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Power Consumption and Processing Time Estimation of CNC Machines Using Explainable Artificial Intelligence (XAI)

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Abstract

Due to environmental issues such as climate change, companies are required to optimize their resource and energy consumption in their production process. Predicting power consumption and processing time of all production facilities is essential for manufacturing to develop mechanisms to prevent energy and resource waste and optimize their use. Machine learning is a powerful tool for prediction tasks using data in digitalized environments. In this paper, we present power consumption and processing time prediction of CNC milling machines using five machine learning regression models, i.e., decision tree, random forest, support vector regression (SVR), extreme gradient boosting (XGBoost), and artificial neural network (ANN). Since most of those models are black-box, we applied two explainable artificial intelligence (XAI) approaches, SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), to give post-hoc explanations of the predictions given by the machine learning models. Our experiments indicated that random forest regression performed the best in predicting power consumption and processing time. The explanation showed that the number of axis rotations and the number of travels to the machine's zero point in rapid traverse were the most important factors that affected the processing time and power consumption. The companies using CNC milling machines can use our prediction models to optimally plan and schedule the operation of the milling machines in a time and energy-efficient manner. They can also optimize the factors that affect power consumption and processing time the most.

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Keywords: machine learning; explainable artificial intelligence (XAI); power consumption prediction; manufacturing; CNC machines

1. Introduction

According to [1], the industrial sector consumed 38% of world energy in 2021, and the consumption trend is increasing yearly. The rapid power demand will increase the quantity of power generated from fossil fuels, although power generation from renewable sources has also grown rapidly. Generating power from non-renewable sources directly affects climate change and sustainable development. To consider climate change and for sustainable develop-

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ment, industrial sectors are trying to optimize power consumption in every process, including milling. Milling is one of the manufacturing processes of removing materials, which occurs when cutting blades that rotate on the spindle with the raw materials [2]. It takes time and consumes energy to complete the task during the process.

Production planning and control tasks, such as planning, scheduling, rescheduling, and quality control, always depend on time. Therefore, industries are required to use the time in the best feasible way. In the era of artificial intelligence, there are many options to optimize such processes. One of the solutions is the use of machine learning (ML) that has predicting capability. Our research focuses on the application of machine learning to predict machine power consumption and processing time so that optimization measures can be taken to minimize power consumption and processing time.

ML algorithms automatically learn from data to make predictions, surpassing traditional statistics due to their ability to handle complex, large datasets and provide higher prediction accuracy [3]. This study employed five supervised ML regression models that understand the relationship between training data and their labels representing the outputs [4]. These models predict outputs based on training data, with prediction accuracy assessed using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

Machine learning models, including deep neural networks, gradient boosting machines, and random forests, typically operate as black boxes, making them challenging to interpret intuitively. Explainable Artificial Intelligence (XAI) addresses this challenge by striving to provide understandable explanations for the decisions made by AI systems, like machine learning models. XAI is a specialized branch of artificial intelligence designed to meet the specific interests, goals, expectations, and needs of human stakeholders [5]. It aims to provide users with explainability to allow sufficient understanding and trust [6]. In predicting power consumption and processing time, XAI can be employed to explain what factors, such as process and machine parameters, influence the predicted values the most. Without XAI, users receive power consumption predictions without any accompanying explanations, leaving them in the dark regarding the rationale behind the predictions.

Despite the evident significance of predicting and optimizing machine power consumption and the potential of eXplainable Artificial Intelligence (XAI) in enhancing the transparency of such predictions and optimizations, there remains a noticeable research gap in applying XAI for this purpose. Our research aims to predict the average power consumption and processing time of milling machines based on the production process, numerical control (NC) codes, and sensor data, using machine learning. We applied five machine learning regression models, namely, decision tree regression, random forest regression, support vector regression (SVR), extreme gradient boosting (XGBoost) regression, and artificial neural network (ANN) regression. This research also aims to determine how much the process parameters affect the power consumption and processing time. We implemented model-agnostic post-hoc explainability methods, i.e., SHapley Additive exPlanations (SHAP) [7] and Local Interpretable Model-Agnostic Explanations (LIME) [8]. Model agnostic methods can be applied to any machine learning model. Post hoc refers to the explainability method approximating the logic of underlying black-box machine learning models [9].

This paper is structured as follows. Section 2 presents the literature review describing the related works and research gaps. Section 3 explains the methodology developed in our research, containing the data pipeline, model building, and XAI. The results after applying the methodology are presented in Section 4. Section 5 discusses the key findings, implications, limitations, and future works. Finally, the conclusions of this work are presented in Section 6.

2. Literature review

Awan et al. predicted the energy consumption of a machine for the cut-off grinding of oxygen-free copper. They used three independent variables to predict energy consumption: feed rates, cutting velocities, and cutting tools, where energy consumption was the dependent variable. They used three different ML models, namely ANN, Gaussian process regression (GPR), and regression tree, and they used RMSE to measure the error margin. After implementing these algorithms, GPR was well suited for this experiment as the RMSE was lowest in both training and test datasets [10].

Kang and Sangwan used ANN to predict the cutting energy of a machine where spindle speed, feed rate, depth of cut, and width of cut were independent variables. They found that the predicted value had an error margin ranging from 0.01% up to 5%, which shows that the ANN algorithm can be used in such cases [11].

El Youbi El Idrissi et al. applied twelve regression models to predict the energy consumption of 3D printing in the printing phase. They included GPR, linear regression, decision tree regression, and random forest regression. The main objective is to minimize energy use in the printing phase. The independent variables were, among others, sliced volume, orientation, printing time, and number of layers. These variables were in intervals. After training the dataset with these algorithms, they used RMSE, MAE, and R-square as evaluation criteria. GPR performed more precisely, fulfilling the criteria which explain that it can predict the energy consumption of this type of problem [12].

Wicaksono applied C4.5 decision tree and M5 model tree models to predict the power consumption, processing time, and costs of customized stainless steel products based on their properties, such as diameters, lengths, materials, and heat treatment. The models were applied in multiple machines used in different processing stages. The results were used to select the best machine for each stage resulting in the lowest total power consumption and costs of the whole production process [13].

SHAP and LIME are the two widely adopted XAI techniques for various purposes. For instance, Parsa et al. harnessed SHAP to elucidate the inner workings of an XGBoost model used in real-time traffic accident detection. This approach unveiled critical factors contributing to accidents, such as speed differentials before and after incidents, average daily traffic volume, and specific locations [14]. SHAP has found applications in manufacturing in conjunction with machine learning models, facilitating predictions and root cause analyses of manufacturing process performance [15]. Moreover, SHAP aids in forecasting post-pandemic recovery in automobile manufacturing while dissecting the various factors influencing this resurgence [16]. LIME has been employed for identifying crucial time-frequency bands that impact the prediction of average surface roughness in smart grinding applications [17]. Notably, both SHAP and LIME have made recent adoptions in explaining the influence of product features on machine power consumption within the steel industry, shedding light on crucial insights in the manufacturing of customized products [18].

Table 1 summarizes the related works from the literature review, including the most relevant ones described above. All works applied machine learning to predict either energy consumption or processing time. None of the works predict both the power consumption and processing time of machines. Furthermore, those works only focus on generating the predictive models without explaining to what extent the influencing factors affect the outputs. Our research addresses this gap by developing machine learning models for predicting the average power consumption and processing time and explaining the models using SHAP and LIME.

Table 1. Related works.

Source	Predicted value	Influencing variables	Machine learning models	XAI
[2]	Energy consumption of a machine tool over time	Feed rate, spindle speed, depth of cut, cutting direction, cutting strategy, etc.	Gaussian process regression	No
[10]	Energy consumption for cut-off grinding of oxygen-free copper (OFC–C10100)	Feed rate, cutting thickness, and cutting tool type	Gaussian process regression (GPR), regression trees, and ANN	No
[11]	Power consumption of cutting machine	Spindle speed, feed rate, depth of cut, width of cut	Artificial neural network (ANN)	No
[12]	Energy consumption of additive manufacturing	Orientation, stl surface area, number of facets, sliced volume, number of layers, etc.	Linear, random sample consensus, ridge, GPR, elastic net, support vector (SVR), regression chain, K-nearest neighbors, and decision tree regressions	No
[13]	Power consumption, processing time, and costs of customized stainless steel products	Product properties, e.g., diameter, length, material type, heat treatment	Decision tree regression, model tree	No
[19]	Energy demand of CNC machining	Spindle speed, tool path length, material removal rate, internal machine variables, etc.	Random forest, decision tree, ada boost and decision tree	No
[20]	Processing time	Process parameters (Number of produced products, process type, required materials, etc.) collected through RFID	K-means clustering, gradient descent optimization	No
[21]	Robustness of production processes	Idle times, number of machines, number of operations, operation duration, slack time, etc.	Linear regression, ANN, gradient boosting, random forest, SVR	No

3. Methodology

3.1. Model training and XAI pipeline

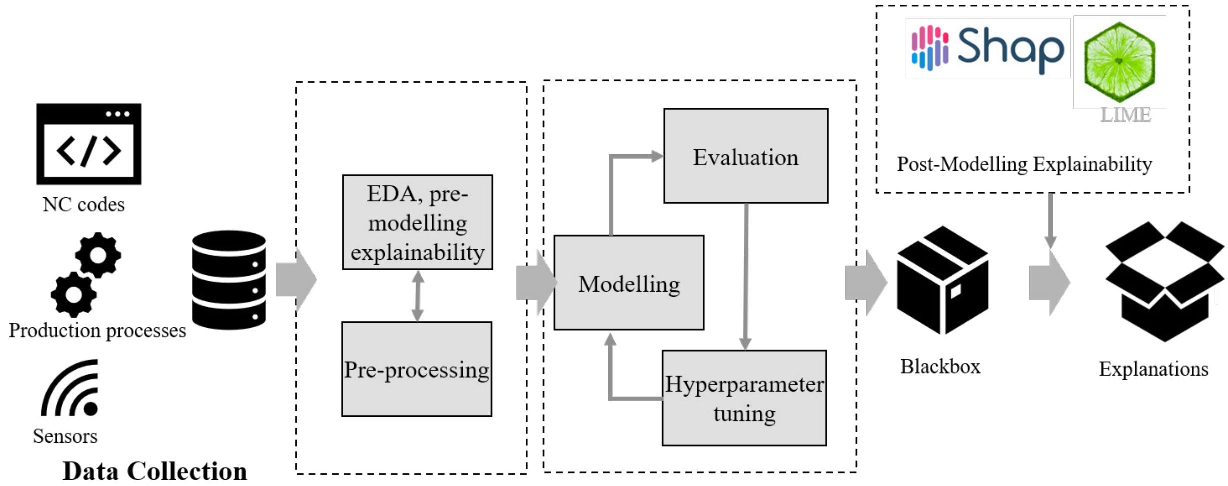


Fig. 1. XAI pipeline.

Fig. 1 illustrates our XAI pipeline that comprises generating ML models by learning from the data and explaining the models using SHAP and LIME. The pipeline consists of several steps as follows. First, the datasets were gathered from different systems. The power consumption data was collected through sensor systems, production process data through process data logger, and NC code through programming interfaces. Those data were then linked and stored in a database, resulting in a dataset containing the relationships between process parameters, NC codes, processing time, and power consumption. Then, we performed exploratory data analytics (EDA) to get preliminary insights into the dataset, including basic statistical features, distributions, outliers, missing values, and multivariate correlations. We also preprocessed the data by imputing the missing values and encoding the categorical values. Then, the five machine-learning models were built using the dataset with the desired hyperparameter. We evaluated the resulting models using MAE, MSE, and RMSE. Hyperparameter tuning was also conducted to improve the model accuracy. As depicted in Fig. 1, the model building, evaluation, and hyperparameter tuning are iterative processes. Most of the resulting machine learning models, such as random forest, XGBoost, SVR, and ANN, are considered black box models. Finally, the SHAP and LIME were applied to open the black box and explain why the models give particular prediction values.

3.2. Data collection and description

Our research analyzed programmable CNC milling machines in a small manufacturing enterprise in Germany. We collected the data containing start time, end time, processing time, average power consumption, number of lines of code, weighted speed, and other variables describing process attributes. Start and end times are timestamps (UTC) when the process starts and finishes. Processing time is the time a machine takes to carry out the task in seconds. Average power consumption is the total power a machine consumes during the execution of a specific task in watts (W). Raw volume is the initial volume of materials before machining. The number of missing data is the number of missing power measurements in one-minute intervals. The number of lines of NC code is the total lines of code to run the machine for a task. The number of tool changes is the count of how many tools have been changed during the task. The number of travels to the machine zero point in rapid traverse is the movement of tools from the initial state to a repetitive process. The number of axes of rotation is the number of changes in the position of the axis of rotation of the tools. Some features, such as speed and cutting length, are weighted using equation 1.

$$\overline{f} = \frac{\sum_{i=1}^{n} f_i c_i}{\sum_{i=1}^{n} f_i} \quad (1)$$

where n is the number of processing steps, f_i is the feature value of i^{th} processing step, and c_i is the number of lines of code in the i^{th} processing step. In a total of 220 data points were obtained to train the models.

3.3. Model training

Decision tree regression serves both regression and classification tasks, employing a tree structure where nodes, except the root, have parent nodes [22]. Data partitions into child nodes based on specific conditions, reducing data randomness and leaving mark endpoint nodes. The splitting stops upon meeting criteria like maximum depth, minimum leaf count, and minimum sample split. Data traverses the tree path from root to leaf nodes to perform the prediction. After tuning, we configured the tree depth to 5 and the minimum sample split to 2, tailored to our smaller dataset. Random forest regression, a powerful ensemble technique, deploys multiple decision trees for regression tasks. It excels even in the presence of missing data or outliers. Each tree uses training data and a random feature subset [23]. Predictions result from averaging multiple tree outputs, lessening the influence of potentially noisy individual trees, such as those affected by outliers. Consequently, it furnishes more precise predictions. Post hyperparameter tuning, we settled on 60 trees for our study.

Support vector regression (SVR) leverages the support vector machine (SVM) concept for both linear and non-linear datasets, utilizing decision boundaries defined by linear or non-linear kernel functions for predictions [24]. The algorithm assesses tolerance levels. The fit is acceptable if the difference between the predicted and actual values falls within the boundary distance. Otherwise, a penalty proportionate to the distance between the decision boundary and the predicted value is applied [24]. Crucial hyperparameters, such as regularization and kernel selection, further fine-tune the algorithm. Following hyperparameter tuning, we settled on a polynomial kernel with a degree of 13. XGBoost regression, an extension of the XGBoost framework, utilizes multiple decision trees to enhance accuracy in regression tasks. The trees iteratively refine predictions by minimizing errors from previous iterations, guided by a carefully chosen loss function. Regularization techniques prevent overfitting, while gradient descent optimization refines tree parameters. Subsequent trees adapt automatically to achieve optimized error margins compared to their predecessors [25]. Post hyperparameter tuning, our configuration includes a learning rate of 0.1, gbtree booster, and 100 estimators.

ANN regression uses the capability of neural networks to perform regression tasks. There are several steps considered to make the model work. First, the model's architecture is defined, comprising input, hidden, and output layers [26]. The input layer initiates the process, with nodes matching input features. Activation and forward propagation yield predictions, while backward propagation minimizes the loss function for network optimization. Gradient descent fine-tunes weights and biases to minimize the loss, iteratively reducing error. Given our dataset of only 220 data points, we employed two hidden layers, aligning with our 13 input features. We applied the ReLU activation function, measured loss using mean average error, and utilized the Adam optimizer. We conducted a grid search to determine batch size and epochs, ultimately adopting a combination of ten batch sizes and one hundred epochs.

3.4. Explainable Artificial Intelligence (XAI)

XAI explains machine learning model decisions in a human-friendly manner. These models produce results as black boxes, concealing the intricate processes leading to those outcomes. XAI steps in to provide visualizations or simpler techniques for human comprehension [27]. In our study, we harnessed SHAP and LIME methods.

SHAP enhances model interpretability by elucidating the contribution of each input feature to the model's output [7, 27]. This method provides a comprehensive breakdown of each input variable's impact on the output, which can be positive or negative. In our study, we utilized SHAP summaries to assess the influence of all input data points on the model's results. Each point in the SHAP plot corresponds to a datapoint, with features organized by importance or their impact on the output variable, as indicated by the point's color.

LIME offers a graphical depiction of the ML model's explanation for an individual observation, detailing the contribution of each input variable to that data point's output. It operates under the premise that, on a local scale, even complex models behave linearly [28, 29]. LIME supplements this by indicating whether the impact is positive or negative.

4. Results

Table 2 presents MAE, MSE, and RMSE scores via 10-fold cross-validation. Table 2a summarizes model performance for average power consumption (APC) prediction, reflecting overall errors across data points. Notably, XGBoost exhibited higher errors compared to random forest. SVR and ANN regressions fared less favorably, with SVR marginally outperforming ANN. In Table 2b, decision tree and random forest excelled in processing time (PT) prediction, while XGBoost exhibited slightly worse performance. ANN regression posted the largest errors, likely due to the limited data points for neural network models.

Table 2. Performance scores of different models.

(a) Average power consumption prediction.

Regression Model	MAE	MSE	RMSE
Decision Tree	398.60	267079.31	474.93
Random Forest	380.75	248378.65	448.99
SVR	558.72	502703.14	651.88
XGBoost	403.87	277778.68	489.06
ANN	2132.36	3272622.73	1994.75

(b) Processing time prediction.

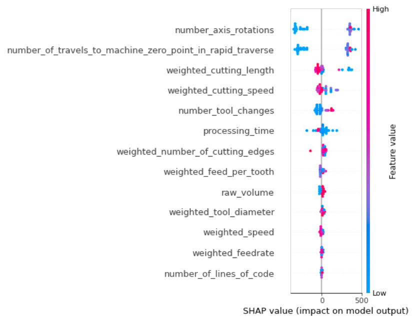
Regression Model	MAE	MSE	RMSE
Decision Tree	217.05	167643.35	312.23
Random Forest	219.74	116271.46	303.14
SVR	782.34	2337837.14	997.82
XGBoost	238.70	208629.19	374.05
ANN	1223.04	1299745.52	1021.36

We utilized SHAP to assess the influence of independent variables (e.g., weighted speed, processing time, raw volume) on average power consumption and processing time, yielding insights depicted in Fig. 2. In SHAP, the first-listed independent variable indicates the most substantial impact on the dependent variable. Remarkably, both decision tree and random forest models exhibit similar variable importance trends (cf. Fig. 2a and Fig. 2b). For average power consumption, the most influential factors include the number of axis rotations, weighted cutting length, and the number of travels to the machine zero point during rapid traverse. Conversely, XGBoost, while sharing similar errors with decision tree and random forest models, displays a varied variable importance order, with the number of tool changes topping the list (cf. Fig. 2d). Notably, SVR and ANN models, less effective for average power consumption prediction, manifest distinct variable importance orders in SHAP analysis, with raw material volume emerging as a crucial factor (cf. Fig. 2h and Fig. 2e). In contrast, since random forest excels in processing time prediction, the number of lines of code, the number of travels to the machine zero point during rapid traverse, and the number of axis rotations emerge as top influencers (cf. Fig. 2g). In SHAP analysis of SVR, raw volume dominates the factors affecting processing time, despite SVR's limited processing time prediction accuracy (cf. Fig. 2h).

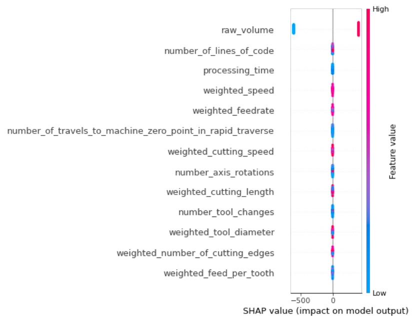
We also implemented LIME to see the positive and negative impacts on average power consumption and processing time. Fig. 3 depicts the LIME results of all models for average power consumption and processing time predictions. The green color shows a positive impact of independent variables on the output, whereas the red color shows a negative impact. The explanation is based on a single data point. LIME of the decision tree and random forest shows that number of axis rotations has a strong negative impact on average power consumption (cf. Fig. 3a and Fig. 3b). Raw volume of material positively impacts the average power consumption in SVR and ANN regressions (cf. Fig. 3c and Fig. 3e). In most of the models, the independent variables are mostly negatively correlated to the average power consumption. The number of lines of code strongly affects the processing time according to all models except SVR (cf. Fig. 3f, Fig. 3g, Fig. 3i, and Fig. 3j). The ANN model has an almost equal number of independent variables that positively impact processing time (cf. Fig. 3j).

(a) Decision tree for APC prediction.

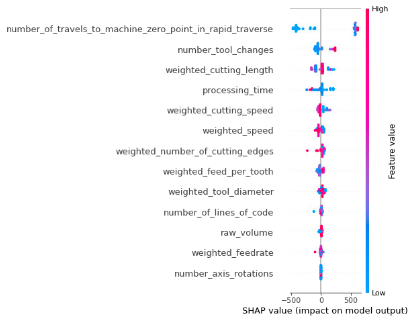
(b) Random forest for APC prediction.



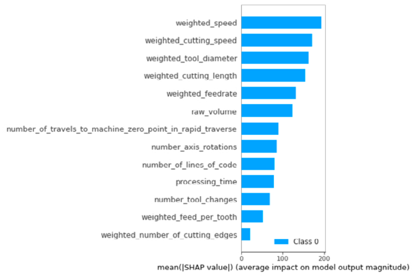
(c) SVR for APC prediction.



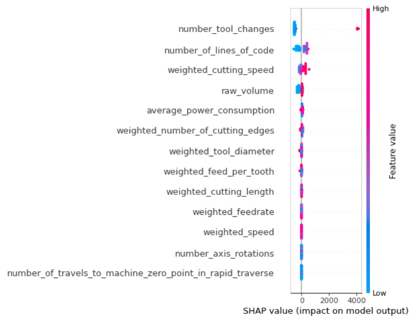
(d) XGBoost for APC prediction.



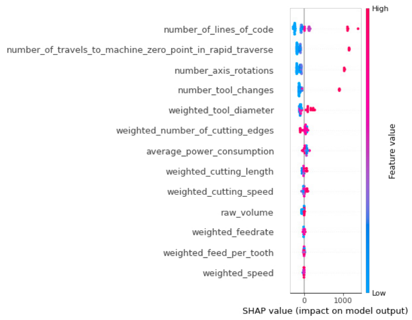
(e) ANN for APC prediction.



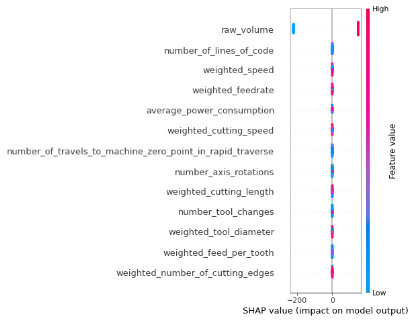
(f) Decision tree for PT prediction.



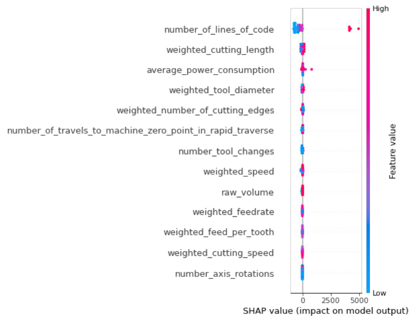
(g) Random forest for APC prediction.



(h) SVR for PT prediction.



(i) XGBoost for PT prediction.



(j) ANN for PT prediction.

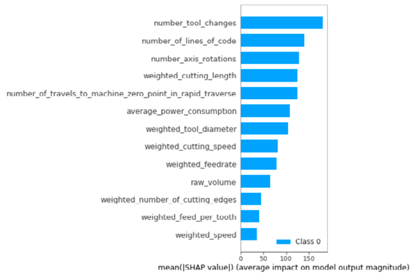
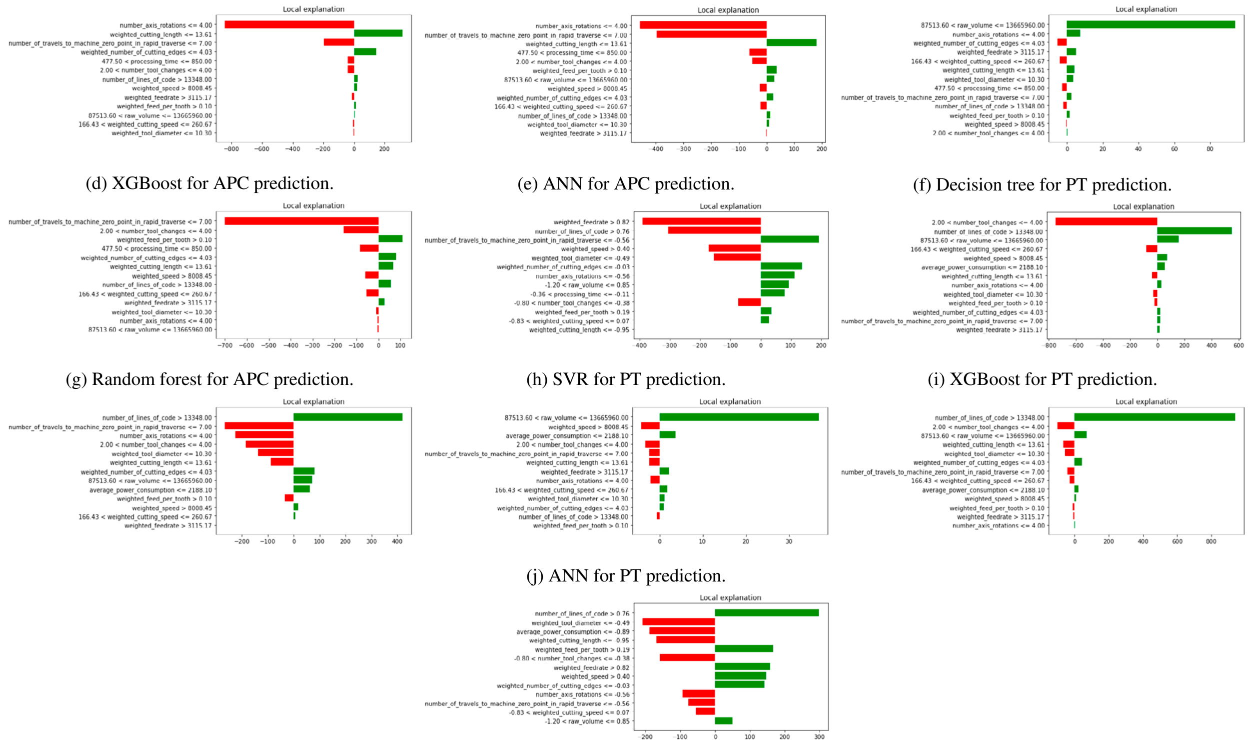


Fig. 2. SHAP values for average power consumption (APC) and processing time (PT) predictions.



(a) Decision tree for APC prediction. (b) Random forest for APC prediction. (c) SVR for APC prediction. (d) XGBoost for APC prediction. (e) ANN for APC prediction. (f) Decision tree for PT prediction. (g) Random forest for APC prediction. (h) SVR for PT prediction. (i) XGBoost for PT prediction. (j) ANN for PT prediction.

Fig. 3. LIME results for average power consumption (APC) and processing time (PT) predictions.

5. Discussion

5.1. Key findings and implications

The decision tree, random forest, and XGBoost regression effectively learned the dataset patterns and predicted average power consumption and processing time. In contrast, both ANN and SVR underperformed in both scenarios. Table 2a illustrates that random forest yielded the lowest error values, establishing it as the most proficient model for predicting average power consumption. Notably, the decision tree consistently had slightly higher error values than the random forest, attributable to the random forest's enhanced resilience against outliers. We further investigated the key factors impacting average power consumption. Surprisingly, variables like the number of lines of code, raw material volume, weighted feed rate, and weighted speed had minimal influence on average power consumption. In contrast, significant factors included the number of tool axis rotations, weighted cutting length, weighted cutting speed, and the frequency of travel to the CNC machine's starting point during rapid traverse.

Table 2b reveals an interesting observation: the decision tree model exhibits a lower MAE score than the random forest, but its MSE and RMSE scores are higher. This suggests that both models perform well in predicting processing time, yet the decision tree occasionally yields predictions farther from actual values. It is essential to consider squared errors (MSE and RMSE), which penalize inaccurate predictions at specific points.

Furthermore, in Fig. 2a, Fig. 2b, and Fig. 2d, the number of travels to the machine zero point in rapid traverse emerges as a critical factor influencing average power consumption, highlighted by the top three models: decision tree, random forest, and XGBoost. Similarly, LIME plots affirm the significance of this variable, indicating a negative impact on average power consumption (cf. Fig. 3a, Fig. 3b, and Fig. 3d).

Moreover, the number of lines of code emerges as a key factor affecting milling machine processing time according to the decision tree, random forest, and XGBoost models (cf. Fig. 2f, Fig. 2g, and Fig. 2d). This aligns with expectations, as more lines of code imply more instructions to execute, consequently increasing execution time. This finding is corroborated by LIME plots (cf. Fig. 3f, Fig. 3g, and Fig. 3i).

For our best prediction model, random forest, the SHAP plot shows that the travels to machine zero point in rapid traverse and the number of axis rotations are the most influencing factors on outputs (cf. Fig. 2). Similarly, the LIME plot of the random forest model depicts that the number of axis rotations negatively impacts the power consumption, and the number of lines of code positively impacts the processing time, as observed in Fig. 3.

Our findings address a significant research gap by demonstrating the effective application of eXplainable Artificial Intelligence (XAI) in uncovering correlations among various milling machine parameters. This contribution serves as a valuable resource for fellow researchers, showcasing the potential of XAI to enhance the interpretability of machine learning models in industrial contexts, particularly for predictive analytics involving complex influencing factors. The utilization of LIME and SHAP allows for precise quantification of the factors' impact on predictions. Furthermore, our results lay a robust foundation for integrating XAI as a strategic tool for manufacturing companies aiming to optimize the performance of milling machines. With a clear understanding of the significance of these influential process parameters, companies can strategically prioritize adjustments, aligning them with available time and resource constraints. This knowledge empowers organizations to make informed decisions to enhance milling machine capabilities effectively.

5.2. Limitation and future work

Currently, our research only focuses on five machine-learning regression models. We will include more models to have a larger population to compare the error metrics. The new models might increase the accuracy level compared to the current ones. ANN is not a good prediction model for our dataset due to the limited number of data points. The limited number of data points is due to the lack of systems that automatically collect the production process data. Further work will focus on developing a system to automatically collect process and machine parameter data with the same time resolution as the collected sensor data. Furthermore, this work only considers thirteen independent variables reflecting the production process parameters. Further work will consider more process and machine parameters incorporated in the model that can be achieved by improving the data collection systems.

6. Conclusions

Power consumption and processing time of milling machines are leading factors that directly affect the production's cost, resources, and quality. It also indirectly impacts the environment due to the required power that might be generated from non-renewable sources. Planning and scheduling must be done to optimize the operation of milling machines, which requires predictions of these factors. Making the prediction is one of the solutions to work it out. Our research aims to predict the processing time and average power consumption of milling machines using different machine-learning models. After implementing the five models, we found that random forest regression is the most suitable model for predicting average power consumption. SHAP explained the random forest model and found that weighted cutting length, number of axis rotations, and the number of travels to machine zero point in rapid traverse were important variables that affected the average power consumption most. The number of axis rotations is the most negatively correlated, and weighted cutting length is the most positively correlated factor on average power consumption, as illustrated by the LIME plot of the random forest. The random forest also predicted the processing time with the utmost accuracy. Its SHAP values explain that the number of lines of code, the number of travels to the machine zero point in rapid traverse, the number of axis rotations, and the number of tool changes are the important factors that affect the processing time. The LIME plot shows that the number of lines of code is the most positively correlated factor, and the number of travels to the machine zero point in rapid traverse is the most negatively correlated factor that affects the processing time. By using the results of our research, manufacturing companies operating CNC machines can get insights into the process parameters that affect the machines' power consumption and processing time the most. Thus, they can adjust the process parameters accordingly or reschedule the processes.

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