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Assessing the performance of state-of-the-art machine learning algorithms for predicting electro-erosion wear in cryogenic treated electrodes of mold steels

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ABSTRACT

In manufacturing, predicting and reducing electro-erosion wear during the electric discharge machining (EDM) process is critical to minimize delays, financial losses and product defects. Achieving this requires developing and evaluating accurate machine learning models. In our study, we focus on cryogenically treated mold steel electrodes to investigate the potential of different machine learning algorithms to predict EDM wear. We considered five machine learning algorithms—artificial neural networks, ensemble learning, boosting algorithms, tree-based algorithms, and k-nearest neighbors—to evaluate their ability to predict wear patterns accurately. Each algorithm was trained and tested using actual experimental data from EDM processes. Our results show that the machine learning models demonstrated exceptional accuracy, accurately predicting EDM wear in training and testing datasets with almost 99% accuracy. In addition, we identified the most influential characteristics that affect wear patterns, including operating current, cryogenic process parameters, and electrode composition. Based on these findings, manufacturers can gain valuable insight into the factors that cause EDM wear and optimize their EDM processes accordingly to improve productivity, reduce wear-related costs, and increase production quality across multiple manufacturing industries. Furthermore, this research provides insights into the possibilities of implementing these models in real manufacturing contexts and motivates future research on this topic. Ultimately, integrating advanced computing techniques and prudent decision-making strategies will shape the future of manufacturing operations management and promote sustainable and profitable business growth.

1. Introduction

Traditional cutting methods frequently fall short when it comes to handling challenging materials [1]. Moreover, when machining intricate shapes of machine parts, conventional techniques often prove nearly impractical for shaping. Consequently, there is a pursuit of innovative methods to enhance the workability of hard-to-cut materials. Electric discharge machining (EDM) is one of the oldest and most widely used unconventional machining methods. It is a non-contact machining process that uses an electrical discharge to machine material from an electrically conductive workpiece [2]. This method is applicable to all materials that conduct electricity, regardless of their hardness, and accommodates both simple and intricate profiles. EDM makes machining complex parts comparatively easy, a task that proves challenging and expensive with alternative methods. Hence, it finds preference in various sectors, including automotive, molding industry, space, and

Abbreviations: AI, Artificial Intelligence; ANFIS, Adaptive Neuro-Fuzzy Inference System; ANN, Artificial Neural Network; CNC, Computer Numerical Control; CT, Cryogenic Treatment; DIN, Deutsche Industrie Norm (German Industrial Standard); EDM, Electric Discharge Machining; ELM, Ensemble Learning; EWR, Electrode Wear Rate; HTCS, High-Thermal-Conductivity Steel; MER, Material Erosion Rate; ML, Machine Learning; MRR, Material Removal Rate; Qiskit-SVR, Quantum Information Science Kit - Support Vector Regression; SR, Surface Roughness; SVR, Support Vector Regression; SW, Slot Width; TW, Tool Wear; TWR, Tool Wear Rate; W-ELM, Weighted Ensemble Learning; XGBoost, eXtreme Gradient Boosting.

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medicine [3].

The EDM process imposes no restrictions on the strength or hardness of materials. This unconventional manufacturing technique is applicable to all engineering materials that conduct electricity [4]. The amount of material removed from the workpiece per unit of time in EDM, considered an unconventional method, is called the material removal rate (MRR). In contrast, the mass loss in the electrode material is referred to as electrode wear rate (EWR) [5–7]. Some studies also consider it as tool wear rate (TWR) [5,6]. An EDM method seeks improvement in terms of higher MRR, lower EWR, and better surface quality [3]. EWR is the most important factor in determining the number of electrodes required to achieve the correct size and dimensions of the desired form. When considering that electrodes are processed by wire erosion, turning, or milling machines, it is seen that EWR is the most significant factor affecting electrode costs. In addition, there is a gap between the electrode and the material, which varies according to the process parameters. From the size of the material to be processed, the electrode should be processed as small as this gap value if it is an internal part or large if it is an external operation. While the process parameters determine this gap value, they also significantly affect the EWR and MRR values. Therefore, studies on higher chip removal and lower electrode wear have gained importance in the EDM process in recent years.

It is known that cryogenic treatment (CT) is a type of heat treatment applied to improve tool performance and workpiece quality in general. In specific research exploring the influence of cryogenic treatment on the EDM process, an approach is identified that seeks to decrease EWR [8,9], However, in other studies, the observed effect is minimal [10]. In the same studies, different results were obtained in terms of MRR. Nas and Kara [11] achieved different results in the shallow cryogenic process at −80 °C and the deep cryogenic process at −145 °C. They successfully performed EDM with ultrasonic-assisted cryogenic cooled tool electrodes on M2 HSS workpiece material. Compared to conventional EDM, the ultrasonically assisted cryogenically cooled tool electrode significantly reduced the wear of the tool electrode due to the ultrasonic property [12]. CT can be applied to the electrode material and the workpiece separately or together in the EDM process.

In recent years, EDM has been employed in conjunction with both conventional and machine learning methods, including artificial neural networks (ANNs) and soft computing techniques such as fuzzy logic. This integration aims to predict output performance parameters like MRR and EWR, relying on optimal processing parameters such as discharge current, pulse duration, and voltage. Ramaswamy et al. [13], conducted variance analysis to assess the significance of test parameters in experimental results, focusing on EDM machinability. In the subsequent phase, researchers identified optimal process parameters and utilized regression analysis and ANNs to predict MRR and EWR. Similarly, Sarıkaya and Yılmaz [14], developed a mathematical model based on ANNs that successfully predicted outputs. In another study, Balasubramaniam et al. [5] used different electrode materials, such as copper, brass, and tungsten, for EDM of Al-SiCp metal matrix composites. Their study considered MRR, EWR, and circularity as output parameters. By leveraging artificial intelligence to optimize processing parameters like current, pulse duration, and flushing pressure, the research identified current as the most crucial parameter. Notably, among the three electrodes, Cu demonstrated the most effective performance. In EDM, the effect of processing parameters such as peak current, pulse interval, and pulse duration are important for the variation in MRR and EWR. Ong et al. [15] developed a model based on the prediction of radial basis function neural networks to predict the MRR and EWR of the EDM process. The researchers used the moth flame optimization algorithm to determine the optimal processing parameters that maximize MRR and minimize EWR. Cakir et al. [16] investigated the capacity of adaptive neuro-fuzzy inference system (ANFIS), genetic expression programming, and ANNs in predicting EDM performance parameters using experimental data. Ramasubbu and Ramabalan [6] indicate that the surface roughness (SR) model exhibits a strong fit, with R-squared and adjusted R-squared both at 80 % performance. However, for a more accurate estimation of MRR and EWR, additional parameters must be considered since the adjusted R-squared values for MRR and EWR are below 80 %, falling short of acceptability. A review of modeling and simulation techniques of the EDM process was made by Bharti and Dhami [17]. The research delves into the development of various models, including statistical prediction models, machine learning (ML)-based prediction models, mathematical models, and finite element methods, highlighting their significance.

ML techniques have become increasingly popular for modeling and optimizing complex material processing processes. Recent studies have investigated the contributions of machine learning algorithms in electro-erosion wear. For example, Ulas et al. [18] used ML to estimate the surface roughness (SR) of Al7075 aluminum alloy processed with wire EDM (W-EDM) using different parameters, such as voltage, pulse-on-time, dielectric pressure, and wire feed rate. They employed ensemble

Table 1
Comparison of latest related works.

Reference	Workpiece material	Inputs	Outputs	Method
[21]	Al7075 + 10 % Al2O3	Voltage Pulse on time Pulse off time Current Bed speed	SR MRR	ML (ANN)
[16]	DIN 1.2080 tool steel	Discharge current	MRR	Genetic Expression Programming
		Pulse on time	EWR	ML (ANN, ANFIS)
		Pulse off time	SR	
[2]	SS630 Stainless Steel	Peak current Pulse period	SR MRR	ANOVA ML (Back Propagated Neural Network)
		Source voltage		
[11]	ASTM B 275 corrosion-resistant superalloy	Peak current Pulse off time Pulse on time Total processing time	SR MRR	ANOVA
[28]	HTCS 150	Discharge current	SR	ANOVA
	high-thermal-conductivity tool steel	Pulse on time	SW	
			TW MRR	
[22]	Aluminium 6061 alloy	Discharge current	MER	Genetic Algorithms
		Spark duration Pause duration Concentration of powder Magnetic field	EWR	
[19]	NiTi NiCu BeCu Alloys	Gap current Gap voltage	MRR	ML (Random Forest, Decision Tree, Gradient Boosting, ANN)
		Pulse on time Pulse off time		
[18]	Al7075 Aluminium Alloy	Voltage Pulse on time Dielectric pressure Wire feed	SR	ML (ELM, Weighted ELM, SVR and Qiskit-SVR)
This study	AISI P20	Cryogenic process conditions	MRR	ML (Weighted Ensemble, ANN, CatBoost
		Current	EWR	XGBoost, Random Forest, Extra Trees, Kneighbors)
		Pulse durations		

learning (ELM), weighted-ELM (W-ELM), support vector regression (SVR), and Qiskit-SVR models to process the samples and estimate the SR values. Similarly, Jatti et al. [19] focused on predicting MRR through ML algorithms, encompassing both supervised regression and classification-based approaches. The study identified gap current, voltage, and pulse on time as the most influential parameters impacting MRR. The researchers concluded that the gradient-boosting regression-based algorithm proved most effective in predicting MRR.

Meanwhile, Nahak and Gupta [20], reviewed the developments and challenges of EDM processes in 2019, emphasizing optimizing process parameters for effective and economical machining. Finally, Cetin et al. [1] experimentally investigated the effect of cryogenic treatment on the performance of CuCrZr alloy and Cu electrodes during EDM of AISI P20 tool steel. They found that pulse current was the most effective parameter in the EDM process and using cryogenically treated electrodes resulted in less wear and decreased surface roughness values. Finally, by Arunadevi and Prakash [21] the performance analysis of the experimental values with five input parameters was made using the ANN to increase MRR and reduce the SR. Rouniyar and Shandilya [22] used teacher-learning-based optimization to determine the optimal process parameters to maximize material erosion rate (MER) and minimize EWR. Świercz et al. (2022) employed multicriteria optimization utilizing Derringer's function to minimize SR, slot width (SW), and tool wear (TW) while simultaneously maximizing MRR. Furthermore, a validation test conducted in their research verified that the maximum error between the predicted and obtained values remained below 7 %. Feng et al. [23] conducted a study on optimizing energy consumption in machining processes. The researchers designed an optimization algorithm that combines genetic and ant colony algorithms to minimize the air-cutting toolpaths and optimize the energy model in CNC machines. Wang et al. [24] also proposed a ML approach to optimize the turning parameters in machining processes. They found that the XGBoost model combined with over-sampling technique for regression with Gaussian noise and center particle swarm optimization provides the best performance for predicting the machining error of the turning process. Dhuria et al. [25] used the entropy weight-based gray relational method to predict MRR and TW rate during ultrasonic machining. Pourasl et al. [26] proposed ANN and ANFIS predictive modeling for EDM on AISI-D6 steel, a material widely used in mold and casting manufacturing. Vishnu et al. [27] developed ANN models using backpropagation algorithms to predict the performance characteristics of MRR, SR and TW rate for EDM machining of Inconel-718, a nickel-based alloy. The previous studies, especially those involving the EDM process related to the current study, are given in Table 1.

Upon reviewing various methods, the key takeaway is the effective application of ML and other artificial intelligence techniques for modeling and optimizing the electro-erosion wear process. However, no studies have been found on the evaluation of the performance of cryogenically treated and untreated Cu and CuCrZr electrodes or the use of ANN predictions for MRR and EWR. This study aims to evaluate the performances of cryogenically treated and untreated CuCrZr and Cu electrodes during the EDM of AISI P20 tool steel in terms of EWR and MRR. The study utilizes Weighted Ensemble, ANN, CatBoost, XGBoost, Random Forest, Extra Trees, Kneighbors from machine learning techniques for regression analysis. The optimal algorithm is identified based on the obtained results, and comments are provided accordingly.

The main contribution of this paper lies in its comprehensive study and validation of ML models for predicting EWR and MRR in EDM, with a focus on cryogenically treated electrodes made of mold steel (1). The research proposes adding to the body of literature by comparing the electrodes under various processing parameters and conducting cryogenic treatment in 10 different periods ranging from 0.25 to 24 h (2). By evaluating different ML algorithms and training them on real experimental trial data, the study achieved a remarkable predictive accuracy of nearly 99 % in forecasting wear patterns (3). Additionally, the research identified factors affecting wear patterns, highlighting critical elements such as operating current, cryogenic process parameters, and electrode composition (4). In addition, performing performance evaluations on two different models with seven different ML algorithms and presenting the hyperparameters that give the best results are among the originality of the article (5). As a result, through the study, manufacturers can optimize their EDM processes, enhance productivity, mitigate wear-related expenses, and elevate overall production quality across diverse industries (6). Furthermore, the study demonstrates the potential of implementing ML models in authentic manufacturing scenarios and catalyzes future research in this area (7).

Table 2
Chemical composition and properties of electrode materials (wt.%).

Material		CuCrZr			Cu
Chemical Composition	Elements (wt.%)	Cu Balance	Cr 1.00	Zr 0.10	Cu 100

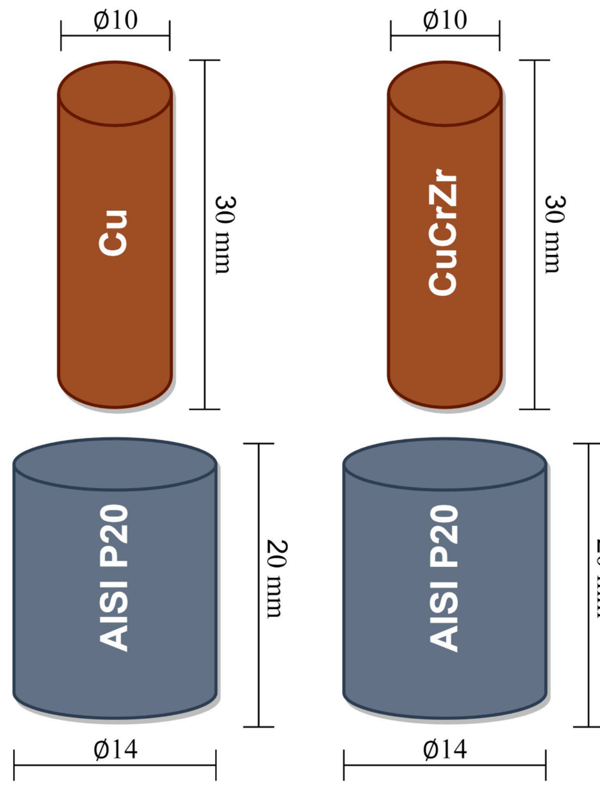


Fig. 1. AISI P20 and Electrode.

2. Material and methods

This study employed tool materials in the form of CuCrZr and Cu electrode pieces, each measuring 10 × 30 mm in dimensions. Table 2 provides the compositional details for CuCrZr and Cu electrodes. To assess the impact of Cryogenic Treatment (CT), the electrodes were categorized into eleven groups comprising both treated and untreated specimens. The cryogenically treated electrodes underwent treatment cycles at −140 °C for durations of 15 and 30 min, as well as 0, 0.25, 0.5, 1, 2, 4, 8, 12, 16, 20, and 24 h, followed by tempering at 175 °C for 1 h.

The experimental study selected AISI P20 tool steel, a commonly utilized material in plastic injection mold applications, as the workpiece material. The dimensions of the AISI P20 material were 14x20 mm, matching the tool electrode specifications and 3D design representations depicted in Fig. 1. Additionally, Table 2 presents the chemical composition of AISI P20 tool steel.

Fig. 2. EDM machine and control panel.

Table 3
Summary statistics of variables in the dataset.

	Mean	σ	Min.	25 %	50 %	75 %	Max.
Cryogenic process conditions	7.98	8.34	0.00	0.50	4.00	16.00	24.00
Current	10.00	4.48	4.00	7.00	10.00	13.00	16.00
Pulse durations	37.50	12.54	25.00	25.00	37.50	50.00	50.00
Electrode wear	16.47	15.24	0.04	2.51	12.68	27.84	54.10
Workpiece wear	154.65	82.69	4.51	91.33	142.73	219.47	298.48

EDM experiments were conducted using pulse currents of 4, 8, 12, and 16 A and pulse durations of 25 μs and 50 μs. The experimental setup employed the King ZNC K3200 model EDM machine, as depicted in Fig. 2. All other processing parameters remained constant throughout the tests when one parameter was altered.

The dielectric fluid used during EDM tests was Petrofer dielectricum 358, a mineral-based oil compatible with electro-erosion processes. To ensure precision, each combination of processing conditions underwent three repeated EDM experiments, and the average values were considered as the test results. One hundred seventy-six experiments were conducted, with each EDM process lasting 20 min.

EWR and MRR values for Cu and CuCrZr electrodes were calculated based on mass losses following EDM. To determine the wear rates of the electrodes and the MRR of the workpieces, samples were weighed both before (MBT - Mass Before Testing) and after (MAT - Mass After Testing) EDM using a high-precision analytical balance with a maximum capacity of 250 g and an accuracy of 0.0001 g. The EWR and MRR were computed using the following equations:

$$EWR = \frac{(MBTelectrode - MATelectrode)}{T} \quad (g/min) \tag{1}$$

$$MRR = \frac{(MBTworkpiece - MATworkpiece)}{T} \quad (g/min), \tag{2}$$

In Eqs. (1) and (2), T represents the EDM process time, which was consistently set to T = 20 min in all experiments. The results are categorized and evaluated based on EWR and MRR values as each parameter varied.

2.1. Data preparation and preprocessing

The dataset encompasses 176 experiments conducted within the Sakarya University of Applied Sciences laboratory. This dataset includes electrode material type, cryogenic process conditions, amperage, and pulse duration parameters. Table 3 presents the summary statistics of the variables in the dataset used for the regression analysis.

When examining the dataset, we can observe a set of histogram graphs illustrating the distributions of variables in the dataset, as shown in Fig. 3. A separate histogram represents each variable.

Fig. 4 displays wear rate relationships for different materials, cryogenic process conditions, and current and pulse durations. The median and interquartile range are presented through boxplots.

Fig. 5 presents the Pearson and Spearman correlation matrices. a) Pearson Correlation Matrix measures linear relationships between variables, b) Spearman Correlation Matrix evaluates relationships between variables based on ranking. These matrices visually describe how data features relate to each other, thus helping to identify important variables in modeling processes.

2.2. Machine learning algorithms

This study utilizes various machine learning algorithms offered by the AutoGluon Automated Machine Learning (AutoML) library by Amazon Web Services(AWS), which offers state-of-the-art ML algorithms spanning categories such as artificial neural networks (ANNs), ensemble learning, boosting, tree-based algorithms, and k-nearest neighbors (KNN) [29]. AutoGluon was selected to automate model selection, hyperparameter tuning, and feature engineering tasks, expediting the identification of optimal solutions. The chosen algorithms were carefully evaluated, with priority given to those offering advantages inherent in the AutoML approach. These advantages encompass efficient exploration of a vast algorithm space, hyperparameter tuning for optimal performance, and automatic feature engineering and selection, ensuring the identification of relevant features and their transformation into a suitable format for ML models. Leveraging these functionalities, AutoGluon streamlines the model development process,

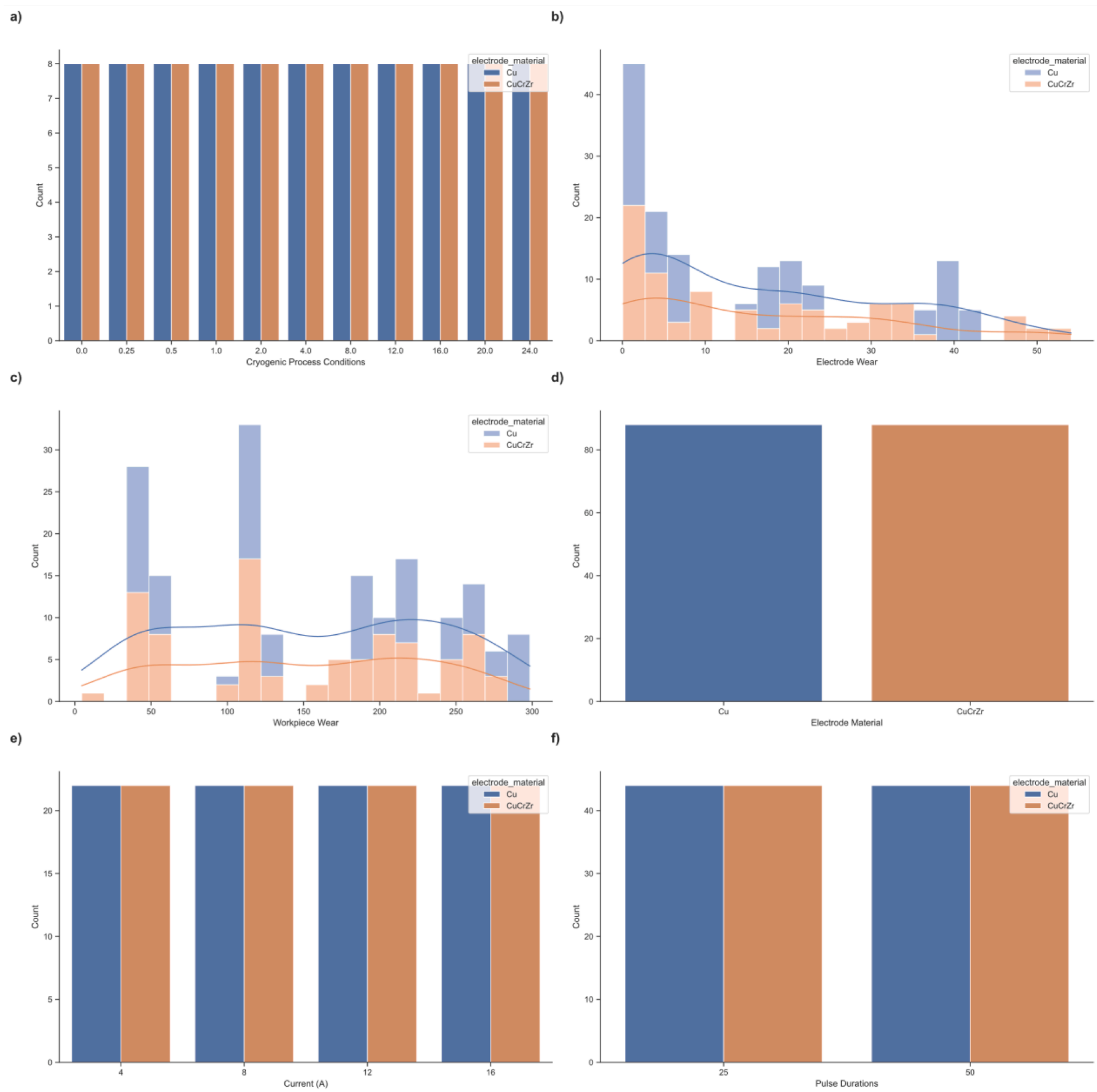


Fig. 3. Distributions of Dataset a) Cryogenic Process Conditions, b) Electrode Wear, c) Workpiece Wear, d) Electrode Material, e) Current, f) Pulse Durations.

facilitating the efficient identification of optimal algorithms for the prediction studies.

2.2.1. *Artificial Neural Networks*

Artificial Neural Networks, often called ANNs or neural networks, are a class of machine learning models inspired by the structure and function of the human brain. ANNs consist of interconnected nodes, known as neurons, organized into layers [30]. These models excel at capturing intricate patterns and relationships in complex data, making them valuable tools in regression tasks. McCulloch and Pitts [31] initially introduced the concept of ANN, and their popularity grew in the 1980s due to the influential work by Rumelhart et al. [32]. In the biological brain, neurons are interconnected through numerous axon junctions, forming a graph-like architecture. These connections can be rewired, facilitating adaptation, information processing, and storage through neuroplasticity. Artificial Neural Networks (ANN) can be visualized as a network of nodes connected. The output of one node serves as the input for another node, and the connections between them allow for subsequent processing. These nodes are usually organized into layers, each responsible for specific transformations. ANNs can have one or more hidden layers besides the input and output. The nodes and edges within these networks possess weights that regulate signal transmission strength. These weights can be adjusted by iterative training. After training, ANNs can make predictions for test data. In our study, we have explored two variants of ANNs, namely “NeuralNetTorch” (Neural Networks by PyTorch) and “NeuralNetFastAI” (Neural Networks by FastAI). Both offer distinct advantages in terms of architecture and training efficiency.

Fig. 6 provides a detailed visual representation of the intricate architecture of the ANN employed in the article. The input parameters, including electrode material, cryogenic process conditions, current, and pulse durations, are integral components influencing the complex interplay within the network. These parameters play a pivotal role in predicting and comprehending the nuanced relationships inherent in the EDM process, particularly regarding material removal rate and electrode wear rate.

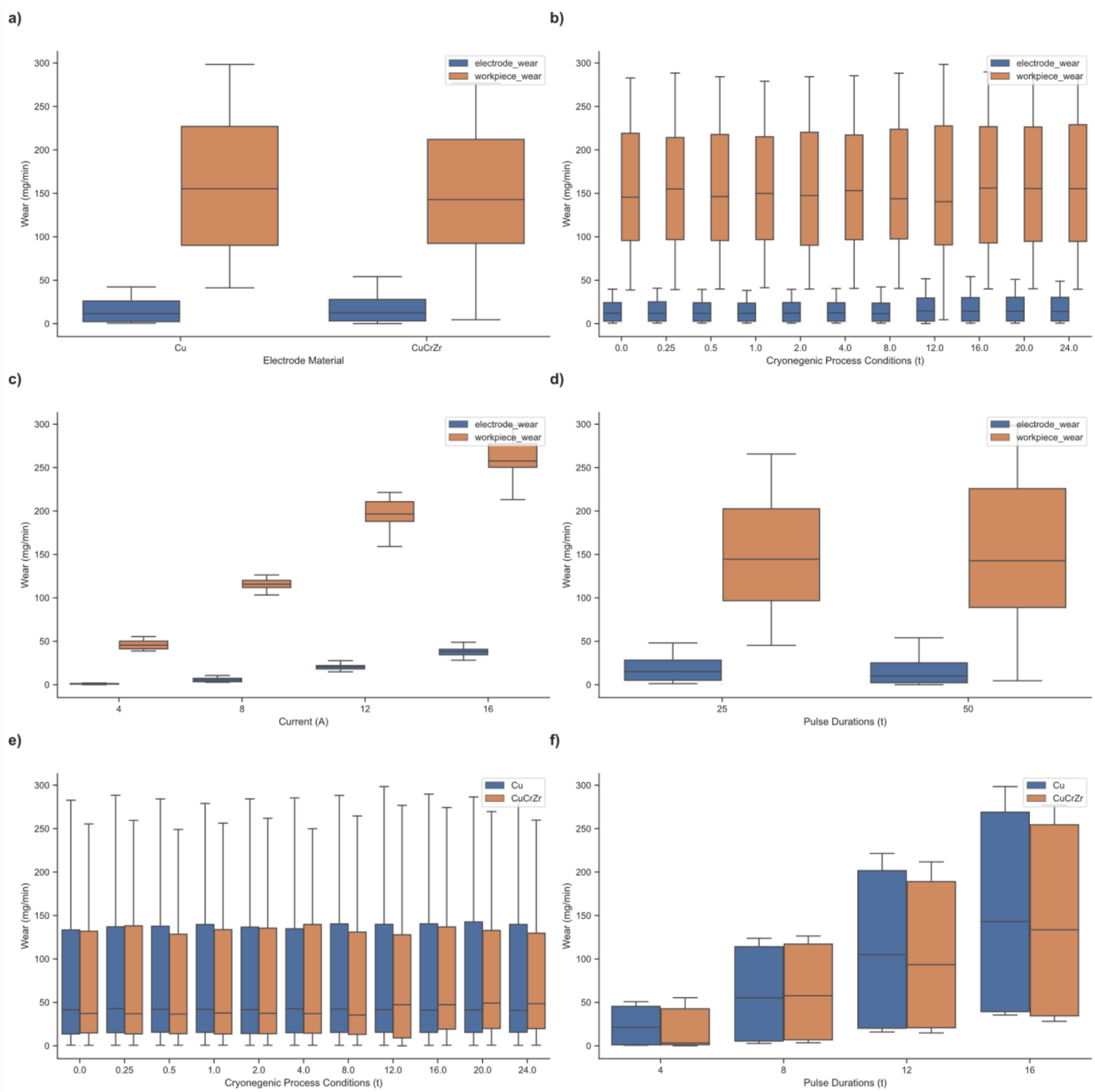


Fig. 4. Relationships between Variables for Electrode and Workpiece Wears a) Electrode Material b) Cryonegenic Process Conditions (t), c) Current(A) and Wear Type, d) Pulse Durations, e) Cryonegenic Process Conditions and Electrode Material, f) Pulse Durations.

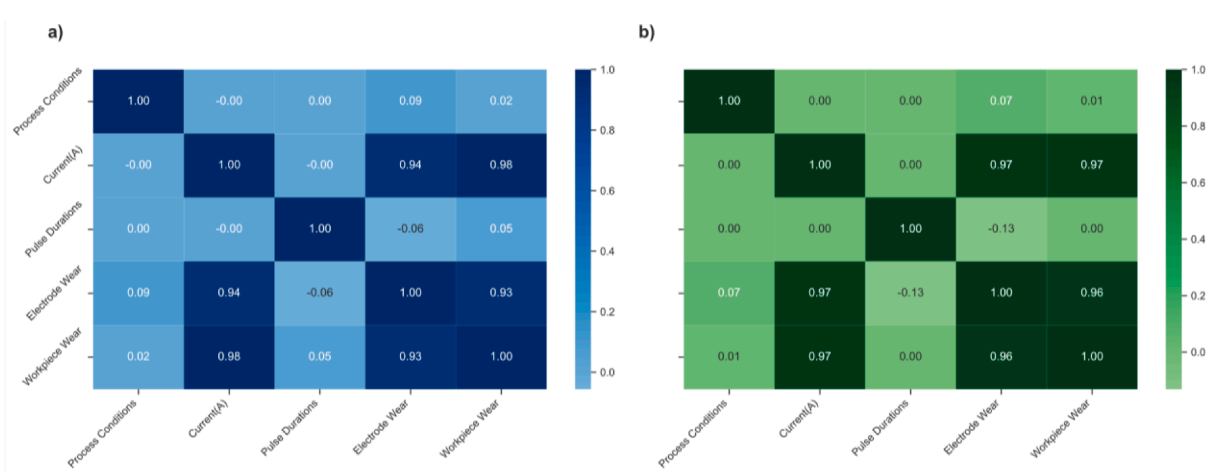


Fig. 5. A) pearson and b) spearman correlation matrices.

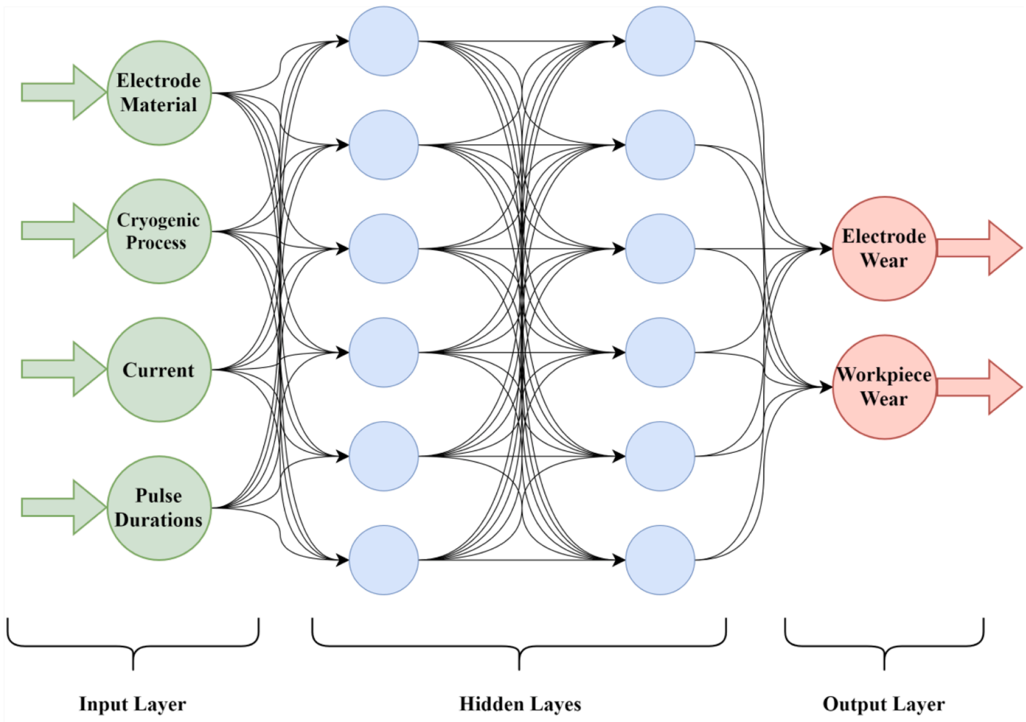


Fig. 6. Schematic Representation of ANN Architecture for Modeling and Optimizing the Electrode and Workpiece Wear in Electric Discharge Machining.

2.2.2. Ensemble learning

Ensemble learning is a powerful machine learning technique that combines the predictions of multiple individual models to improve overall performance and robustness [33]. Ensemble learning is a technique that involves training multiple base learners, combining their results using a defined rule, and achieving the best possible output. The crucial steps in the ensemble learning algorithm include selecting and building the base learners and then integrating the outcomes of these multiple base learners. One of the ensemble methods we used in our research is called "WeightedEnsemble_L2″, which uses a weighted combination of base models. Ensemble methods are known for reducing model variance, enhancing predictive accuracy, and providing valuable insights into feature importance.

2.2.3. Boosting algorithms

Friedman [34] introduced gradient boosting as an ensemble strategy for classification and regression. However, it's worth noting that GB is primarily employed for regression tasks. The boosting algorithm involves tuning parameters, such as the number of trees (n-trees) to be generated and the shrinkage rate. It's important to avoid setting n-trees too small, and the shrinkage factor, often referred to as the learning rate applied to all trees during development, should not be set too high [35]. Boosting algorithms are machine learning techniques that enhance the model's performance by giving importance to the samples that previous models struggled to predict accurately. CatBoost [36], a gradient boosting algorithm, is one of the boosting techniques we utilize. Additionally, we employ XGBoost [37], an Extreme gradient-boosting algorithm renowned for its efficiency and accuracy. XGBoost's regularization techniques and handling of missing data make it a popular choice for regression tasks, particularly in machine learning competitions.

2.2.4. Tree-based algorithms

Tree-based algorithms are machine learning models that employ decision trees as their fundamental building blocks. The decision tree algorithm falls under the category of supervised learning algorithms. It is predominantly chosen for tackling classification problems, although it can be applied to classification and regression scenarios. It comprises inner nodes representing branch structures, the dataset reflecting the algorithm's decisions, and each leaf node denoting an outcome. In this structure, there are two types of nodes: decision nodes, used for making choices and branching into various options, and leaf nodes, which serve as the final output without further branching. The name "Decision Tree" is derived from its tree-like appearance, with the root node as the starting point that branches out into multiple sub-trees based on answers to questions, typically "yes" or "no" [38]. We employed Random Forest Regression [39] and ExtraTrees [40], in our study. Both these methods are ensemble approaches that utilize decision trees. Random Forest Regression pools the predictions of multiple decision trees, making it robust and capable of capturing complex relationships in the data. Similarly, ExtraTrees is also an ensemble approach that delivers accurate predictions while minimizing the risk of overfitting.

2.2.5. K-Nearest Neighbors (k-NN)

The K-NN algorithm was created by Evelyn Fix and Joseph Hodges in 1951 to address discriminant examination challenges, particularly when determining probabilistic densities via parametric estimation was difficult [41]. K-NN is a simple, effective instance-based learning algorithm for classification and regression tasks [42]. This algorithm assesses the relationship between new, unseen data and existing data within a given dataset. Based on this assessment, it assigns the new data to a category that best matches it. Consequently, the K-NN algorithm is adept at accurately classifying fresh data. It arranges the new data point by considering its neighboring data points. K-NN is often called a "lazy learner" algorithm because it initially stores the dataset but defers the learning process until there is a need for classifying or predicting new data. Furthermore, K-NN is non-parametric, meaning it doesn't rely on a predefined model or relationship between input and output [42]. Our study investigates k-NN in three forms: KNeighbors, KNeighborsUnif (uniform weighting), and KNeighborsDist (distance-based weighting). K-NN operates on the assumption that similar data points have the same outcomes, making it a useful method for regression analysis when the underlying data distribution displays local patterns.

Table 4
Summary of the performance scores of Model 1 and the hyperparameters.

ML Algorithms	Score	Hyperparameters
WeightedEnsemble_L2	0.98	use_orig_features: False, max_base_models: 25, max_base_models_per_type: 5, save_bag_folds: True
NeuralNetTorch	0.97	num_epochs: 500, epochs_wo_improve: 20, activation: relu, embedding_size_factor: 1.0, embed_exponent: 0.56, max_embedding_dim: 100, y_range: None, y_range_extend: 0.05, dropout…
NeuralNetFastAI	0.96	layers: None, emb_drop: 0.1, ps: 0.1, bs: auto, lr: 0.01, epochs: auto, early. stopping.min_delta: 0.0001, earlier.stopping.patience: 20, smoothing: 0.0
CatBoost	0.96	iterations: 10000, learning_rate: 0.05, random_seed: 0, allow_writing_files: False, eval_metric: R2
XGBoost	0.96	n_estimators: 10000, learning_rate: 0.1, n_jobs: −1, proc.max_category_levels: 100, objective: reg:squared error, booster: gbtree
RandomForestMSE	0.95	n_estimators: 300, max_leaf_nodes: 15000, n_jobs: −1, random_state: 0, bootstrap: True, criterion: squared_error
ExtraTreesMSE	0.94	n_estimators: 300, max_leaf_nodes: 15000, n_jobs: −1, random_state: 0, bootstrap: True, criterion: squared_error
KNeighborsUnif	0.92	weights: uniform
KNeighborsDist	0.91	weights: distance

Table 5
Summary of the performance scores of Model 2 and the hyperparameters.

ML Algorithm	Score	Hyperparameters
WeightedEnsemble_L2	0.99	use_orig_features: False, max_base_models: 25, max_base_models_per_type: 5, save_bag_folds: True
XGBoost	0.99	n_estimators: 10000, learning_rate: 0.1, n_jobs: −1, proc.max_category_levels: 100, objective: reg:squared error, booster: gbtree
NeuralNetTorch	0.99	num_epochs: 500, epochs_wo_improve: 20, activation: relu, embedding_size_factor: 1.0, embed_exponent: 0.56, max_embedding_dim: 100, y_range: None, y_range_extend: 0.05, dropout…
NeuralNetFastAI	0.99	layers: None, emb_drop: 0.1, ps: 0.1, bs: auto, lr: 0.01, epochs: auto, early. stopping.min_delta: 0.0001, early.stopping.patience: 20, smoothing: 0.0
CatBoost	0.99	iterations: 10000, learning_rate: 0.05, random_seed: 0, allow_writing_files: False, eval_metric: R2
ExtraTreesMSE	0.99	n_estimators: 300, max_leaf_nodes: 15000, n_jobs: −1, random_state: 0, bootstrap: True, criterion: squared_error
RandomForestMSE	0.98	n_estimators: 300, max_leaf_nodes: 15000, n_jobs: −1, random_state: 0, bootstrap: True, criterion: squared_error
KNeighborsUnif	0.97	weights: uniform
KNeighborsDist	0.96	weights: distance

2.3. Performance criteria

The developed model's performance was assessed during the training and testing phases using commonly employed statistical criteria. These criteria include Mean Absolute Error (MAE), which measures the average absolute difference between predicted and actual values; Mean Squared Error (MSE), quantifies the average squared difference between predicted and actual values, Root Mean Square Error (RMSE), which is the square root of MSE and represents the typical magnitude of prediction errors, the coefficient of determination (R-squared), indicates the proportion of variation in the dependent variable captured by the regression model. Higher prediction accuracy is associated with smaller values for MAE, MSE and RMSE. A higher R-squared value suggests that the model effectively explains the data's variability. The expressions for these criteria are as follows:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N}|X_{P_i} - X_{O_i}|}{N} \tag{3}$$

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}(X_{O_i} - X_{P_i})^2}{N} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum\limits_{i=1}^{N}(X_{P_i} - X_{O_i})^2}{N}} \tag{5}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}(X_{P_i} - X_{O_i})^2}{\sum_{i=1}^{N}(X_{O_i} - \overline{X_O})^2} \tag{6}$$

In these equations, X_{O_i} represents the observed data for the i-th data point, X_{P_i} represents the predicted data for the same data point, $\overline{X_O}$ is the mean observed data, $\overline{X_P}$ is the mean predicted data, and N represents the total number of observations.

3. Results and discussions

In this research, we harnessed the capabilities of two distinct machine learning models to address the multifaceted challenges posed by electrode and workpiece wear prediction. Model 1 was meticulously crafted to specialize in forecasting electrode wear, a critical factor in manufacturing processes. In contrast, Model 2 was purposefully engineered to excel in predicting workpiece wear, another pivotal aspect of industrial operations. To unlock their predictive potential, both Model 1 and Model 2 were empowered by AutoGluon, a state-of-the-art AutoML (Automated Machine Learning) package renowned for its exceptional efficiency and effectiveness. By leveraging AutoGluon capabilities, we sought to create robust and accurate models to navigate the intricacies of wear prediction in manufacturing scenarios with precision and reliability [29]. In the data preprocessing stage, we addressed the categorical variable 'electrode material' by applying one-hot encoding. This transformation simplified the representation of electrode materials such as Cu and CuCrZr, making them suitable for machine learning algorithms.

3.1. EWR prediction model results

Table 4 summarizes the various hyperparameters used for Model 1 and their respective validation scores. Multiple combinations of hyperparameters have been tried to ensure the optimized performance of the model. As a result of these trials, it is aimed to determine the hyperparameters that provide the best performance. These validation processes to evaluate the model's success help us better understand how effective Model 1 is in predicting electrode wear. Detailed analysis of these hyperparameters and their respective validation scores shows that Model 1 has an optimized structure, and its predictive ability produces reliable and precise results.

3.2. MRR prediction model results

Similarly, the results obtained for Model 2 and the hyperparameters used are presented in detail in Table 5. For Model 2 to make successful predictions, various combinations of hyperparameters were tried, and optimized hyperparameters were determined as a result of these trials. Evaluation of Model 2′s performance demonstrates its effectiveness in predicting workpiece wear. A careful analysis of the relevant hyperparameters and validation scores shows that Model 2 has a structure that produces reliable and precise results. These results highlight how powerful and dependable the Model 2 is for predicting workpiece wear

Table 6
Comparison of performance metrics between the latest related works.

Reference	[19]	[18]	[21]		[2]		[11]		[28]			[22]		Current study	
Output	MRR	MRR	MRR	SR	MRR	SR	MRR	SR	SR	MRR	TW	MER	EWR	EWR	MRR
Algorithms	GB	Q-SVR	ANN	ANN	ANN	ANN	ANOVA	ANOVA	ANOVA	ANOVA	ANOVA	ANOVA	ANOVA	Weighted Ensemble	Weighted Ensemble
MAE	0.529	0.033	–	–	–	–	–	–	–	–	–	–	–	1.66	6.66
MSE	0.360	–	–	–	–	–	–	–	–	–	–	–	–	5.79	122.75
RMSE	–	–	–	–	–	–	–	–	–	–	–	–	–	2.41	11.08
R-squared (R^2)	0.930	0.961	99.4	77.6	0.9154	0.9124	95.54	89.61	0.98	0.96	0.96	0.9441	0.9484	0.973	0.980

in industrial processes.

R-squared measures how well the regression model explains the variance in the target variable. It ranges from 0 to 1, where higher values indicate a better fit. R-squared of 1 means that the model perfectly explains the variance, while 0 means the model does no better than predicting the mean of the target values. The R-squared score shows that both models have fairly high explanatory power; it is important to note that Model 2 had a better fit with a slightly higher R-squared score. MAE measures the average absolute difference between predicted and target values. It gives you an idea of how far off, on average, your predictions are from the true values. Lower MAE indicates better model performance. MAE value shows that Model 1′s predictions have more insufficient mean absolute errors, while Model 2 seems to have made predictions with a larger mean absolute error.

MSE is another commonly used metric that measures the average difference between the predicted and actual values. It is a more sensitive metric to large errors than MAE, as it penalizes larger errors more heavily. Like MAE, lower RMSE are better. The MSE value indicates that Model 1 made predictions with smaller errors, while Model 2 has slightly larger errors with a higher MSE.

Table 6 presents three important regression evaluation metrics used to compare the performance of Model 1 and Model 2. In addition, the results obtained in the study are also presented in the table to compare them with the performance metrics of other studies in the literature. "-" symbols in the table indicates metrics not reported in the corresponding study. Comparing the R-squared performances across different studies, it is evident that the present study has achieved notably high R-squared values for both the Weighted Ensemble models, standing at 0.986 and 0.990, respectively. Although Arunadevi and Prakash [21] obtained the highest R-squared value for the prediction of MRR, SR value was considerably very lower in the study. This shows that it works with low sensitivity in terms of surface roughness. In contrast, the prior studies reported comparatively lower R-squared values [2,18,19]. Specifically, Jatti et al. [19] found an R-squared value of 0.856, and Ulas et al. [18] reported an R-squared value of 0.814. The significant difference in R-squared values implies that the models in the present study, especially the Gradient Boosting and Q-SVR models, outperform those in the referenced studies in terms of explaining the variability in the data. It's noteworthy to emphasize that in this study, MAE and MSE performances are calculated directly from the data without normalization, whereas in the other studies, normalization techniques were applied to these metrics. This distinction is crucial when interpreting and comparing the performance metrics, as it indicates a different approach to error calculation. Therefore, the reported MAE and MSE values in this study should be considered in the context of their direct derivation from the original data, offering a distinct perspective on model accuracy. Several studies, including those by Nas and Kara [11], Oniszczuk-Świercz et al. [28], and Rouniyar and Shandilya [22], employed the Analysis of Variance (ANOVA) technique for their investigations. However, as ANOVA does not fall under the purview of ML algorithms, its results are excluded from the direct comparative analysis of this study. Nevertheless, the R2 values obtained from these ANOVA-based studies are included in the table for informational purposes. The studies did not report MAE, MSE, and RMSE values, limiting the scope of direct comparison with the present study's findings.

The graph of the models' prediction performance and errors are visualized in Fig. 7, allowing us to analyze in more detail how much the predictions of both models deviate from the experimental wears. As seen in Fig. 6, the predicted and experimental wear for both electrode and workpiece exhibit a high level of accuracy, indicating a strong alignment between the predictions and the experimental observations. Notably, electrode wear shows minimal error, underscoring the robustness of the predictive models for this variable. In contrast, a singular instance of relatively high error is observed in workpiece wear, albeit this error does not significantly impact the overall performance. Therefore, it can be concluded that the models perform exceptionally well, demonstrating a

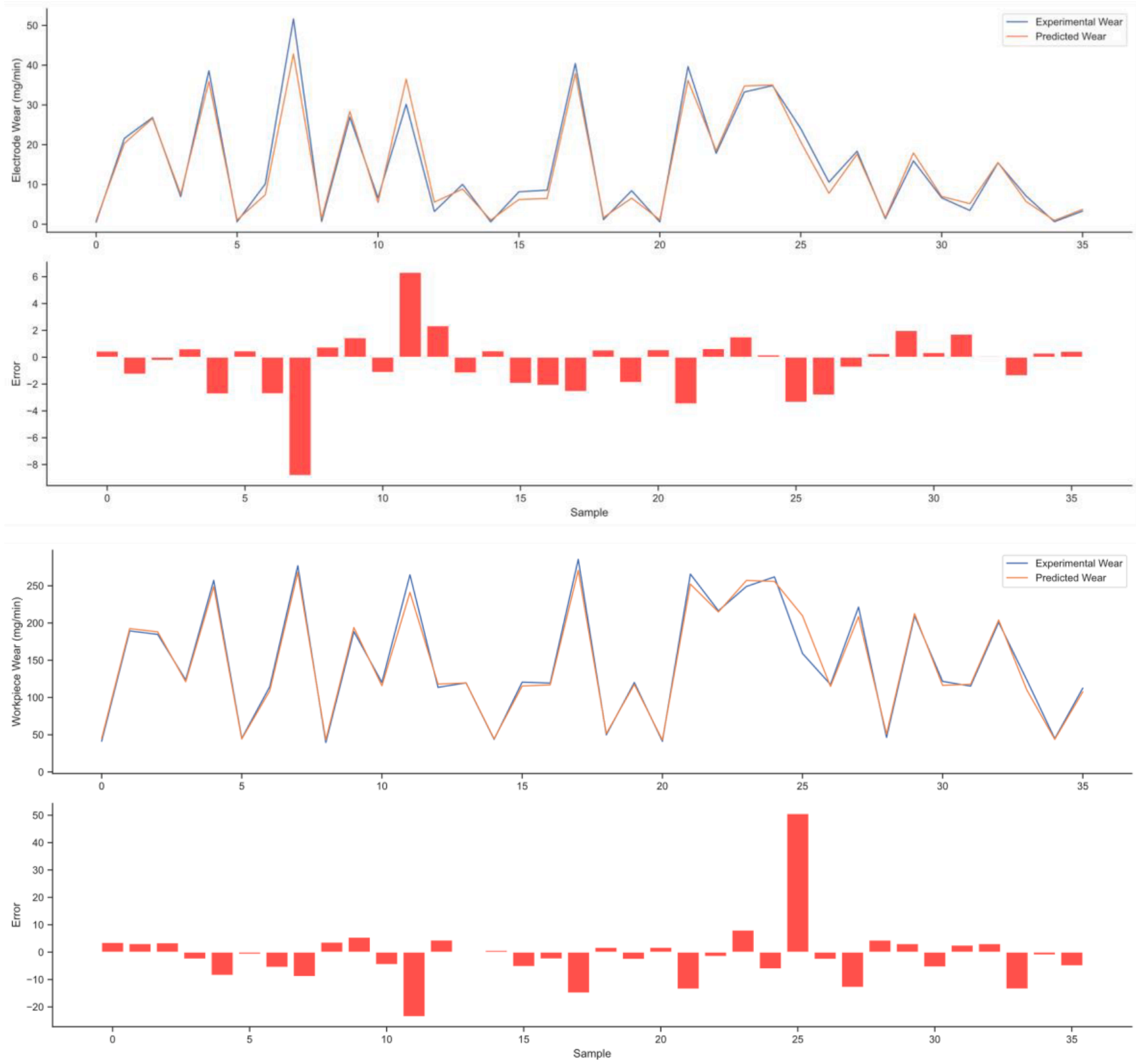


Fig. 7. Comparison of Experimental and Predicted Electrode and Workpiece Wears with Errors.

strong fit with the relevant variables. Despite the isolated error in workpiece wear, the overall predictive performance remains high.

The algorithms used in this study have shown strong performance on the training and testing datasets, demonstrating a successful implementation of machine learning. The presence of balanced learning in both datasets further highlights the effectiveness of the applied algorithms. Notably, a high accuracy of 99 % has been achieved on both the training and testing datasets. Additionally, the errors and regression plots specific to the training datasets are illustrated in Fig. 8. As shown in Fig. 8, a slight variance exists between the experimental and predicted electrode and workpiece wears. This suggests that all the models are capable of making accurate and satisfactory predictions of EDM performances by comprehensively understanding the intricate relationships between input and output parameters.

Table 7 summarizes the significance of various features (variables) in the prediction models. The "importance" column indicates the contribution of features to the prediction model. Additionally, the confidence interval of this contribution, measured by the standard deviation ("stddev"), the statistical significance of the feature ("p_value"), the number of data points used ("n"), and the 99th percentile confidence interval ("p99_high" and "p99_low") are presented.

The presented results and analyses provide valuable insights into the prediction models developed for electro-erosion wear of electrodes and workpieces in the context of different machine learning algorithms. Using two distinct models, Model 1 for electrode wear prediction and Model 2 for workpiece wear prediction, enabled a comprehensive examination of the factors influencing these wear processes. Both models demonstrated exceptional performance, achieving 99 % accuracy on the training and testing datasets. This remarkable accuracy underscores the effectiveness of the applied algorithms and suggests their potential applicability in real-world scenarios.

Examining feature importance in both models revealed valuable information about the driving factors behind electrode and workpiece wear. In Model 1, the "Current" feature emerged as the most influential, indicating that the electric current plays a pivotal role in electrode wear. The "Cryonegenic Process Conditions" and "pulse durations" features significantly contributed to the model's predictions. In Model 2, "Current" retained its prominence, suggesting its importance in electrode and workpiece wear. "Pulse durations" and "Electrode Material" also exhibited noteworthy impacts on workpiece wear.

3.3. Comparing machine learning performance

When choosing the best machine learning model, it can be challenging to determine which is superior, especially when the difference in accuracy between two models is minimal. This is where statistical methods become crucial in ensuring the selected model is significantly more accurate than its counterparts. In this study, we explore using the

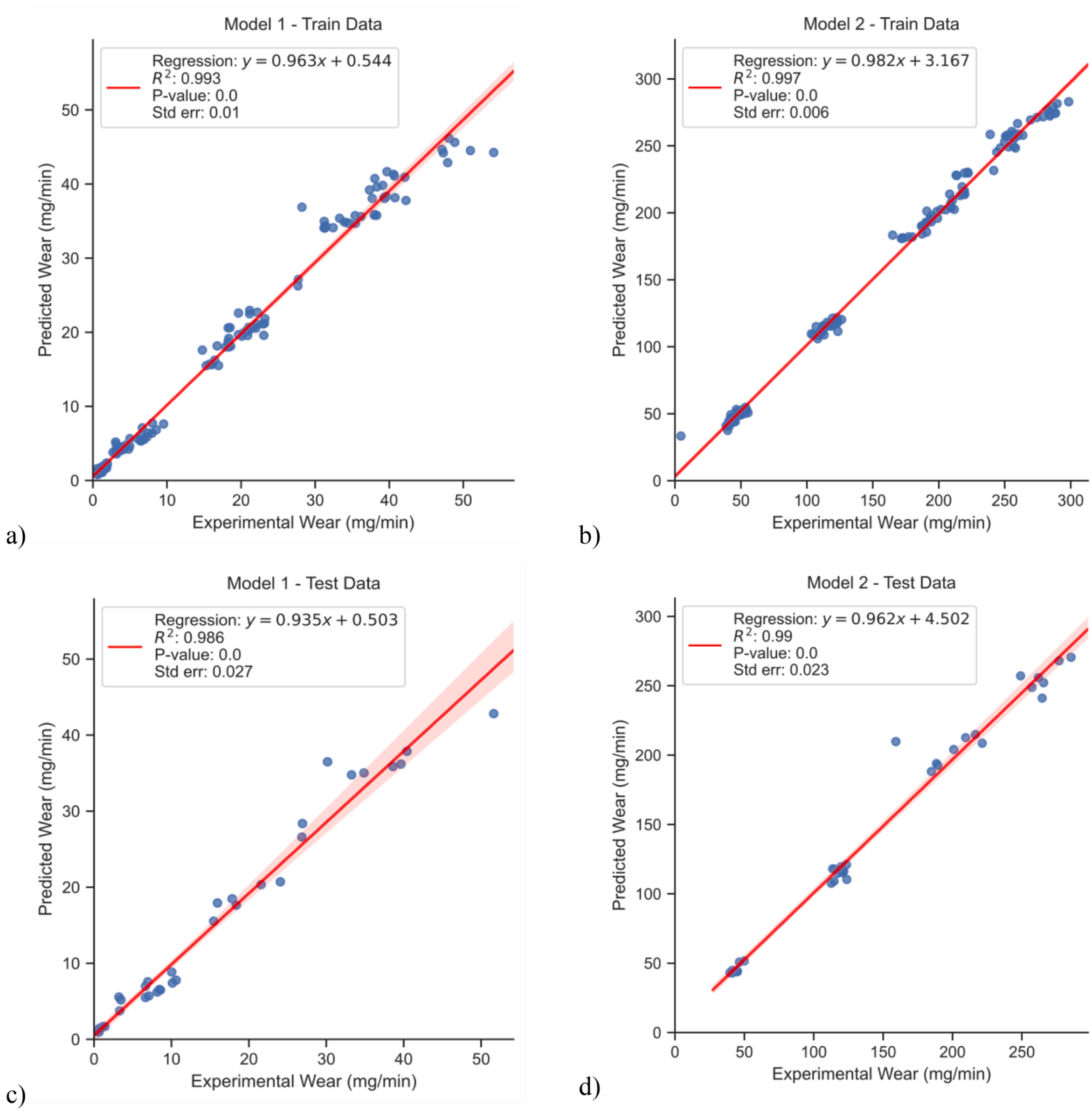


Fig. 8. Comparisons of training and test performance of best method for a) EWR - train b) MRR – train c) EWR – Test d) MRR - Test.

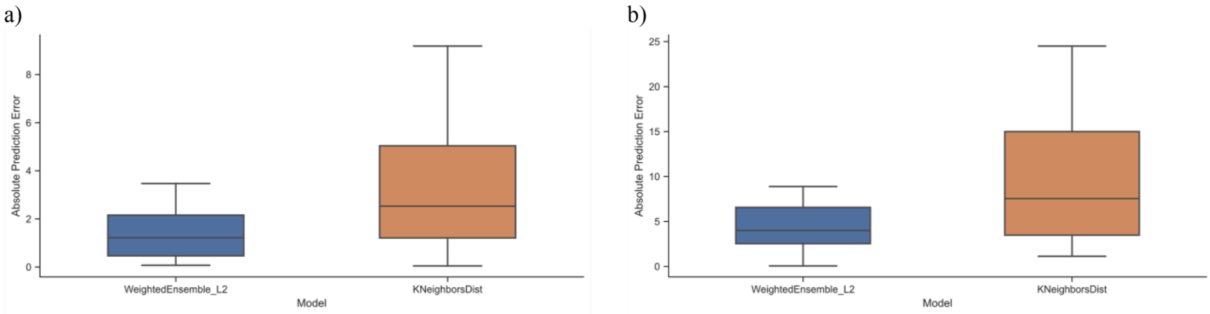
Table 7
The Effect of Variables on the Prediction Model and Statistical Measures.

	Model 1						Model 2					
	importance	stddev	p_value_	n	p99_high	p99_low	importance	stddev	p_value	n	p99_high	p99_low
Current	2.37	0.43	0.00	5	3.26	1.47	2.30	0.36	0.00	5	3.05	1.55
Cryogenic Process Conditions	0.05	0.02	0.00	5	0.09	0.01	−0.00	0.00	0.53	5	0.01	−0.01
pulse durations	0.02	0.00	0.00	5	0.03	0.02	0.02	0.00	0.00	5	0.03	0.01
Electrode Material	0.01	0.00	0.00	5	0.02	0.01	0.01	0.00	0.00	5	0.02	0.00

Wilcoxon signed-rank test, a non-parametric statistical test, to compare machine learning models.

The Wilcoxon signed-rank test is an excellent alternative to the paired Student's *t*-test for comparing machine learning models. This test is particularly useful when dealing with small sample sizes and non-normally distributed data. It provides a robust approach to assess the model's accuracy using a prediction error approach for comparison. The test generates prediction errors through validation, resulting in two samples, one for each model. Statistical tests such as the Wilcoxon signed-rank test are then used to determine if there is a significant difference in the performance of the two models.

The Wilcoxon signed-rank test is a non-parametric test that does not assume that the data is normally distributed. Instead, it compares the differences between the data pairs, making it ideal for comparing two models. The p-value obtained from the test is critical in determining the significance of differences between the models. The conventional significance threshold is set at 0.05 in statistical hypothesis testing. If the calculated p-value is lower than 0.05, it suggests that the observed differences between the models are statistically significant. Therefore, the model with the lower prediction error is considered superior.



Statistics=81.000, p=0.000, Different distributions (reject H0)

Statistics=147.000, p=0.003, Different distributions (reject H0)

Fig. 9. Distributions of Prediction errors for a) Electrode Wear b) Workpiece Wear.

It is important to note that the Wilcoxon signed-rank test is just one of many statistical methods available for comparing machine learning models. However, it is a valuable tool, especially when dealing with small sample sizes and non-normally distributed data. We can confidently choose the best machine learning model by using statistical tests like the Wilcoxon signed-rank test.

According to Fig. 9, the two models have distinct distributions regarding the compared features. The p-value is below 0.05 in both cases, indicating a statistically significant difference between the models. This means that the null hypothesis (H0) is rejected, and there is a meaningful distinction between the models.

3.4. Limitations of machine learning algorithms

It's worth noting that there are still uncertainties and challenges in machine learning despite all the considerations that go into it. The quality and representativeness of training data are critical factors that can impact the performance of machine learning models. If the training data is incomplete or lacks representation, the model's ability to handle new data could suffer. This underscores the importance of ensuring that training data is comprehensive and meaningful. Models' generalizability is also crucial, as some might overfit the training data, leading to suboptimal performance on new, unseen data. Proper algorithm selection and parameter tuning can mitigate these issues, but incorrect choices or misaligned parameters can significantly impact the model's overall performance. Training and evaluating machine learning models entail time and resource-intensive experimental processes. Additionally, obtaining accurate results often requires iterative trial-and-error methods. Insufficient or non-representative data presents a significant challenge to accurately learning from data. When datasets are scarce for a specific topic, obtaining a sufficiently large and diverse dataset can hinder the model's effectiveness. As a result, it's crucial to address the limitations posed by data scarcity in machine learning applications.

4. Conclusions and future directions

The research findings suggest that electrodes reduce EWR values after CT. However, the duration of CT can impact the results obtained. It was observed that CuCrZr electrodes outperformed Cu electrodes, and an increase in current discharge caused a more significant rise in EWR and MRR compared to pulse duration and CT. Machine learning models, such as those made using AutoGluon, are powerful tools for modeling and comprehending the intricate relationship between electrode material and wear. These insights could aid in making informed decisions regarding manufacturing processes, thereby enhancing product quality and equipment longevity.

The highly accurate prediction models developed, and the insights gleaned from feature importance analyses offer valuable tools for understanding and potentially optimizing electro-erosion wear processes in various industrial applications. Future research could explore these models' practical implications and potential integration into manufacturing processes to enhance efficiency and cost-effectiveness.

Conducting similar analyses on different materials or electrode types could lead to a more comprehensive evaluation of the generalization capabilities of machine learning algorithms. Exploring the effects of various processing conditions on erosion wear, such as temperature, pressure, and material quality, could provide a more detailed and extensive understanding. Testing the applicability of these models in real manufacturing environments and assessing their practical usage in operations could be a significant step for further research.

5. Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT 3.5 for grammar correction and expression improvement in spelling. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Abdurrahman Cetin: Writing – review & editing, Writing – original draft, Supervision, Resources, Investigation, Formal analysis, Data curation, Experimental Study. **Gokhan Atali:** Writing – review & editing, Writing – original draft, Validation, Supervision, Investigation, Data curation, Conceptualization. **Caner Erden:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis. **Sinan Serdar Ozkan:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aei.2024.102468.

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