a normal distribution. This can be evaluated using a normal probability plot for a regression model. The theoretical quantiles of a typical normal distribution are displayed against the standardized residuals in this figure. The points should generally lie along a straight diagonal line if the residuals are regularly distributed. The validity of statistical tests and confidence intervals obtained from the model may be impacted by deviations from this line, such as curves or outliers, which indicate violations of normalcy assumption.The figure 6 and figure 7 shows the normal probability curve obtained for predicting MRR and TWR by using Random forest algorithm where we got the best results and figure 8 and figure 9 shows normal probability curve for predicting surface roughness and hardness values where XGBoostregressor gave the best results. From the graphs it can be concluded that the values obtained were near to straight line which indicates the residuals are regularly distributed and model has good accuracy.

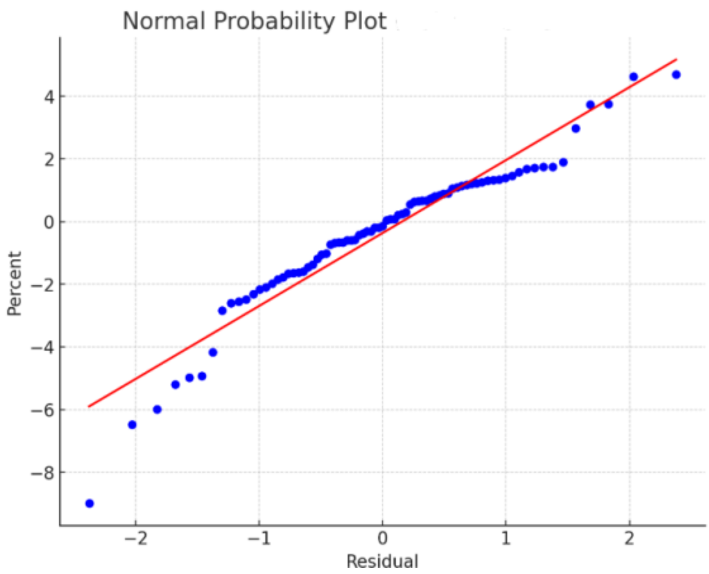

Fig. 6. Normal probability plot for predicting MRR from Random forest alogorithm

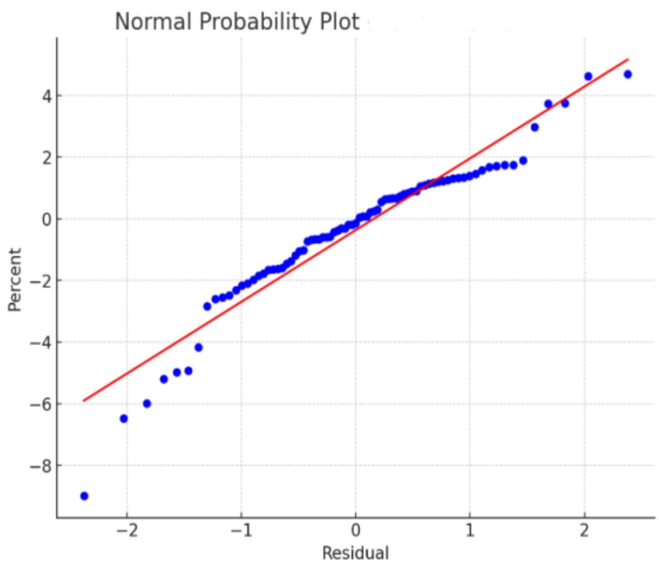

Fig. 7. Normal probability plot for TWR from Random forestalogorithm

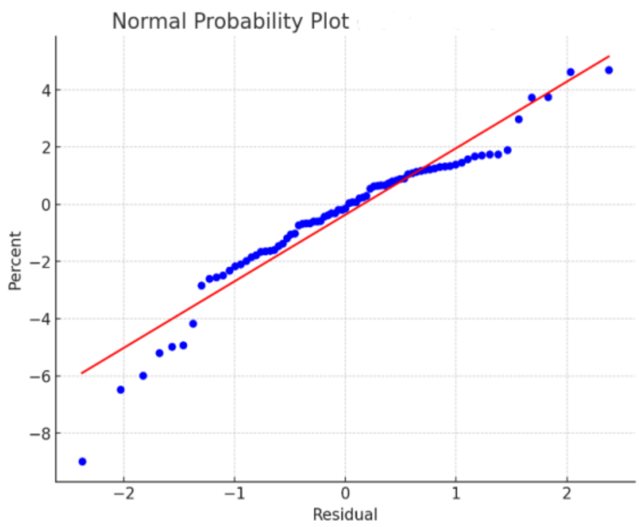

Fig. 8. Normal probablity plot for predicting surface roughness from XGBoostalgorithm

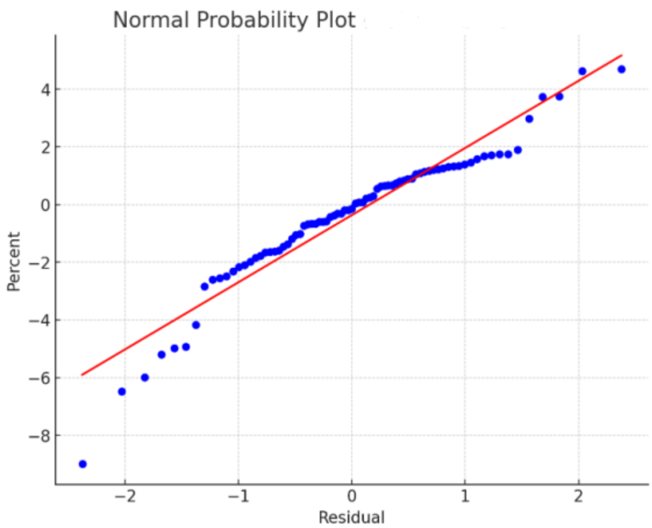

Fig. 9. Normal probablity plot for predicting hardness value from XGBoost algorithm

A residuals plot of fitted values versus residuals in a regression algorithm visualizes the relationship between the predicted values (fitted values) and the corresponding residuals (errors). On the x-axis, the fitted values are plotted, and on the y-axis, the residuals are displayed. Ideally, this plot should show a random scatter of points around the horizontal line at zero, with no clear patterns. This randomness indicates that the model has captured the underlying structure in the data well and that the errors are randomly distributed, which supports the assumptions of linearity and constant variance of errors. The importance of this plot lies in its ability to reveal model issues. If the residual plot shows patterns-such as curves, funnels (increasing or decreasing spread), or clusters–it suggests violations of key regression assumptions. For example, a curved pattern might indicate on-linearity, while a funnel shape could signal non-constant variance, both of which can lead a biased estimates and incorrect conclusions, detecting these issues early allows analysts to refine their models by transforming variables, adding polynomials terms, or using alternative modelling approaches. The significance of the residual plot lies in its ability to visually diagnose issues such as non-linearity, heteroscedasticity, or model misspecification. For instance, if the plot displays a funnel shape (residuals increase or decrease with fitted values), it suggests heteroscedasticity-where the variance of the errors is not constant. If a curve or systematic pattern is visible, it indicates that a linear model may not be appropriate, and a non-linear transformation or polynomial regression might be needed. Thus, the residual plot is crucial for verifying whether the chosen regression model is suitable and whether its predictions can be trusted for inference or forecasting. The residual plot offers several advantages in regression analysis, primarily by serving as a visual diagnostic tool to validate model assumptions. It helps detect non-linearity, heteroscedasticity, and outliers, which may indicate that the model is not capturing the underlying data structure correctly. By identifying these issues early, analysts can make necessary adjustments-such as transforming variables, refining the model, or using alternative regression techniques-leading to improved model accuracy and reliability.

The figure 10 shows the bar graph of accuracy ie R2 score obtained by applying different machine learning algorithm before and after applying polynomial interpolation for predicting surface roughness and hardness value. We can conclude from the graph that after applying polynomial interpolation accuracy of the models have been enhanced. Similarly figure 11 shows the bar graph of MSE obtained by applying different machine learning algorithm before and after applying polynomial interpolation for predicting surface roughness and hardness value .Here also we can see that MSE decreases after applying intepolation and increasing the data the machine learning algorith performed well. The figure 12 and figure 13 shows RMSE and MAE obtained by applying different machine learning algorithm before and after applying polynomial interpolationfor predicting surface roughness and hardness value.. From the graphs we can conclude that performance of machine learning algorithm in terms of R2 score, MSE,MAE,RMSE improved by increasing the observation in the dataset. Polynomial interpolation could increase the data from 27 to 200 datas which resulted in better performance of machine learning models.

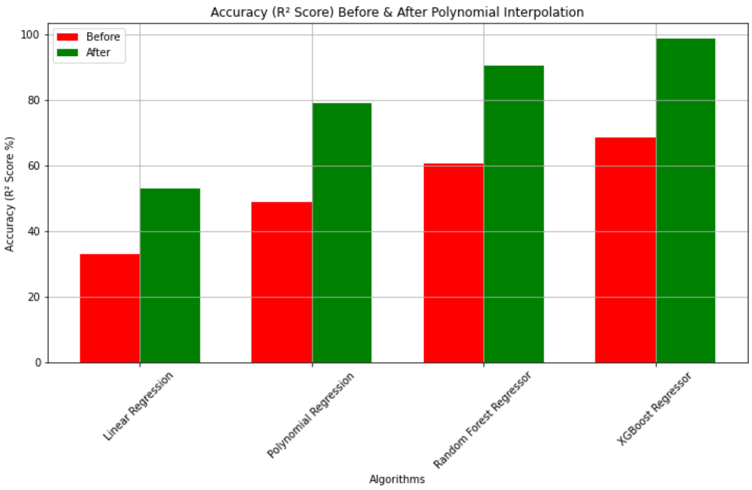

Fig. 10. R2 score before and after applying polynomial interpolation for Surface roughness and hardness value prediction

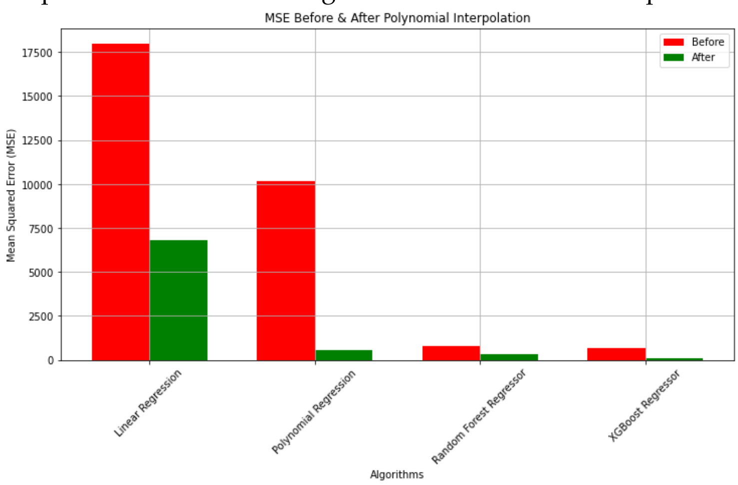

Fig. 11. MSE before and after applying polynomial interpolation for Surface roughness and hardness value prediction

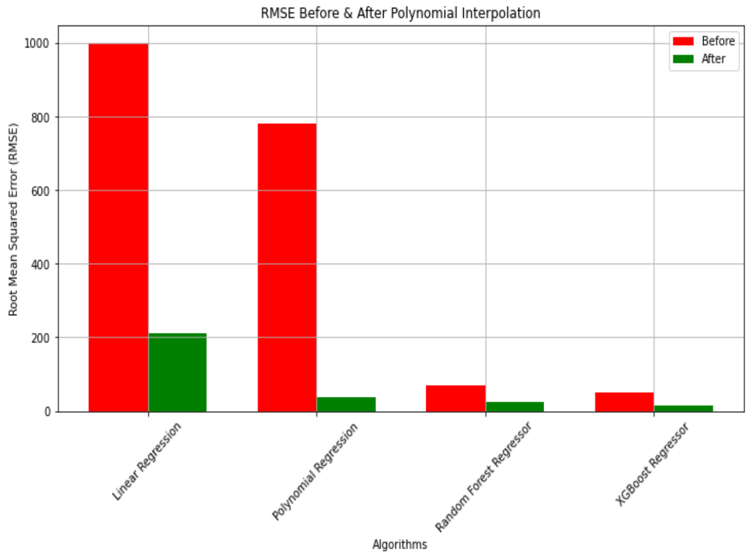

Fig. 12. RMSE before and after applying polynomial interpolation for Surface roughness and hardness value prediction

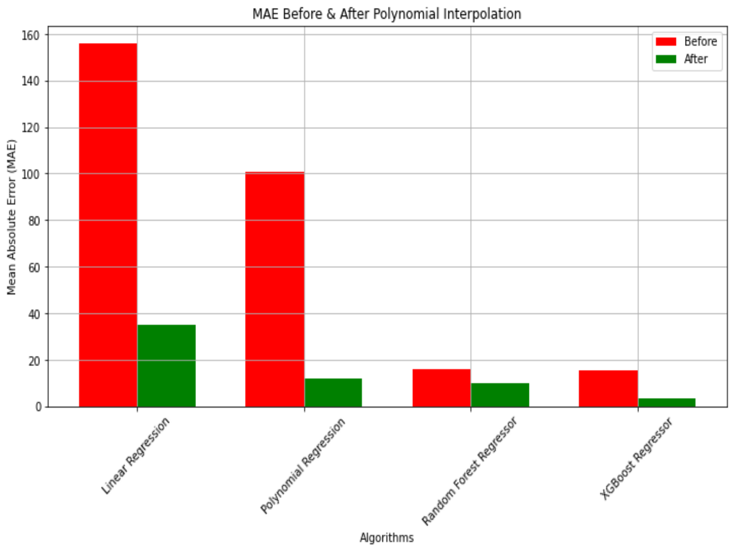

Fig. 13. MAE before and after applying polynomial interpolation for Surface roughness and hardness value prediction

From the graphs and tables as discussed in this section we can conclude that for predicting MRR and TWR Random forest algorithm gave the best results after applying polynomial interpolation to increase the observations in the dataset. And for predicting surface roughness and hardness value XGBoost regressor gave best results. One of the important conclusion from the discussion is number of observation in dataset played a vital role in determining accuracy of the model and ensemble machine learning methods and boosting algorithms gave best results as compared to conventional machine learning models.

5. Conclusion

The efficiency of 3D-printed SS316L electrodes in the electric discharge machining (EDM) of Ti6Al4V Grade-5 alloy is demonstrated in this work, along with their influence on important performance parameters such surface roughness, tool wear rate (TWR), and material removal rate (MRR). According to the experimental results, SS316L electrodes improve MRR and surface integrity by increasing EDM efficiency through their better thermal conductivity, wear resistance, and microstructural stability. The smoother surfaces and reduced wear of 3D-printed SS316L electrodes were confirmed by comparison with conventional electrodes. Furthermore, SEM analysis shed light on the surface morphology, revealing homogeneous material degradation and fewer microcracks, both of which improve the dependability of Ti6Al4V components produced by EDM. The prediction was greatly enhanced by the incorporation of machine learning (ML) models. While the XGBoostRegressor produced the most accurate forecasts for surface roughness and hardness values, the Random Forest Regressor produced the most accurate predictions for MRR and TWR. Even novice users may now more easily navigate the process thanks to these models, which allow for real-time EDM parameter customization. A data driven strategy for increasing EDM efficiency and decreasing reliance on trial-and-error is provided by the capability to forecast machining results based on input parameter. This study demonstrated the effectiveness of machine learning (ML) model in accurately predicting and optimizing key EDM performance parameters, including Materials Removal Rate (MRR), Tool Wear Rate (TWR), surface roughness, and hardness, during the machining of TI6AL4V using 3D printed SS316L electrodes. By applying various regression algorithms-such as Linear Regression, Polynomial Regression, CART, Random Forest, and XGBoost-the study identified ensemble method as the most effective. Notably, Random Forest Regressor achieved an R2 of 95.6% for MRR and TWR Prediction, while XGBoostRegressor achieved 98.6% R2 for surface roughness and hardness prediction. To overcome the limitations of a small dataset (initially 27 samples), polynomial interpolation was used to increase the data to 200 samples, significantly improving model accuracy while reducing RMSE to 18.2 for MRR and 15.2 for surface roughness. This approach illustrates the power of ML in capturing complex, nonlinear relationships in EDM processes and provides a reliable, user-friendly framework for real-time process prediction and parameter optimization, reducing dependency on manual expertise and trial-and-error methods.

References

[1]. Zhang, S., Zhang, W., Chang, H., Liu, Y., Ma, F., Yang, D. and Sha, Z., 2019. Study of the thermal erosion, ejection and solidification processes of electrode materials during EDM. Engineering Applications of Computational Fluid Mechanics, 13(1), pp.1153-1164.

[2]. Al-Ahmari, A.M.A., Rasheed, M.S., Mohammed, M.K. and Saleh, T., 2016. A hybrid machining process combining micro-EDM and laser beam machining of nickel–titanium-based shape memory alloy. Materials and Manufacturing Processes, 31(4), pp.447-455.

[3]. Nishanth, B.S., Kulkarni, V.N. and Gaitonde, V.N., 2019, December. A review on conventional and non-conventional machining of titanium and nickel-based alloys. In AIP conference proceedings (Vol. 2200, No. 1). AIP Publishing.

[4]. Ishfaq, K., Asad, M., Anwar, S., Pruncu, C.I., Saleh, M. and Ahmad, S., 2020. A comprehensive analysis of the effect of graphene-based dielectric for sustainable electric discharge machining of Ti-6Al-4V. Materials, 14(1), p.23.

[5]. Zhang, Z., Dong, H., Zhou, J. and Sun, Q., 2024, April. Application of electrical discharge machining technology in Ti6Al4V. In Third International Conference on Advanced Manufacturing Technology and Electronic Information (AMTEI 2023) (Vol. 13081, pp. 278-286). SPIE.

[6]. Ishfaq, K., Maqsood, M.A., Anwar, S., Harris, M., Alfaify, A. and Zia, A.W., 2022. EDM of Ti6Al4V under nano-graphene mixed dielectric: a detailed roughness analysis. The International Journal of Advanced Manufacturing Technology, 120(11), pp.7375-7388.

[7]. Kao, J.Y., Tsao, C.C., Wang, S.S. and Hsu, C.Y., 2010. Optimization of the EDM parameters on machining Ti–6Al–4V with multiple quality characteristics. The International Journal of Advanced Manufacturing Technology, 47, pp.395-402.

[8]. O'Hara, C., McAfee, M., Raghavendra, R. and Tormey, D., 2025. An additive manufacturing assisted electric discharge machining technique to produce complex, thin-walled, injection mould cavities in 316 L stainless steel. Additive Manufacturing, 105, p.104800.

[9]. D'Andrea, D., 2023. Additive manufacturing of AISI 316L stainless steel: A review. Metals, 13(8), p.1370.

[10]. Goiogana, M. and Elkaseer, A., 2019. Self-flushing in EDM drilling of Ti6Al4V using rotating shaped electrodes. Materials, 12(6), p.989.

[11]. Singh, H., Patrange, P., Saxena, P. and Puri, Y.M., 2022. Multi-objective optimization of the process parameters in electric discharge machining of 316L porous stainless steel using metaheuristic techniques. Materials, 15(19), p.6571.
[12]. Luis-Pérez, C.J., 2024. Multi-objective optimization of electrical discharge machining parameters using particle swarm optimization. Applied Soft Computing, 153, p.111300.
[13]. Vivekanandhan, M., Senthilkumar, N., Deepanraj, B. and Naik, N., 2025. Assessment on Electrical Discharge Machining of Ultrasonication Assisted Stir-casted AA8081-B4C-Gr Hybrid Composites and Prediction using Levenberg-Marquardt Technique. Journal of Materials Research and Technology.
[14]. Bellotti, M., Wu, M., Qian, J. and Reynaerts, D., 2020. Tool wear and material removal predictions in micro-EDM drilling: Advantages of data-driven approaches. Applied Sciences, 10(18), p.6357.
[15]. Kant, G. and Sangwan, K.S., 2015. Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm. Procedia Cirp, 31, pp.453-458.
[16]. Cogun, C. and Ayli, E., 2025. Machine Learning-Driven Approach for Reducing Tool Wear in Die-Sinking Electrical Discharge Machining. Arabian Journal for Science and Engineering, pp.1-21.
[17]. Kosarac, A., Tabakovic, S., Mladjenovic, C., Zeljkovic, M., &Orasanin, G. (2023). Next-gen manufacturing: machine learning for surface roughness prediction in Ti-6Al-4V biocompatible alloy machining. Journal of Manufacturing and Materials Processing, 7(6), 202.
[18]. Mollik, M.S., Saleh, T., Nor, K.A.B.M. and Ali, M.S.M., 2022. A machine learning-based classification model to identify the effectiveness of vibration for μEDM. Alexandria Engineering Journal, 61(9), pp.6979-6989.
[19]. Cetin, A., Atali, G., Erden, C. and Ozkan, S.S., 2024. Assessing the performance of state-of-the-art machine learning algorithms for predicting electro-erosion wear in cryogenic treated electrodes of mold steels. Advanced Engineering Informatics, 61, p.102468.
[20]. Abbas, A.T., Sharma, N., Al-Bahkali, E.A., Sharma, V.S., Farooq, I. and Elkaseer, A., 2023. A machine learning perspective to the investigation of surface integrity of Al/SiC/Gr composite on EDM. Journal of Manufacturing and Materials Processing, 7(5), p.163.
[21]. Surleraux, A., Lepert, R., Pernot, J.P., Kerfriden, P. and Bigot, S., 2020. Machine learning-based reverse modeling approach for rapid tool shape optimization in die-sinking micro electro discharge machining. Journal of Computing and Information Science in Engineering, 20(3), p.031002.
[22]. Pramanik, A., Basak, A.K., Littlefair, G., Debnath, S., Prakash, C., Singh, M.A., Marla, D. and Singh, R.K., 2020. Methods and variables in Electrical discharge machining of titanium alloy–A review. Heliyon, 6(12).
[23]. Ulhakim, M.T., Mulyadi, D., Susilo, H. and Setyo, M., 2025. Electrical Discharge Machining: Recent Advances and Future Trends in Modeling, Optimization, and Sustainability. International Journal of Lightweight Materials and Manufacture.
[24]. Ulhakim, M.T., Mulyadi, D., Susilo, H. and Setyo, M., 2025. Electrical Discharge Machining: Recent Advances and Future Trends in Modeling, Optimization, and Sustainability. International Journal of Lightweight Materials and Manufacture.
[25]. Ishfaq, K., Asad, M., Harris, M., Alfaify, A., Anwar, S., Lamberti, L. and Scutaru, M.L., 2022. EDM of Ti-6Al-4V under nano-graphene mixed dielectric: a detailed investigation on axial and radial dimensional overcuts. Nanomaterials, 12(3), p.432.
[26]. G. James, D. Witten, T. Hastie, and R. Tibshirani, An Introduction to Statistical Learning: With Applications in R, 2nd ed. New York, NY, USA: Springer, 2021.
[27]. D. C. Montgomery, E. A. Peck, and G. G. Vining, Introduction to Linear Regression Analysis, 5th ed. Hoboken, NJ, USA: Wiley, 2012
[28]. G. Dudek, "A Comprehensive Study of Random Forest for Short-Term Load Forecasting," Energies, vol. 15, no. 20, art. 7547, Oct. 2022
[29]. MiladShojaei Nasir Abadiet al., "Comparative Analysis of XGBoost Algorithm and Linear Regression in Predicting the Trend of Investor Overreaction," Business, Marketing and Finance Open, vol. 2, no. 2, pp. 125–137, Mar. 2025
[30]. J. Yang, L. Zhang, and G. Liu, "Linear interpolation algorithm of machining tool path with curvature smoothing," Proc. Inst. Mech. Eng. Part C: J. Mech. Eng. Sci., vol. 236, no. 15, pp. 3047–3063, Aug. 2022.

[31]. R. L. Burden and J. D. Faires, Numerical Analysis, 9th ed., Boston, MA, USA: Brooks/Cole, 2011, ch. 3, pp. 98–112.