

Optimizing Manufacturing Processes With AI: A Signal-Based CNC Machining Case Study In The Automotive Industry

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Abstract

Signal-based monitoring of CNC processes is critical in optimizing automotive manufacturing since the existence of abnormalities in machining states may lead to negative consequences on the manufacturing process. This paper attempts to solve the issue of identifying abnormal CNC machining states from the raw vibration/acceleration data and converting the performance of the identification into manufacturing process-optimization metrics. An end-to-end signal-based pipeline was created for abnormal machining-state detection by utilizing the Bosch CNC Machining dataset, consisting of 1702 HDF5 machining-run files taken from three CNC machines and fifteen operations. Files within each operation were viewed as one machining run with labels of either normal or abnormal based on good or bad folders. Feature vectors were obtained from HDF5 files in numeric signals form and then transformed to both time and frequency domains. Eight models were tested; those include Logistic Regression, Support Vector Machine, Random Forest, Extra Trees, Gradient Boosting, XGBoost, LightGBM, and CatBoost. The Support Vector Machine delivered optimal balanced performance with a result of 0.9971 accuracy, 0.9807 macro F1 score, 0.9661 ROC-AUC, one missed abnormal case, and zero false positives.

Keywords- Artificial intelligence, CNC machining, automotive manufacturing, process optimization, vibration signal analysis.

1. Introduction

AI has evolved into an important enabler for modern manufacturing systems, especially those that rely on monitoring and measuring complex machine behavior to maintain the quality of their products, the reliability of their operations, and their efficiency. The utilization of AI methods in smart manufacturing systems is now prevalent in scheduling, planning, predicting maintenance activities, detecting anomalies, and making autonomous decisions. Deep reinforcement learning has been seen as an exciting research area for manufacturing systems due to its capacity to enable adaptive decision making in dynamic manufacturing systems [1]. Furthermore, the use of robot learning and intelligent robotic manufacturing represents a shift from automating manufacturing tasks through AI to making learning systems that adapt to the dynamics of manufacturing processes [2].

In the automobile industry, the manufacturing processes have high demands for accuracy, consistency, and early identification of any deviation from standard operations. The components of an automobile are often manufactured through machining, assembly, manipulation by robots, and inspection processes, in which even slight errors in the condition of the tools used, vibrations, machine status, and other elements of the process can lead to defects, unnecessary reworking, downtime, and higher production costs. Therefore, digital twin and deep learning technologies have recently attracted attention in improving manufacturing processes, particularly where real-time monitoring and predictive decision-making are needed [3]. Another significant area of interest has been machine learning-based condition monitoring, which is essential in transforming the collected data from sensors into operational insights about machine conditions [4].

In spite of all of these developments, an ongoing issue within the automotive industry is the transformation of raw machine signals into optimization decision-making. The CNC

machining process produces vibrations and acceleration signals, which may have valuable insights about both proper and improper operations during machining. Yet, the signal information is usually difficult to access due to being encoded in proprietary forms, involves feature engineering, and necessitates reliable model building amid class imbalance, machine variation, and heterogeneous operations. Research into advanced precision machining has demonstrated the benefits of machine learning through its capacity for improving quality control, process prediction, and intelligent manufacturing; nevertheless, actual application would require comprehensive frameworks of processing signals, AI modeling, interpretation, and decision-making [5]. There are attempts in applying AI and machine learning for tool condition monitoring, process control, and fault detection; however, much of these applications are merely theoretical or focus solely on prediction without optimization [6].

Another area in predictive maintenance research that demonstrates the ability of DL-based monitoring as an effective approach to early fault diagnosis is the role of proper model training and evaluation criteria. Proper preprocessing of training data, selection of relevant evaluation metrics, and correct use of model results are important aspects that determine the quality of prediction made by DL-based approaches [7]. Such an issue becomes especially topical for the use of anomaly detection in the industry, when it comes to the case when normal samples are more numerous than abnormal samples. Under such circumstances, a model may provide accurate prediction while failing to recognize important abnormalities. Thus, it becomes essential in comparative studies to consider not only the accuracy but also some other model-related features for anomaly detection in industry [8].

This research resolves the problem through the development of a signal-based AI pipeline designed to optimize the monitoring of manufacturing processes in the automotive industry. This study employs the signal dataset generated from CNC machining operations as a proxy for an automotive component manufacturing process and seeks to distinguish between the normal and abnormal machining states based on the extracted features from the signal data. The current research is limited to the classification of the machining process conditions using vibration/acceleration signals stored in HDF5 format. It should be noted that this research does not propose a novel stand-alone classification algorithm or the first AI model dedicated to CNC machining. The uniqueness of this study is associated with the implementation of the pipeline involving the processing of raw HDF5-based CNC signal data, generation of features in both time and frequency domains, comparative analysis of different AI classification models, AI model agnostic explainability, and process optimization interpretations within the scope of automotive manufacturing process monitoring.

What distinguishes the significance of the study is its relevance to the use of classification algorithms based on artificial intelligence in optimizing the manufacturing process rather than the focus on accuracy as the main result. It is clear from dynamic scheduling research and manufacturing optimization that the use of artificial intelligence can optimize decision-making in manufacturing processes [9], whereas digital twin-based machining research emphasizes the importance of intelligent monitoring and control in current machining processes [10]. In light of these findings, the current study frames the problem of detecting an abnormal condition as a process-optimization problem, where the objective function minimizes classification errors, false negatives, and false positives. The fulfilled research objectives of this study are:

- To develop a complete AI-based workflow that converts raw HDF5 CNC machining signals into structured time-domain and frequency-domain features for normal-abnormal process-condition classification.

- To compare multiple machine-learning classifiers and identify the best-performing model using balanced evaluation metrics suitable for imbalanced manufacturing process-monitoring data.
- To interpret the selected model through signal-feature importance and relate abnormal-process detection to manufacturing process optimization in the automotive industry.

2. Literature review

In intelligent machining systems, current research works have been more concentrated towards making the machine signals useful for predicting the process state, tool condition, and quality aspects of manufacturing. Abnormal cutting in CNC machining results in dimensional variations, surface irregularities, tool wear, and even damage to the machine itself. Machine-learning-assisted monitoring of CNC machines indicates that the decomposed signals along with learning algorithms can discriminate healthy and faulty cutting processes successfully [11]. Decomposition-based methodologies are found to be sensitive to feature selections and machining conditions.

Monitoring of machine signal characteristics online has also been explored in the field of CNC grinding. Real-time machine signal characteristics were utilized for identifying states of grinding in a study [12]. This research area is significant since the identification of states would need to be done online at some point, as opposed to offline, in order to ensure efficient performance of the process. Nonetheless, online state recognition tends to be process-specific and may rely on stable measurement of machine signals. Multi-target condition monitoring of milling has also been attempted through vibration energy characteristics, indicating the value of energy characteristics in machine condition representation [13].

Tool-condition monitoring based on digital twins has become an emerging research area in intelligent manufacturing. Real-time monitoring of tool condition has been achieved via digital-twin-based anomaly detection by integrating data-driven models with dynamic simulations of machining operations [14]. While enhancing process understanding, digital-twin systems usually need detailed information about the process. Physics-guided neural modeling has also been used for predicting wear of machining tools, proving that physics-based domain knowledge can help increase the reliability of predictions [15]. However, physics-guided models could be hard to generalize if the datasets lack tool geometry, material, and cutting force information.

Further investigations on condition monitoring support the use of machine learning in predictive maintenance. Studies on machine learning algorithms for monitoring bearings and grinding machines have focused on ongoing issues in feature selection, signal integrity, and generalization [16]. Research in milling operations has similarly demonstrated that the reliability of measurements and the interpretation of signals are necessary for successful tool condition monitoring [17]. Based on the above analysis, it is clear that AI-based machining monitoring needs to consider signal measurement and feature extraction beyond just classification.

Machining prediction can also be accomplished using deep-learning and sequence modeling methodologies. The application of advanced encoders and recurrent networks for intelligent prediction of tool wear has demonstrated the feasibility of using sequential modeling for describing tool wear dynamics [18]. Nevertheless, such approaches typically necessitate abundant sequential data and can be more resource-intensive than traditional machine-learning algorithms. Real-time monitoring of tool breakage in varying machining conditions has also emphasized the requirement for reliable measures for monitoring tools under non-stationary machining conditions [19].

However, such research tends to concentrate on certain fault types without relating abnormal-state detection to process improvement.

Recently, there have been efforts made towards bridging process modeling with process monitoring and control. The concept of integrated cutting-model-based digital twins has been considered in process monitoring in small-batch machining applications by emphasizing the benefits of integrating machining domain knowledge with intelligent monitoring systems [20]. This may pose challenges when working only with archived data sets such as industrial HDF5 signal files.

Indeed, earlier research provides solid foundations in CNC health monitoring, vibration analysis for condition monitoring, digital twin anomaly detection, tool wear, predictive maintenance, and measuring systems for machining processes. However, most of these works pay particular attention to specific problems like tool wear, grinding conditions, tool failure, or digital twin control. What is novel about this current work, however, is not developing another machine learning classifier, but rather the combination of raw signal extraction in HDF5 format, time-frequency features, comparison of various machine learning techniques, model agnostic explanation techniques, and process optimization interpretation in one automotive CNC case study framework.

3. Methodology

3.1 Research Design

In this study, a quantitative experimental research approach is used in order to develop a new workflow that relies on artificial intelligence for the optimal process monitoring in manufacturing processes, particularly in the automobile manufacturing sector. It should be mentioned that this study does not aim at offering a brand-new AI model for CNC machining operations but aims at showing how a signal-processing to AI approach can lead to such a development. In this study, CNC machining data, which is available in HDF5 format, is processed into both time and frequency domain features to train machine learning classifiers.

The workflow process involves six steps, namely HDF5 file cataloging, machine operation labeling, numerical signal data acquisition, signal feature engineering, AI classification, and process optimization inference. Every HDF5 file is considered a single machining run observation. Process condition is determined by the label of the folder, where good denotes normal machining conditions and bad denotes abnormal machining conditions. The central modelling formulation is:

$$X_i = \{f_1, f_2, \dots, f_n\} \quad (1)$$

where X_i denotes the extracted signal-feature vector of the i^{th} CNC machining run, and $f_1, f_2, \dots, f_n$ represent the engineered signal descriptors. The corresponding target label is defined as:

$$y_i \in \{\text{normal}, \text{abnormal}\} \quad (2)$$

The AI model learns the mapping:

$$\hat{y}_i = f(X_i) \quad (3)$$

where $\hat{y}_i$ is the predicted process condition. In this design, manufacturing optimization is interpreted through the model's ability to reduce process-monitoring errors, especially missed abnormal machining states.

3.2 Data Collection Method and Dataset Description

For the experiment, the Bosch CNC Machining dataset was selected, a real-life industry dataset including HDF5 signal files from CNC machining processes. The dataset hierarchy is formed by machine ID, operation type, and process condition. The files present in the dataset are nested in CNC machine directories like M01, M02, and M03, operation directories spanning OP00 through OP14, and good and/or bad subdirectories in each operation directory, indicating process-condition labels.

The Bosch CNC Machining dataset consists of 1702 .h5 machining-run files. Because the data exist in the form of HDF5 files instead of a plain tabular dataset, the preprocessing step entailed the discovery of all files recursively, metadata reading, extraction of internal HDF5 numeric arrays, and construction of the feature table. Instead of manually specified sensor columns, the independent variables comprise signal descriptions drawn from the numeric arrays stored within the HDF5 files. The output variable is the binary process condition – normal if the file is contained in the good subdirectory, otherwise abnormal.

3.3 Population and Sampling

The population that is represented in the dataset is CNC machining operations related to manufacturing of automotive components. Each individual HDF5 file denotes one such machining run relevant to manufacturing. This is why the data can be used for AI-based process monitoring studies in the domain of automotive manufacturing.

For the modelling sample, each individual HDF5 file was considered one observation, post feature extraction and selection. The selected features were then used for binary classification-based learning models. For splitting the data into train and test sets, an 80-20 split with stratification was implemented. The rationale for stratification was the relative scarcity of abnormal machining runs compared to normal runs. As a result of this class imbalance, stratification was required to maintain the class distribution in the training and test splits.

3.4 Data Analysis Technique

Initially, the numeric data was extracted automatically from every file. Whenever necessary, numeric signals were transformed to one-dimensional signal vectors. Using these vectors, features were extracted in time and frequency domains. The features considered in the time domain included mean, standard deviation, variance, minimum, maximum, median, root mean square, skewness, kurtosis, peak-to-peak amplitude, energy, mean absolute value, crest factor, shape factor, impulse factor, and zero-crossing rate. Frequency-domain features were extracted through fast Fourier transformation and included dominant frequency, spectral centroid, spectral energy, spectral entropy, spectral spread, and band-power features over different frequency ranges.

In the second step, constant features, non-informative features, and labels were removed. The missing data was imputed using the median technique, and then binary encoding was applied on the labels. Several machine learning classifiers were tested against each other, which included Logistic Regression, Support Vector Machine, Random Forest, Extra Trees, Gradient Boosting, XGBoost, LightGBM, and CatBoost.

Performance metrics for the model included accuracy, macro precision, macro recall, macro F1 score, weighted F1 score, ROC AUC, confusion matrix, and cross-validation macro F1 score. The F1 scores and recall for the abnormal class, along with the model's behavior with regards to false negatives, take precedence over accuracy since the dataset is skewed. The technique used for interpreting the models was permutation feature importance.

The optimization objective was formulated as:

$$\min J = \alpha E_r + \beta \text{FNR} + \gamma \text{FPR} \quad (4)$$

Optimization is defined in this work in terms of process monitoring optimization rather than physical optimization of the manufacturing process. Optimization goals include minimizing classification error, false negative, and false positive errors to enable more reliable detection of abnormal states of CNC machining. As such, the machine learning model serves as a support tool in quality monitoring and maintenance, but does not control the manufacturing process autonomously.

where E_r is the overall classification error rate, FNR is the false-negative rate for abnormal machining states, FPR is the false-positive rate for normal machining states, and α , β , and γ are weighting coefficients. This statement is pertinent for manufacturing purposes as failure to identify any abnormality will lead to malfunctioning parts, damaged machinery, or even unnecessary downtime in production.

3.5 Ethical Consideration

Since the research involves artificial intelligence in generating signal data from industrial processes without any human subjects and their personal information, the threat associated with confidentiality and risk of informed consent violations is minimal. However, there are still other ethical issues in the development of AI that should be considered, especially when quality control decisions are made using AI process monitoring models.

The issue of bias has been addressed through class imbalance awareness, the application of stratified sampling methods, and macro-scale performance indicators. This model should be used as a tool in making judgments rather than an independent tool itself, and hence, should always be supervised whenever deployed in real-life settings since a negative prediction can miss abnormal states in the processes while positive predictions can unnecessarily cause inspections.

4. Results

4.1 Dataset Distribution and Experimental Sample Structure

The experimental data set consisted of 1702 HDF5 machining run files from the Bosch CNC machining data set [21]. Each file corresponds to a single CNC machining run and has a process condition label based on the directory hierarchy, where good was considered normal and bad was considered abnormal. The total number of normal data entries was 1632, while the number of abnormal data entries was only 70. This demonstrates that the data set was highly unbalanced, indicating a strong industrial fault detection scenario.

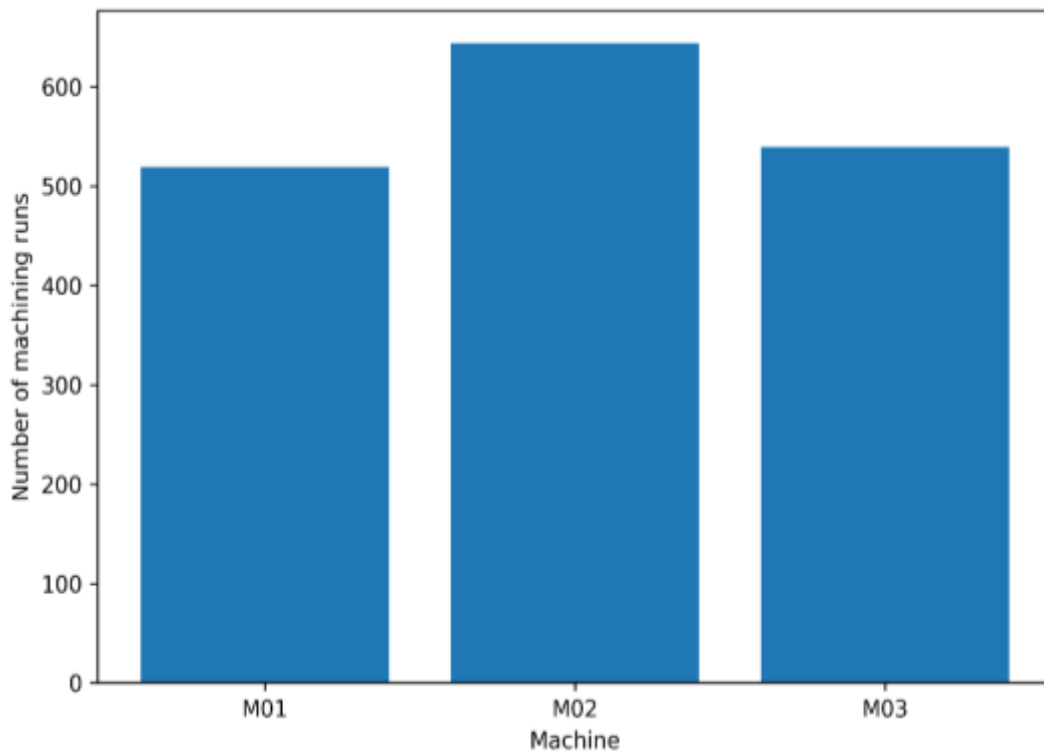


Figure 1. Distribution of samples across CNC machines.

The distribution of samples within the three CNC machines used in the experiment is shown in Figure 1. The maximum number of samples was provided by M02, followed by M03 and M01. The existence of three sources of samples makes the model more robust since it will not be limited to a particular machine.

The distribution of samples between the machines was relatively uniform, with M01 having 519 samples, M02 having 644 samples, and M03 having 539 samples. Therefore, it can be deduced that the model was trained on machining signals obtained from different CNC machines. At the operation level, there were 15 operation classes, ranging from OP00 to OP14. The operation classes with the most samples were OP07, OP02, OP01, and OP13, whereas OP03, OP11, OP00, and OP14 had fewer samples.

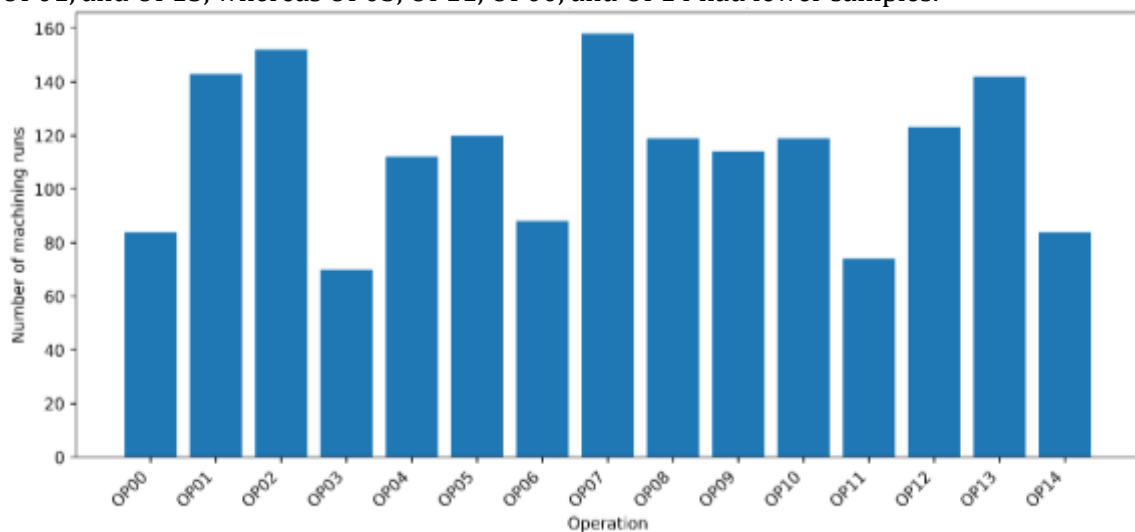


Figure 2. Distribution of samples across CNC operations.

Figure 2 displays the machining runs possible per operation type. All the operations ranging from OP00 to OP14 have been considered in the dataset, indicating that the selected data represents different manufacturing scenarios and not just one repetitive operation.

Such a distribution highlights that the dataset contains various manufacturing scenarios, including different machining processes, allowing it to be used as a case study for monitoring an automotive component manufacturing process.

Table 1. Dataset composition used for AI-based CNC process classification

Dataset component	Value
Total HDF5 machining runs	1702
Normal samples	1632
Abnormal samples	70
CNC machines	3
CNC operations	15
Extracted signal-feature columns	89
Final modelling features	81
Sampling frequency	2000 Hz

4.2 Signal-Feature Representation and Exploratory Analysis

The original HDF5 machining data files were translated to structured signal feature vectors employing time domain and frequency domain features. The final model matrix included 81 meaningful signal features while excluding non-meaningful and constant features. The list of these features includes root mean square, variance, mean absolute value, zero crossing rate, spectral entropy, spectral spread, spectral center of gravity, dominant frequency, and band power.

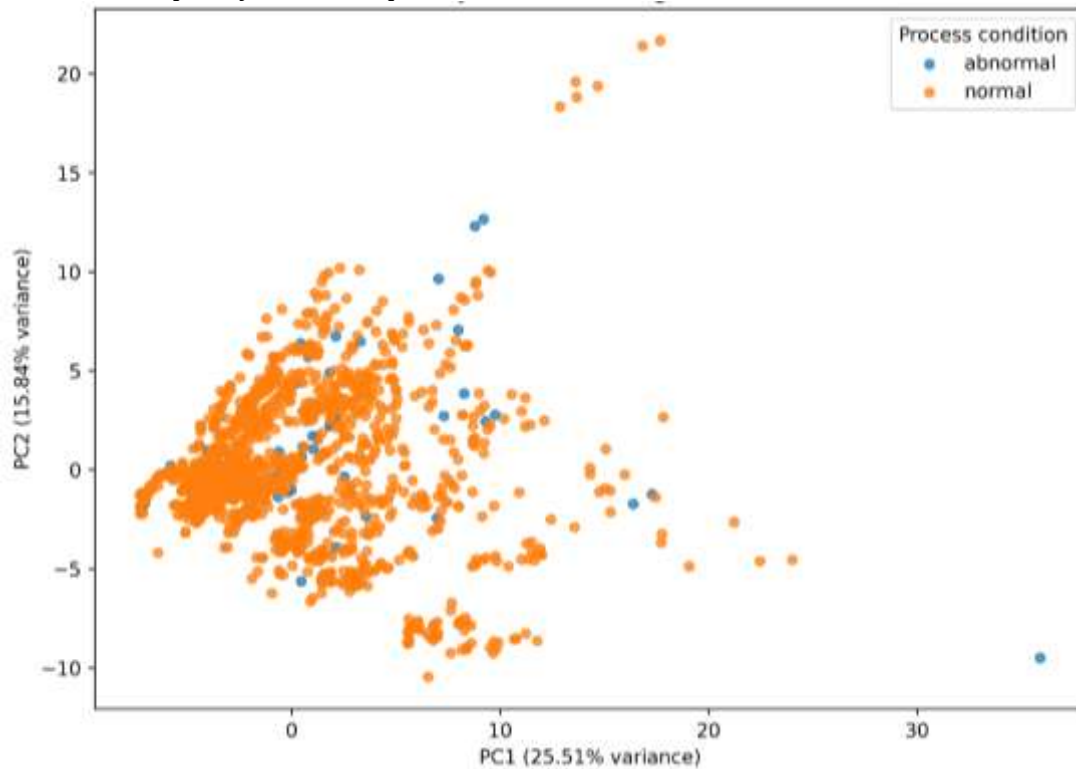


Figure 3. PCA projection of CNC signal features.

Figure 3 depicts the visualization of the extracted signal features in the PCA projection plane, which is a two-dimensional representation of the feature space. The proportion of variance explained by the first and second principal components was 25.51% and 15.84%, respectively. The normal samples were densely clustered, whereas the abnormal samples were relatively scattered in the figure, indicating that the abnormal cases of machining were infrequent and heterogeneous in nature.

The PCA projection presented the low-dimensional projection of the extracted CNC signal features. The first two principal components explained 41.35% of the total variance. From the projection, it was evident that normal samples were densely clustered, whereas abnormal samples were relatively sparse. This observation indicates that, in industrial settings, there is usually repetitive behaviour in production processes, making it high-density in nature, whereas abnormal machining behaviour is relatively infrequent and occurs under multiple vibration conditions.

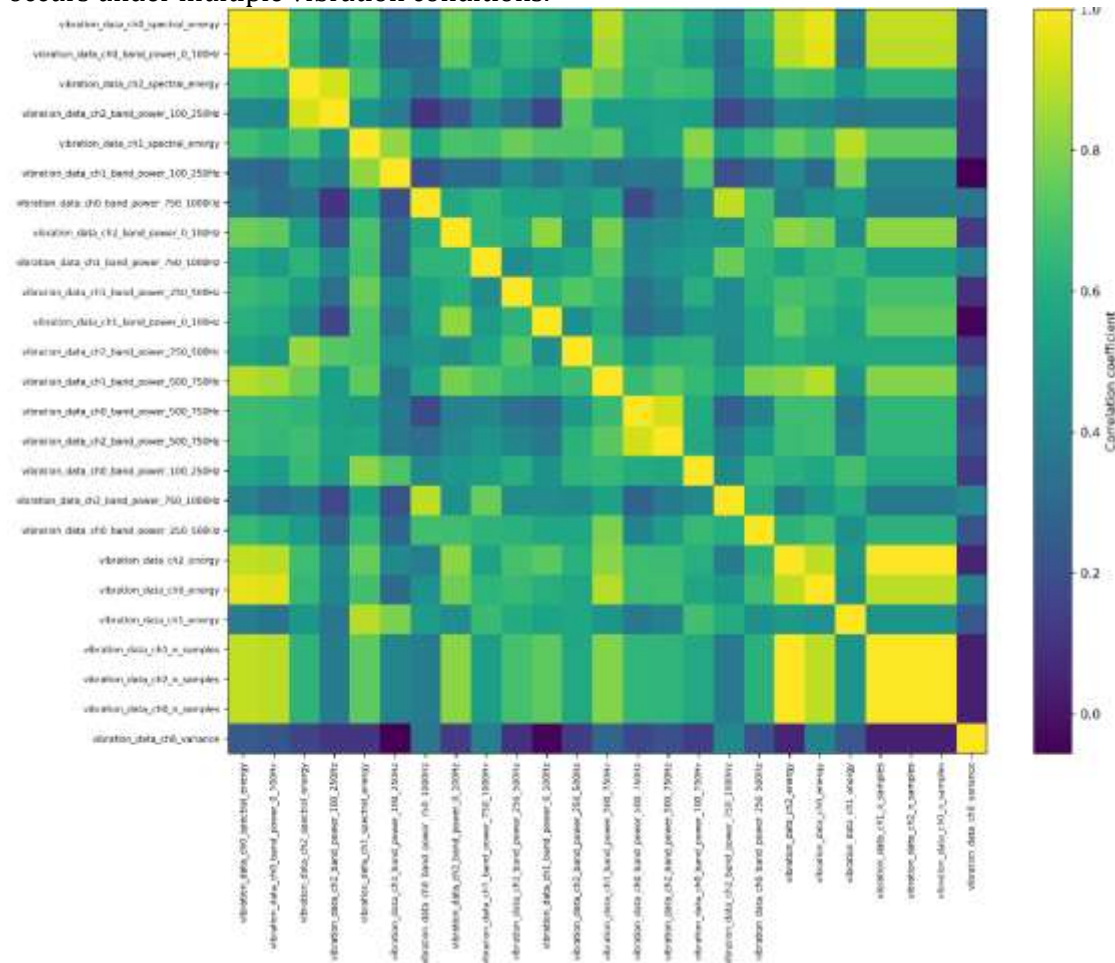


Figure 4. Correlation matrix of top-variance CNC signal features.

Figure 4 demonstrates the structure of correlations between the high-variance signal descriptors. High correlations can be noticed for energy, spectral-energy, and band-power signal descriptors. It suggests that multiple signal descriptors reflect similar vibration-energy behavior.

The correlation matrix of high-variance descriptors revealed high correlation levels for energy, band-power, and spectral-energy signal descriptors. Such results were anticipated since frequency domain power-related signal descriptors often describe

overlapping signal-energy behavior. Nevertheless, the use of both amplitude and frequency-related signal descriptors was still beneficial due to complementary nature of various dynamic machining processes.

4.3 Comparative AI Model Performance

The following eight machine learning classifiers were used for classification: Logistic Regression, SVM (Support Vector Machine), Random Forest, Extra Trees, Gradient Boosting, XGBoost, LightGBM, and CatBoost. The classification results were compared based on accuracy, precision, recall, F1 score, weighted F1 score, and ROC-AUC. Due to the extreme class imbalance, macro precision and recall gained more importance than accuracy.

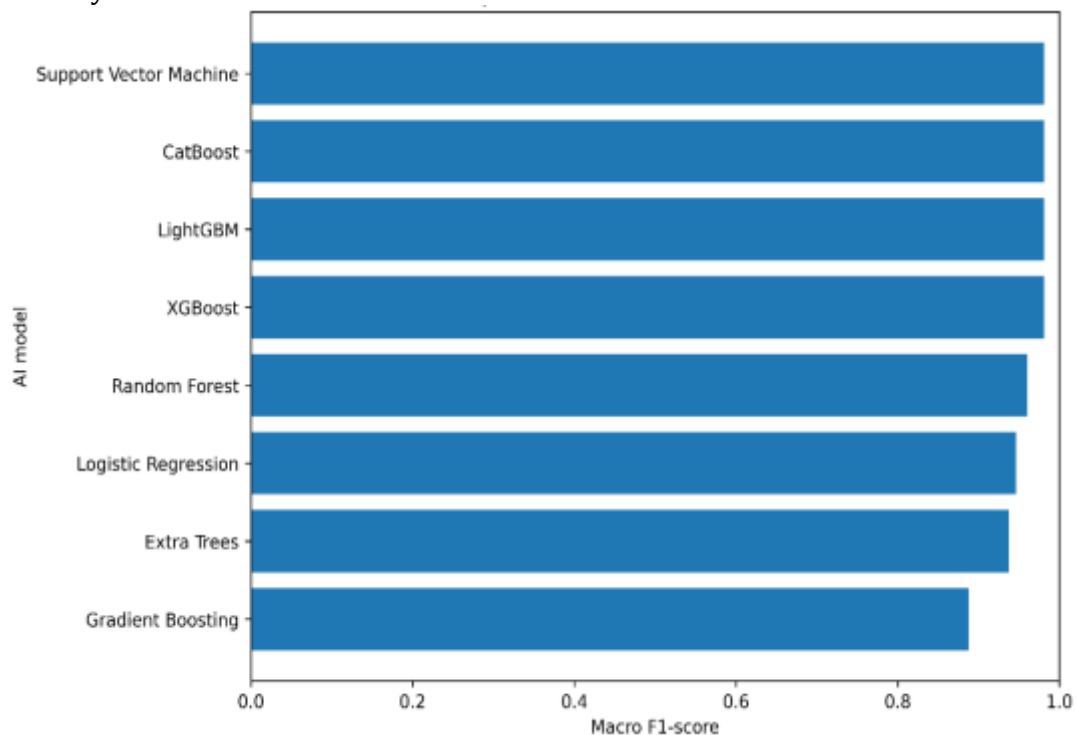


Figure 5. AI model comparison based on macro F1-score.

Figure 5 shows the classifier comparison results through macro F1-score that gives a better indication than accuracy for the case of imbalanced normal vs abnormal classification.

In terms of overall performance, it was clear that the performance of Support Vector Machine, CatBoost, LightGBM, and XGBoost classifiers was outstanding, with each classifier obtaining 0.9971 accuracy and 0.9807 macro F1-score. It should be noted that Support Vector Machine was considered the final classifier due to having the highest macro F1-score and giving the most balanced normal-abnormal classification behavior.

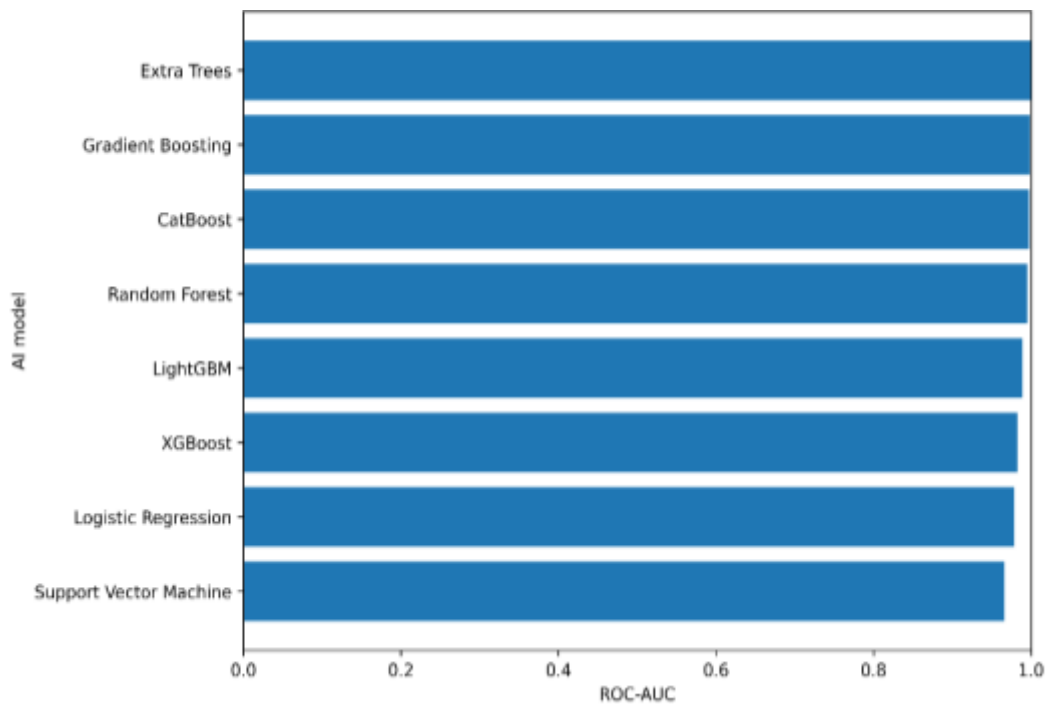


Figure 6. ROC-AUC comparison of AI models.

Table 6 shows the ROC-AUC of the various classifiers used. The Extra Trees classifier, Gradient Boosting classifier, CatBoost, Random Forest classifier, LightGBM classifier, and XGBoost classifier all performed well with high ROC-AUC values, implying a clear separation between normal and abnormal states of machine machining.

The CatBoost model scored the same macro F1 score as the Support Vector Machine model while achieving a high ROC-AUC of 0.9974, which means the boosted tree models had learned highly discriminative boundaries of the signals. The Extra Trees classifier and the Gradient Boosting classifier obtained very high ROC-AUC, but they had lower macro F1 scores.

Table 2. Comparative model performance for normal-abnormal CNC process classification

Model	Accuracy	Macro precision	Macro recall	Macro F1	ROC-AUC
Support Vector Machine	0.9971	0.9985	0.9643	0.9807	0.9661
CatBoost	0.9971	0.9985	0.9643	0.9807	0.9974
LightGBM	0.9971	0.9985	0.9643	0.9807	0.9891
XGBoost	0.9971	0.9985	0.9643	0.9807	0.9825
Random Forest	0.9941	0.9970	0.9286	0.9600	0.9953
Logistic Regression	0.9912	0.9318	0.9612	0.9460	0.9786
Extra Trees	0.9912	0.9955	0.8929	0.9377	0.9989
Gradient Boosting	0.9853	0.9925	0.8214	0.8875	0.9983

4.4 Best Model Classification Behaviour

Support Vector Machine Model was chosen as the most accurate model owing to its higher macro F1 score and balanced classification. Confusion Matrix for the model

revealed that there were 13 true positive abnormalities, 327 true positive normals, one false negative abnormality, and zero false negative normals.

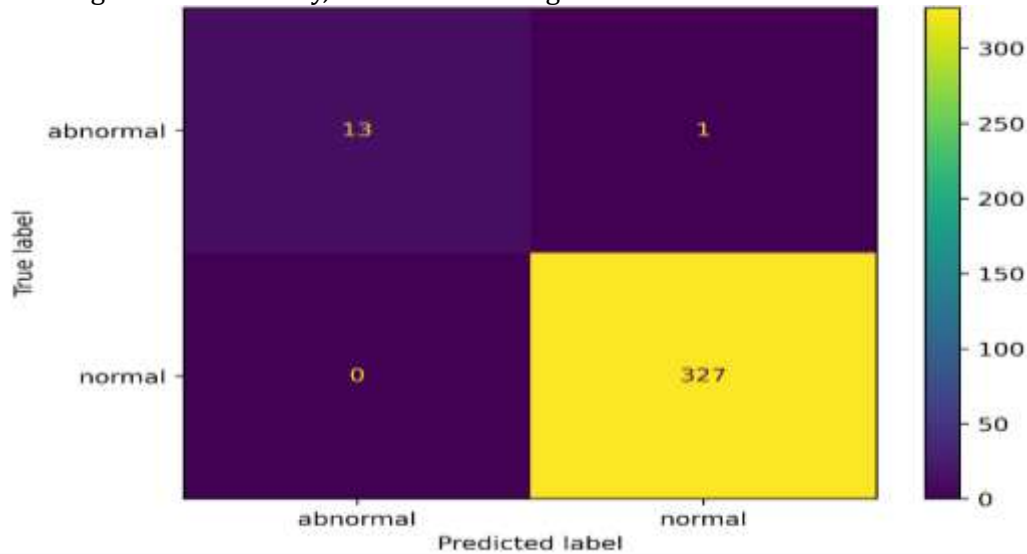


Figure 7. Confusion matrix of the Support Vector Machine model.

As shown in Figure 7, the chosen SVM machine accurately classified almost all test samples. This was because it successfully detected 13 out of 14 abnormal machining runs and accurately classified all 327 normal runs, resulting in the failure to detect just one instance of abnormality while giving zero false abnormal classifications.

The significance of this finding lies in the fact that the classification algorithm used in the model gave no false positive cases for normal machining runs but missed just one abnormal case in the test data set. This was confirmed by the classification report that showed a precision of 1.0000, abnormal recall of 0.9286, and abnormal F1-score of 0.9630 for the minority class.

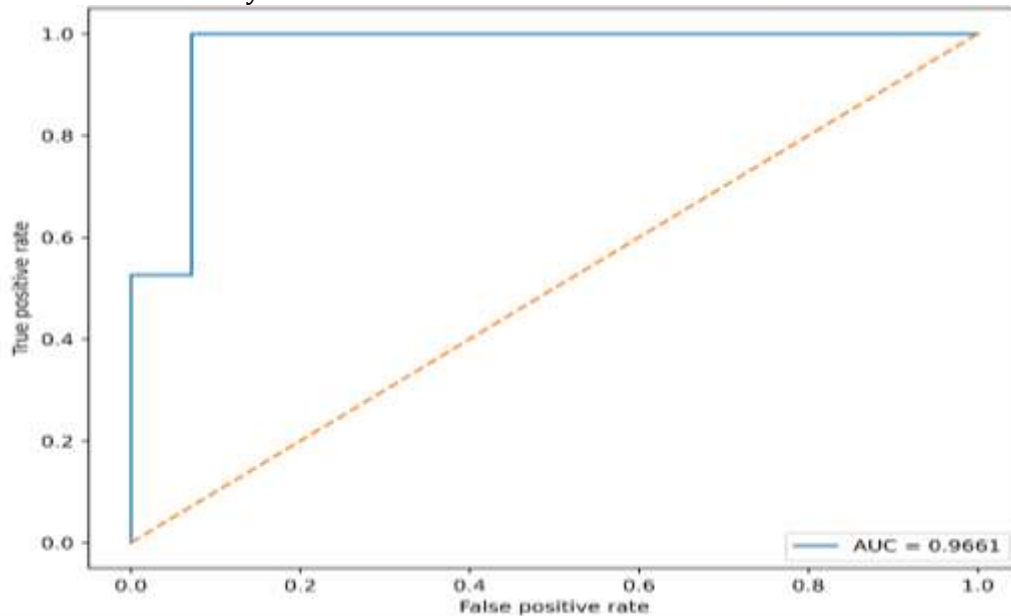


Figure 8. ROC curve of the Support Vector Machine model.

Figure 8 is the ROC plot of the chosen SVM classifier. The classifier obtained an AUC value of 0.9661, which suggests that there is a significant separation between the normal and abnormal CNC machining conditions.

In terms of manufacturing, the one incorrect abnormal classification is much more crucial than the excellent accuracy. The error rate for the abnormal class was 7.14% (one incorrect abnormal classification out of fourteen abnormal test cases). The misclassification rate of the normal class was zero percent, meaning that all normal runs were correctly classified as normal. Hence, the SVM classifier possesses tremendous practical applicability for process monitoring purposes.

4.5 Explainability and Signal Feature Importance

Permutation Feature Importance was utilized for the interpretation of the Support Vector Machine model because it is an explanation technique that is independent of the machine learning algorithm. It involves measuring the decrease in accuracy that results from the random shuffling of one feature at a time.

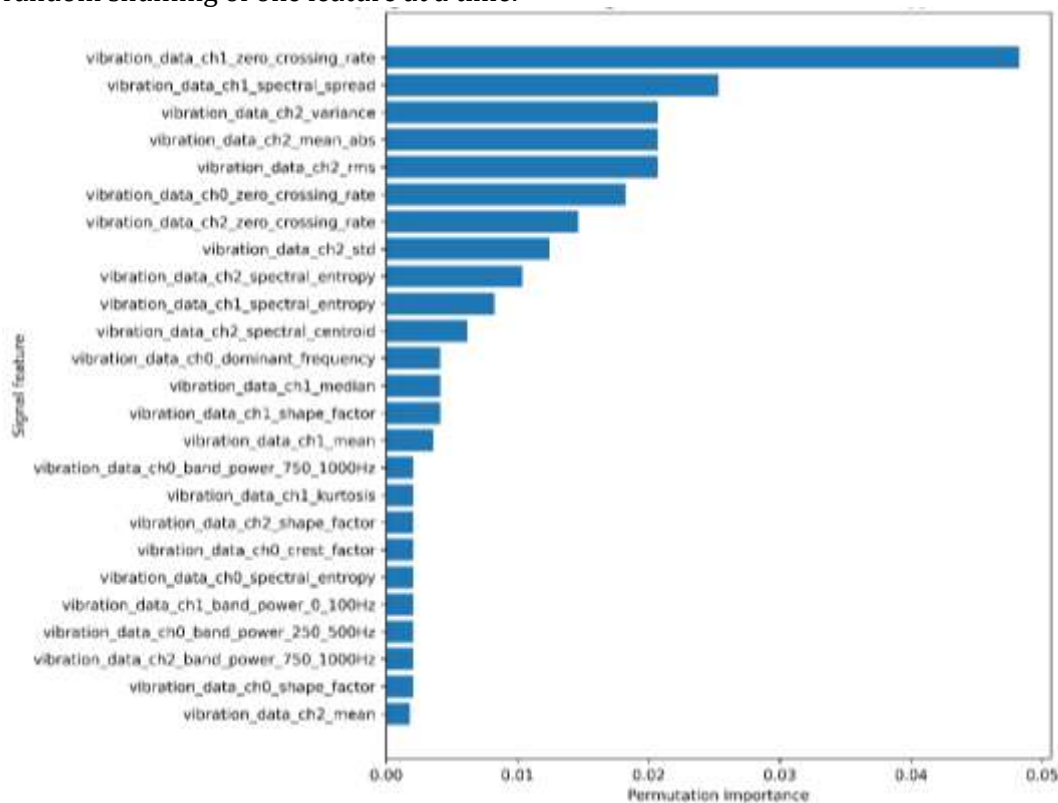


Figure 9. Top signal features influencing CNC process-condition detection.

Figure 9 ranks the most influential signal descriptors according to permutation importance. The most important feature was vibration_data_ch1_zero_crossing_rate, followed by vibration_data_ch1_spectral_spread, vibration_data_ch2_variance, vibration_data_ch2_mean_abs, and vibration_data_ch2_rms.

From the feature-importance findings, one can conclude that the presence of an abnormal CNC process status has a high degree of relationship with the occurrence of abnormalities in vibration oscillation characteristics, vibration amplitude variation, and vibration spectrum variability. Zero-crossing rate is a dominant feature, showing how temporal vibration transition information can help detect unstable machining conditions. On the other hand, RMS, variance, and mean absolute amplitude indicate how

the vibration amplitude and vibration energy change because of unstable interactions between the tool and the workpiece.

4.6 Cross-Validation Stability and Process-Optimization Implications

Five-strata cross-validation was done in order to determine the consistency of the chosen AI model about various train and test sets. This was done since abnormal machined samples are scarce, and one set of train-test split could over or underestimate its performance in the real world.

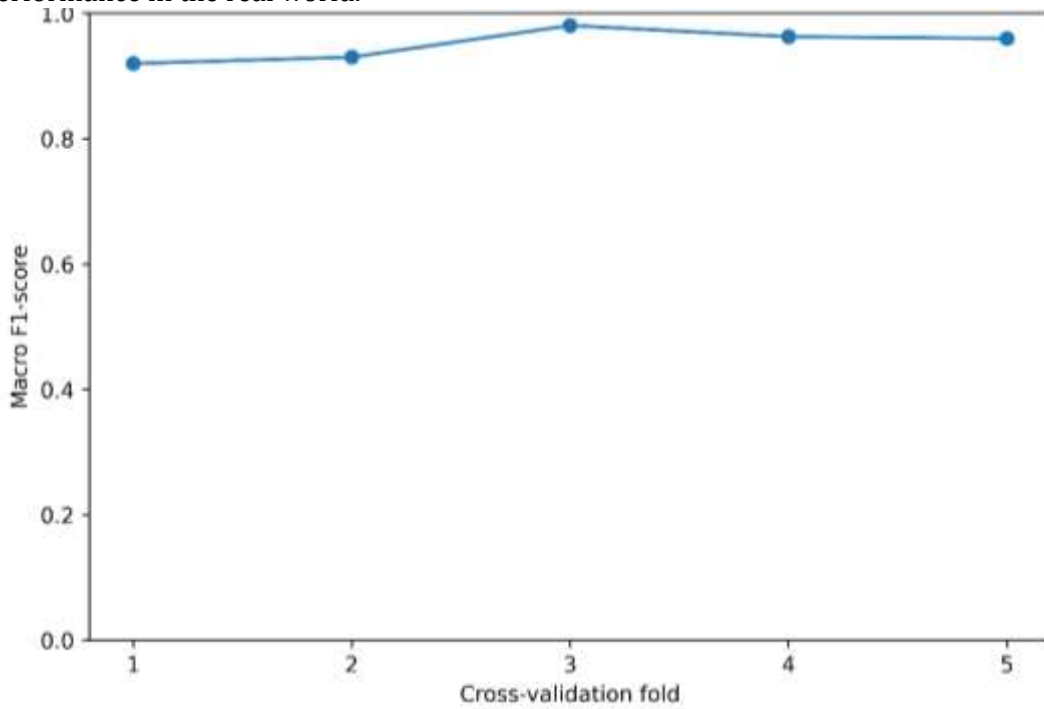


Figure 10. Cross-validation stability of the best AI model.

The Support Vector Machine performed consistently well in terms of its macro F1-score on five validation folds, as indicated by Figure 10. Though some variations existed in individual folds, each one still exceeded 0.92, suggesting a stable balance despite class imbalance.

The five folds' macro F1-scores were 0.9200, 0.9303, 0.9807, 0.9628, and 0.9600. The relatively low macro F1-scores on the first two folds might be caused by the insufficient number of abnormalities, yet both still exceed 0.92, which confirms the consistency of the pipeline.

The results validate the proposed optimization formulation:

$$\min J = \alpha E_r + \beta FNR + \gamma FPR$$

The final model achieved an overall error rate of 0.0029, macro F1-score of 0.9807, macro recall of 0.9643, false-negative rate of 0.0714, and false-positive rate of 0.0000.

Table 3. Process-optimization indicators derived from the best model

Optimization indicator	Value
Overall error rate	0.0029
Macro F1-score	0.9807
Macro recall	0.9643
False-negative rate	0.0714
False-positive rate	0.0000

Correct abnormal detections	13
Missed abnormal detections	1
Correct normal detections	327

This indicates that AI technology can be used for process optimization through analysis of vibration signals and conversion of the information into an indicator of process conditions. Not only does this approach have great potential in terms of precision classification, but it can also help detect abnormalities in time, avoid missing abnormal cases, and aid in decision-making based on data analysis.

5. Discussion

Results indicate the feasibility of converting the raw CNC machining data into a dependable indicator of the process conditions using AI techniques. In addition to being highly imbalanced, meaning that abnormal data points accounted for only a few samples, there is a need to use macro F1-score, abnormal class recall, and false negative rate to measure the effectiveness of the selected Support Vector Machine model in light of its accuracy. The model had a macro F1-score of 0.9807 while identifying 13 out of 14 instances of abnormal machinings in the test data, without making any false alarms in the abnormal sample set. This means that the time domain and frequency domain features successfully captured discriminating properties of the abnormal data points. However, one misclassification is still important because in manufacturing operations, the cost of making a false negative is too high.

These results corroborate past research on health monitoring of CNCs where machine learning coupled with signal-based features could successfully classify normal and abnormal states of machining [11]. Nevertheless, what sets apart the current study is the use of an end-to-end pipeline from HDF5 data to classification and the analysis of the classification results in terms of optimization of the machining process instead of purely relying on fault detection efficiency. Another important point of convergence concerns the relevance of real-time behaviour of machine signals in CNC health monitoring. Similar emphasis can be observed in research on online grinding state identification wherein machine signals were used to estimate process states while operating [12]. Among the most important features derived from vibration signals were zero crossing rate, spectral spread, variance, RMS, and mean absolute amplitude.

The findings provide additional backing to vibration monitoring applications in milling systems, in which it was demonstrated that indicators related to energy could be successfully applied in multi-target condition monitoring applications [13]. In the current case study, energy indicators, as well as amplitude and spectral parameters, have not been utilized individually; rather, they were used as an integral part of a more complex AI-based methodology based on comparing multiple models. At the same time, the results obtained here align with studies based on digital twins that highlight the significance of intelligent monitoring for online information on the state of the tools used [14].

Implication

In practice, an analysis system based on AI can be used to optimize the process of automobile manufacture through the detection of abnormal states in CNC milling operations that may develop into defects or production stoppages. This optimization approach, which aims at reducing classification errors, false negatives, and false positives, is a useful tool for decision-making in industries since any failure in detecting abnormal states is detrimental to operations. Therefore, the proposed model can be used to alert quality control teams, maintenance technicians, and supervisors regarding any unusual behavior of machines in terms of signal analysis.

The present study has certain limitations. Firstly, the evaluation of the workflow occurred in an offline experimental setup based on stored HDF5 vibration/acceleration datasets, instead of real-time streaming data collected from a running production line. Secondly, the model utilizes feature engineering techniques; while time-domain and frequency-domain features increase interpretability, they do not guarantee that all temporal dependencies in the original signal will be retained. Lastly, the dataset suffers from abnormal-class imbalanced learning, since there are many fewer abnormal machined samples than normal machined samples. These limitations were overcome by applying stratified train-test splits, macro F1-scores, ROC-AUC scores, five-fold cross-validations, and false-negative analysis. Nonetheless, additional validation studies are necessary prior to actual application in real-time manufacturing processes.

Potential future work includes extending the framework via leave-one-machine-out validation and leave-one-operation-out validation for testing generalization capacity across different equipment and operating conditions. The deep sequence model, one-dimensional convolutional neural network, and signal transformer models can be applied directly to the raw vibration sequences. In addition, the classifier could be integrated into real-time monitoring dashboard systems, digital twin systems, and adaptive process control systems. Lastly, more abnormal samples from other machines, materials, and cutting conditions should be acquired.

6. Conclusion

The problem considered in the present study is that of optimal automotive process condition monitoring using artificial intelligence for detecting abnormal CNC machining conditions. The issue of interest is whether raw industrial HDF5 vibration/acceleration data can be transformed into useful signals and features indicative of certain machining process conditions, which may allow for process optimization. The solution implemented in the current study involves designing a signal-based procedure, including HDF5 file inspection, machine operation labels extraction, feature engineering (time domain + frequency domain), supervised AI classifiers (multiple algorithms), model comparison, cross-validation, and permutation-based interpretation. The signals collected during each CNC machining process have been processed as vectors, then labeled as either abnormal or normal, and subsequently classified with several machine learning approaches. The results demonstrated that the application of AI-based signal analytics enables distinguishing between normal and abnormal CNC machining behavior. In terms of performance metrics, SVM yielded the highest score in macro-F1 (0.9807), ROC-AUC (0.9661) and missed just one case of abnormal operation within the testing dataset. Permutation-based analysis revealed that zero crossing rate, spectral spread, variance, mean absolute amplitude, and RMS were important features indicative of abnormal machining condition. The novelty of the current study does not lie in the implementation of an artificial intelligence algorithm (such algorithms are widely used), but in the creation of a whole process workflow (extraction, feature engineering, classification, explainability) related to the use of AI for monitoring CNC machine operations in the automotive industry. The most significant limitation of this research is the imbalanced distribution of training and testing sets.

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