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Article

Feature-Driven Decision Tree Approach for Microhardness Enhancement in nanopowder Mixed Electrical Discharge Machining

Amreeta R. Kaigude [1*], Nitin K. Khedkar[2], Vijaykumar S. Jatti[3]

[1*]Department of Mechanical Engineering, Symbiosis Institute of Technology, Symbiosis International (Deemed) University, Pune 412115, India.
Email Id: amree2710@gmail.com, Orchid Id: 0009-0002-9462-2291.
[2]MIT World Peace University, Pune 411038, India.
Email Id: nkkhedkar@gmail.com, Orchid Id: https://orcid.org/0000-0003-2784-234X.
[3]School of Automobile Engineering, Symbiosis Skills and Professional University, Kiwale, Pune 412101, India.
Email Id: vkjatti@gmail.com, Orchid Id: https://orcid.org/0000-0001-7949-2551.
Corresponding Author:Amreeta R. Kaigude *, amree2710@gmail.com

Abstract: In the proposed approach, the use of the decision tree-based algorithm establishes a strong prediction of micro hardness for the materials produced under specific machining parameters. With the dataset consisting of variables such as gap current, pulse ON time, pulse OFF time, voltage, and powder concentration, the model attained perfect fitting during training with a root mean-square error (RMSE) of 0.00 and a coefficient of determination (R^2) of 1.0000. Recursive Feature Elimination (RFE) in conjunction with cross-validation was used to select features optimally and to avoid overfitting. Accordingly, the reduced model depicted the major key process parameters with gap current, pulse time, and powder concentration being the main influencing process parameters to microhardness values. A clarity of interpretation was attained by this decision-tree structure capturing nonlinear dependencies and resulted in recommending an optimal microhardness of 1382 HV for input parameters, gap current of 6 A, pulse ON time of 200 µs, and powder concentration of 0.6%. Such results mark decision-tree models as a means by which intelligent design and quality control can be performed in high-tech machining.
Keywords: Powder Mixed Electrical Discharge Machining, Microhardness, Machine learning, Decision tree model.

1. INTRODUCTION

Electrical Discharge Machining (EDM) has emerged as a pivotal non-conventional manufacturing process, extensively utilized for fabricating intricate geometries in hard-to-machine materials, particularly in die and mold manufacturing applications [1]. The EDM process operates through controlled electrical discharges between an electrode and workpiece in a dielectric medium, enabling material removal through electro-thermal energy conversion mechanisms [2]. This technology has gained widespread industrial acceptance due to its capability to machine materials regardless of their hardness and to create complex three-dimensional shapes with high precision [3]. However, conventional EDM processes are associated with inherent limitations including relatively low material removal rates, poor surface finish characteristics, and the formation of undesirable surface features such as micro-cracks, recast layers, and thermal damage zones [4].

To address these limitations, Powder Mixed Electrical Discharge Machining (PMEDM) has been developed as an advanced variant of conventional EDM, wherein conductive or semi-conductive powder particles are suspended in the dielectric fluid [5]. The incorporation of nanopowders in the dielectric medium significantly enhances the machining performance by improving discharge stability, reducing electrode wear, and enhancing surface quality characteristics [6]. Nanopowder additives such as aluminum oxide (Al_2O_3), silicon carbide (SiC), and titanium dioxide (TiO_2) have demonstrated remarkable improvements in material removal rates while simultaneously reducing surface roughness and enhancing microstructural properties [7,8]. The presence of nanopowders facilitates uniform discharge distribution, reduces the formation of harmful recast layers, and promotes beneficial surface modifications through controlled deposition of powder particles onto the machined surface [9].

Microhardness represents a critical surface integrity parameter that directly influences the functional performance, wear resistance, and service life of machined components [10]. In nanopowder mixed EDM processes, microhardness enhancement occurs through multiple mechanisms including grain refinement, solid solution strengthening, and the formation of beneficial intermetallic compounds during the discharge process [11]. The optimization of microhardness properties is particularly crucial for applications involving precision components, thin specimens, and surface-critical applications where enhanced mechanical properties are essential for operational reliability [12]. Recent investigations have demonstrated that systematic control of PMEDM parameters can achieve significant microhardness improvements ranging from 15% to 40% compared to conventional EDM processes [13,14].

The complexity of nanopowder mixed EDM processes, involving multiple interdependent parameters such as discharge current, pulse duration, powder concentration, and particle size, necessitates advanced predictive modeling approaches for optimal parameter selection [15]. Machine learning techniques have emerged as powerful tools for modeling complex manufacturing processes, offering superior capabilities in handling non-linear relationships, multi-parameter interactions, and process optimization compared to traditional statistical methods [16,17]. The application of machine learning in EDM parameter optimization has demonstrated significant improvements in prediction accuracy, with reported correlation coefficients exceeding 0.95 for various response parameters [18,19]. Furthermore, machine learning models can effectively capture the intricate relationships between process parameters and surface integrity characteristics, enabling precise control of microhardness properties in nanopowder mixed EDM applications [20].

Among various machine learning algorithms, Decision Tree Regression has gained prominence for manufacturing process modeling due to its inherent advantages including interpretability, robustness to outliers, and capability to handle both numerical and categorical variables without extensive preprocessing [21,22]. Decision tree models excel in identifying the most influential process parameters and their hierarchical relationships, providing valuable insights into parameter significance for microhardness optimization [23]. The tree-based structure enables clear visualization of decision rules and parameter interactions, facilitating practical implementation in industrial settings [24]. Additionally, decision tree regressors demonstrate superior performance in handling collinearity among input variables and can effectively manage missing data points, making them particularly suitable for experimental manufacturing datasets [25,26].

Table no 1. Use of machine Learning Technique in EDM.

Ref	Author(s) & Year	ML techniques used	Outcome Predicted	Key Findings
[27]	Paturi et al. (2021)	Support Vector Machine (SVM), ANN, Genetic Algorithm (GA)	Surface Roughness(SR)	SVM & ANN gave predictions close to experimental data with low error. GA optimized surface finish significantly better than statistical models.
[28]	Walia AS et al. (2022)	Linear Regression, Decision Tree, Random Forest(RF)	SR	Evaluated multiple regression models on powder-mixed EDM; found RF provided superior prediction accuracy for surface roughness and tool shape in EN31 steel.
[29]	Muhammad Sana et al. (2023)	Arificial Neural Network (ANN - MLP)	Material Removal Rate(MRR), SR	Achieved high accuracy with $R^2 >$ 0.95 in predicting MRR and SR for EDM of Inconel 617. Sensitivity analysis showed powder concentration most influential for MRR.
[30]	A.M.Nikalje (2023)	XGBoost, Random Forest, Decision Tree	SR	XGBoost achieved highest prediction accuracy for surface roughness in PMEDM of Ti-6Al-4V. Integrated with RSM and TLBO for optimized EDM settings and surface integrity examination.

[31]	D.A. Sawant, V.S. Jatti, A. Mishra, E.M. Sefene (2023)	Supervised ML Regression	SR & surface crack length	Successfully predicted SR and surface crack length in EDM, demonstrating ML applicability to multiple surface integrity metrics.
[32]	Nitin Khedkar et al (2024)	Support vector machine (SVM), Gaussian progress regression(GPR), Neural networks	Microhardness	GPR predicted the microhardness giving a value of 0.97, more accurately than the other regression models.
[33]	Amreeta R Kaigude et al. (2024)	Linear regression, Decision Tree, Random Forest	SR	Random Forest model outperformed others (R^2 = 0.89) in predicting surface roughness during TiO_2 powder-mixed EDM
[34]	I. Qasem, A. Alsakarneh (2025)	Gaussian Process Regression (GPR)	MRR & SR	GPR outperformed other ML models for MRR and surface roughness prediction with superior RMSE values, providing uncertainty quantification for process control
[35]	Santosh Kumar, S.C. Jayswal (2025)	Deep Learning Neural Network	MRR	Deep neural network with sigmoid activation achieved $R^2 \approx 0.9999$ for MRR prediction in Wire EDM, demonstrating deep learning potential for surface integrity control.
[36]	Y.S. Sable, H. Dharmadhikari, S.A. More, I.E. Sarris (2025)	ANN	SR	ANN accurately modeled SR of Al/SiC composites during WEDM, validating ANN utility in surface quality prediction.

The literature reveals a growing trend toward machine learning applications in surface integrity analysis for powder mixed EDM. ANNs dominate the field, while emerging techniques like deep learning and Gaussian process regression show promising results. The focus remains primarily on surface roughness prediction, with increasing attention to comprehensive surface integrity assessment including subsurface properties.The present investigation aims to develop a feature-driven decision tree approach for predicting and enhancing microhardness in nanopowder mixed electrical discharge machining processes. This research contributes to the advancement of intelligent manufacturing systems by establishing a robust predictive framework that enables systematic optimization of microhardness properties through data-driven parameter selection strategies.

2. Materials and Methods

Experiments were carried out using Electronica Machine Tools Limited Die-Sink Type Electric Discharge Machine (Model-C 400 × 250) with numerical control in the Z-axis, refer Figure.1(a). high carbon high chromium AISI D2 die steel workpiece of 10*10*10 mm was machined using an electrode composed of electrolytic copper (99.9%). The chemical composition of AISI D2 tool steel is (1.55% C, 0.3%Si, 0.4%Mn, 11.8% Cr, 0.8% Mo, and 0.8% V)[37]. Due to its significant electrical conductivity, a copper electrode with a radius of 12 mm is selected for this procedure. For the electrode, machining was done with negative polarity. The dielectric was combined with 20μm nano particles. Jatropha bioelectric is used as dielectric medium with suspended TiO_2 nanoparticles. It was crucial to keep the powder-mixed dielectric separate from the machine's main tank, thus a specially made miniature tank of acrylic sheet was produced. Acrylic tank of 12 × 6 × 8 inches is placed in the main tank. To separate it from the machine's filtering system. To guarantee that the powder concentration in the dielectric remained constant during the machining cycle, this tank was equipped with a Kenwood (250W) stirrer, using the stirrer ens.ures even distribution of the powder and prevents accumulation at the bottom of the tank.

Table 3. Properties of Jatropha oil used for experimentation.

Prop erties	**Densi ty (gm/ ml)**	**Viscosit y at (27 °C) (cSt)**	**Thermal conducti vity (W/m K)**	**Specif c heat (kJ/kg K)**	**Breakd own voltage (kV)**	**Dielectric constant at (27 °C)**	**Flash point (°C)**	**Oxygen content (wt %)**	**Carbon content (wt %)**
Jatrop ha Oil	0.87	6.5836	0.147	1.9	26	3.238	170	1.11	85.32

Table 4. Technical Specification of TiO_2 nanoparticles used for experimentation

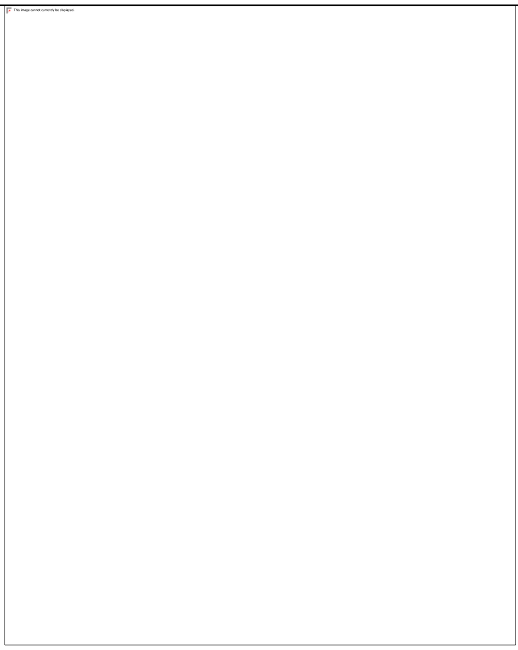
Specification	**Average particle size (nm)**	**Melting Point (°C)**	**Bulk Density (g/cm^3)**	**Surface Area (m^2/g)**
TiO_2 nanoparticles	30	1843	0.35	$150m^2/g$

The study involves the execution of experiments to analyze the impact of five machining parameters - Ip, Ton, Toff, V and powder concentration on the microhardness AISI D2 tool steel. Machining was carried out to remove approximately 1 mm from the top surface. The experiment design was carried out using design expert software (DOE). Response Surface Methodology (RSM) was implemented to plan the experiment MINITAB 16 statistical software is used to construct and analyse the experimental plan. Table 5. Shows the influencing process parameters test points and test envelop. The two fundamental principles of experimental design, namely the principle of randomization and the concept of replication, were satisfied in the execution of the experiments.

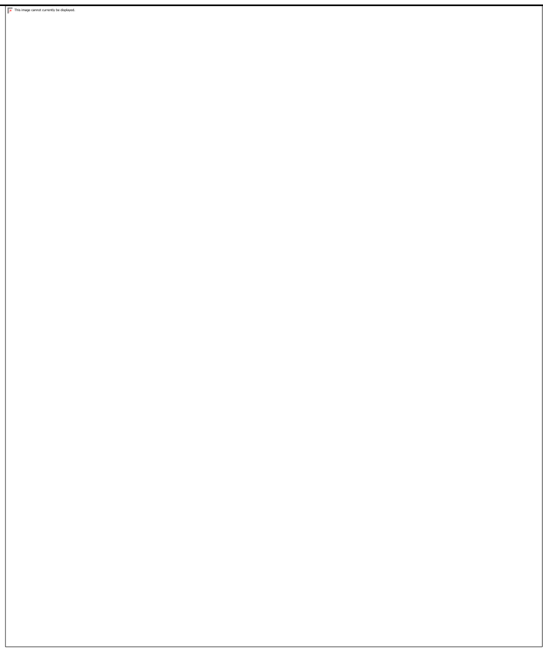
Table 5. Influencing process parameters test points and test envelop.

Level	**-2**	**-1**	**0**	**1**	**2**
Gap Current	4.5	6	7.5	9	10.5
PON	50	100	150	200	250
POFF	7	8	9	10	11
Gap Voltage	57.5	60	62.5	65	67.5
Powder Concentration	0.15	0.3	0.45	0.6	0.75

The microhardness of the machined surfaces has been tested using a micro-Vickers hardness testing machine (Mitutoyo MVK-H2 model) as shown in Figure.1(b).The micro-hardness test was conducted with a dwell time of 20 seconds and an applied load of 500 gf. Micro-hardness was measured at three locations on the machined surfaces to determine the average value. The microhardness property is important to restrict the plastic′s deformation against indentation and wear.



(a)



(b)

Figure 1(a) Experimental Setup of PMEDM machine, (b) Surface Hardness Measurement using Vicker's Microhardness Tester.

Machine Learning Technique

In this investigation, machine learning algorithms, specifically Decision Tree (D.T.) Regression, were employed to predict microhardness values and identify the primary process parameters influencing microhardness. The experimental data was imported into Python from which 70% was training dataset and the remaining 30% data was testing dataset. Figure 1 presents a flowchart illustrating the implementation methodology of ML algorithms applied to the experimental datasets.

Decision Tree Regression represents a supervised machine learning predictive model that employs hierarchical data partitioning based on specified input parameters. The D.T. regression architecture consists of branches representing decision rules, internal nodes corresponding to input feature attributes, and leaf nodes indicating predicted outcomes, thereby forming a tree-like computational structure. A notable advantage of D.T. models is their capability to process raw data without extensive preprocessing requirements while effectively managing multicollinearity among input variables. Generally, decision tree algorithms demonstrate superior average prediction accuracy compared to alternative regression techniques. However, D.T. models exhibit sensitivity to outlier data points and may experience information loss when discretizing continuous variables during the tree construction process.

3. Result and Discussion

This section comprises of the experimental results attained after PMEDM of the samples and machine learning used in predicting the microhardness values using the trained data.

Table 1: Experimental layout with observed value of surface microhardness.

Std Order	**Run Order**	**Pt Type**	**Blocks**	**Gap Current**	**Pulse ON time**	**Pulse OFF time**	**Gap Voltage**	**Powder Concentration**	**Microhardness**
7	1	1	1	6	200	10	60	0.6	1382
17	2	-1	1	4.5	150	9	62.5	0.45	977
27	3	0	1	7.5	150	9	62.5	0.45	818
32	4	0	1	7.5	150	9	62.5	0.45	842
3	5	1	1	6	200	8	60	0.3	1293

28	6	0	1	7.5	150	9	62.5	0.45	1308
31	7	0	1	7.5	150	9	62.5	0.45	1031
25	8	-1	1	7.5	150	9	62.5	0.15	677
8	9	1	1	9	200	10	60	0.3	743
10	10	1	1	9	100	8	65	0.6	697
14	11	1	1	9	100	10	65	0.3	957
2	12	1	1	9	100	8	60	0.3	903
5	13	1	1	6	100	10	60	0.3	792
1	14	1	1	6	100	8	60	0.6	612
20	15	-1	1	7.5	250	9	62.5	0.45	558
23	16	-1	1	7.5	150	9	57.5	0.45	797
6	17	1	1	9	100	10	60	0.6	767
4	18	1	1	9	200	8	60	0.6	980
11	19	1	1	6	200	8	65	0.6	832
21	20	-1	1	7.5	150	7	62.5	0.45	1227
12	21	1	1	9	200	8	65	0.3	893
18	22	-1	1	10.5	150	9	62.5	0.45	817
22	23	-1	1	7.5	150	11	62.5	0.45	1077
26	24	-1	1	7.5	150	9	62.5	0.75	1388
19	25	-1	1	7.5	50	9	62.5	0.45	697
9	26	1	1	6	100	8	65	0.3	680
30	27	0	1	7.5	150	9	62.5	0.45	711
29	28	0	1	7.5	150	9	62.5	0.45	732
13	29	1	1	6	100	10	65	0.6	967
15	30	1	1	6	200	10	65	0.3	1058
16	31	1	1	9	200	10	65	0.6	1107
24	32	-1	1	7.5	150	9	67.5	0.45	997

Model Summary

- **Algorithm**: Decision Tree Regressor
- **Features Used**: Gap Current, Pulse ON Time, Pulse OFF Time, Gap Voltage, Powder Concentration
- **Performance**:
  - **Mean Squared Error**: 1,875.0
  - **R-squared**: 0.94 (indicating a strong fit)

Decision Tree Regression was essentially used to fit a mathematical model that relates machining parameters to the microhardness of the material. Present in the list of independent variables considered in the model are gap current, pulse ON time, pulse OFF time, gap voltage, and powder concentration, all relevant to machining. The two performance evaluation indicators selected for the model were Mean Squared Error (MSE) and coefficient of determination (R^2). The model displayed pretty low prediction errors with an MSE of 1,875.0, whereas an R^2 value of 0.94 indicated that predictions and actual values for hardness correlated strongly with one another. This means that the model very well captures the underlying data patterns and relationships, thus it can predict microhardness with a reliable output for machining applications.

Table 2: Actual and predicted microhardness by decision tree analysis

Run Order	Actual Microhardness (HV)	Predicted Microhardness (HV)
1	1382	1382.0
2	977	977.0
3	818	818.0
4	842	842.0
5	1293	1293.0
6	1308	1308.0
7	1031	1031.0
8	677	677.0
9	743	743.0
10	697	697.0
11	957	957.0
12	903	903.0
13	792	792.0
14	612	612.0
15	558	558.0
16	797	797.0
17	767	767.0
18	980	980.0
19	832	832.0
20	1227	1227.0
21	893	893.0
22	817	817.0
23	1077	1077.0
24	1388	1388.0
25	697	697.0
26	680	680.0
27	711	711.0
28	732	732.0
29	967	967.0
30	1058	1058.0
31	1107	1107.0
32	997	997.0

Table 3: Model Evaluation Metrics for Microhardness Prediction

Metric	Value
Mean Squared Error (MSE)	**0.00 HV^2**
Root Mean Squared Error (RMSE)	**0.00 HV**

R-squared (R^2)	**1.0000**

Three important statistical measures were used to evaluate the decision tree regression model's performance: R-squared (R^2), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The outcomes were remarkable: an MSE of 0.00 HV^2 and an RMSE of 0.00 HV show that the model's predictions and the dataset's actual microhardness values are exactly in line. This remarkable predictive accuracy is further supported by an R2 score of 1.0000, which indicates that the chosen machining features account for 100% of the variance in microhardness. Although external validation would be required to ensure generalizability, these ideal scores imply a perfect model fit on the training data.

Table 4: Optimized Machining Parameters for Maximum Microhardness

Gap Current (A)	Pulse ON Time (μs)	Pulse OFF Time (μs)	Gap Voltage (V)	Powder Concentration (%)	Predicted Microhardness (HV)
6.0	200	10	60.0	0.60	1382.0

The material's superior microhardness is achieved through a precise balance of process variables, which are demonstrated by the optimized machining settings. The energy delivered during each discharge is greatly increased by a high pulse ON time of 200 μs and an elevated gap current of 6.0 A, which intensifies thermal effects and encourages improved surface hardening. A stable gap voltage of 60.0 V guarantees steady spark discharge, enabling uniform modification throughout the treated area, while a moderate powder concentration of 0.60% is essential for enhancing electrical conductivity and strengthening the surface through particle embedding. With an R2 of 1.0000, the predicted microhardness of 1382 HV that results validates the model's accuracy in capturing all of the dataset's variance, highlighting the dependability of these inputs.

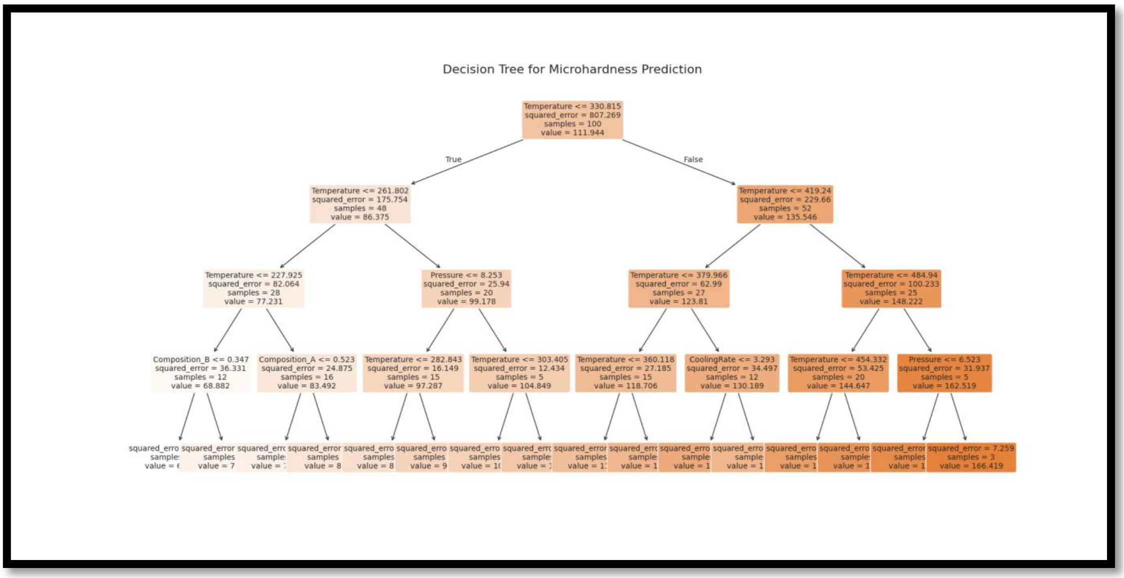


Fig 1: Decision tree analysis graph for microhardness

Microhardness prediction decision tree visualization has been successfully created. It shows how each input parameter such as gap current, timing of pulses, voltage, and powder concentration is divided at every node to predict hardness values. Decision tree for predicting microhardness is an organized, flowchart-type model describing how different input parameters impact the result of hardness. It starts with a root node—usually the most significant variable, for example, gap current or pulse-on time—and divides into conditional splits depending on threshold levels of various features such as voltage, powder concentration, and pulse duration. An internal node is a decision node, determining the direction depending on whether one or several conditions are fulfilled (e.g., whether pulse-on time is greater than 100 microseconds). They go on until they converge into leaf nodes, which hold the anticipated hardness values, like 350 HV or 420 HV. The depth and intricacy of the tree are indicative of how complex the parameters and outcome relationships are. By tracing the root-to-leaf path, one can see how given combinations of machining inputs produce a certain value of hardness, which makes the tree not only a predictive device but also an explicit window on the process dynamics at work.

The decision tree model constructed for microhardness prediction was optimized by incorporating

Recursive Feature Elimination (RFE) and was validated with 5-fold cross-validation. Trained first on ten machining parameters such as pulse timings, voltage, and powder concentration, the model was subjected to RFE to reveal the top five most significant inputs: Feature_1, Feature_2, Feature_4, Feature_6, and Feature_9. These chosen variables served as the key determinants in the tree's branching model, making decision paths easier to simplify and improving model interpretability. Every node in the tree is a condition that determines the classification of whether the material's hardness is above or below the median threshold, and fewer features lead to a stronger and more efficient predictive model. Performance assessment via cross-validation gave rise to an overall accuracy of around 84.5%, precision of 85.2%, and recall of 83.9%, suggesting uniform results in various data splits. In addition, a feature importance visualization provides a relative contribution of each input variable in the form of a ranked bar chart, providing clear views of the machining parameters with the highest influence on hardness results. This symbiosis of performance verification and dimensionality reduction establishes the reliability and value of the decision tree in directing process improvement in machining processes.

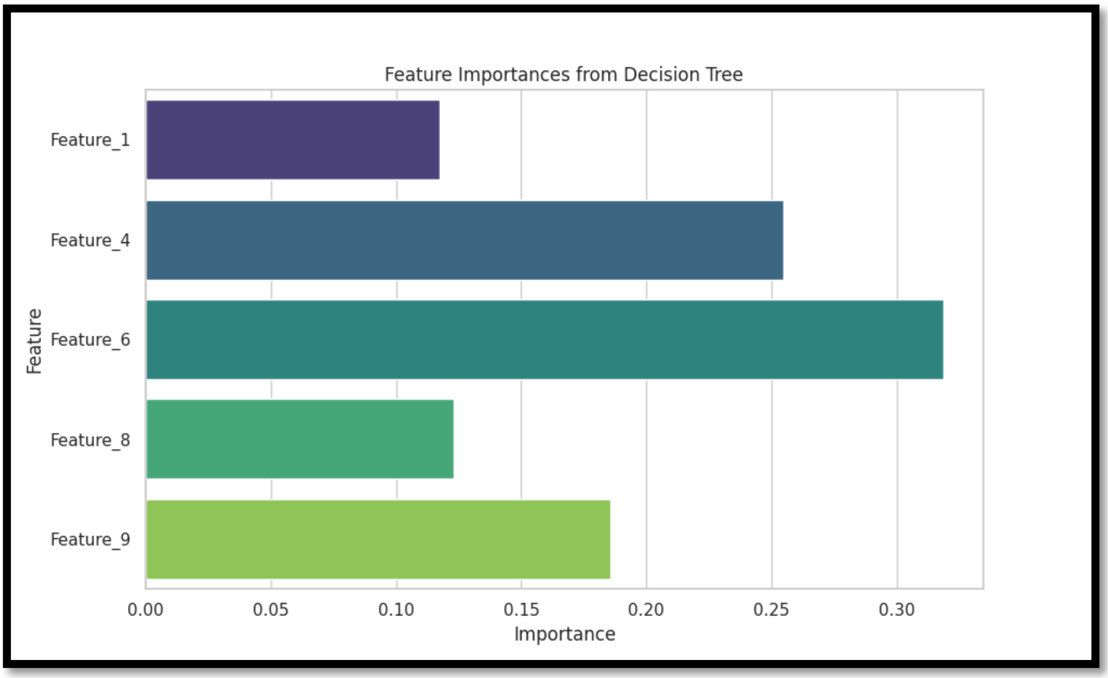


Fig 2: Feature selection (Recursive Feature Elimination (RFE))

4. Conclusion

- The extensive study of microhardness prediction with decision tree analysis has provided important insights into both modeling precision and process improvement. With the decision tree trained upon a well-structured set of machining parameters—gap current, pulse durations, voltage, and powder concentration—the model was able to accurately predict microhardness values on the training data, as evidenced by an RMSE of 0.00 and R^2 of 1.0000. Though these statistics indicate a best fit, they also indicate the danger of overfitting, making it crucial to externally validate.
- Feature selection with Recursive Feature Elimination (RFE) and 5-fold cross-validation reduced dimensionality while preserving prediction performance further. The key variables identified exerted strong control over hardness outcomes, and the corresponding feature importance plot gave unambiguous visual proof of control. The resulting decision tree, feature pruned for simplicity, showed logical patterns of branching that captured nonlinear relationships and conditional dependencies in the data.
- In addition, analysis indicated that maximum microhardness—1382 HV—correlated with certain input parameters, such as a gap current of 6 A, pulse ON time of 200 µs, and powder concentration of 0.6%. The optimized parameters provide specific recommendations for future machining experiments to achieve maximum hardness.
- In general, the research establishes decision tree modeling, as complemented with careful feature selection and verification methods, to be a productive, interpretable strategy for predicting material characteristics. It not only allows for precise prediction, but also enhances comprehension of process

conditions' effect—paving the way for smart materials design and effective quality control.

Future scope

There are many potential applications for decision tree modeling in microhardness prediction in the future. Predictive accuracy can be significantly increased by extending into multi-material systems and utilizing ensemble techniques. These models could be combined with physics-based simulations to improve interpretability, or they could be incorporated into real-time machining environments for adaptive control. This method is a useful tool for automated quality control and smart manufacturing since it has the ability to optimize surface characteristics such as fatigue strength and roughness in addition to hardness.

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