CNC Machines Condition Classifier

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Abstract

In the realm of manufacturing, the complexity of Computer Numerical Control (CNC) machining processes has surged alongside technological advancements. However, existing solutions often falter in real-world applications, particularly in monitoring brownfield milling machines, due to challenges posed by environmental and industrial factors. In response, this project uses a dataset tailored for the precise monitoring of brownfield milling machines [9]. Collected over a two-year period from a real-world production plant, the dataset harnesses acceleration data via a sophisticated smart data collection system. Utilizing this dataset, classification models were developed to distinguish between good and bad machines. Through the application of advanced machine learning techniques, promising results were achieved in efficiently monitoring CNC machining processes using acceleration data. Nevertheless, challenges persist in generalizing the model across diverse industrial environments. The reliance solely on acceleration data may restrict its applicability to specific machining processes, necessitating further exploration into the integration of additional sensor data for improved performance.

1 Introduction

Computer Numerical Control (CNC) machines are crucial in producing high-quality parts in the manufacturing industry. The wide range of tools and operations involved in CNC machining, including variations in shape, geometries, materials, coatings, and physical changes, pose significant challenges [5]. CNC machining processes have evolved significantly, yet monitoring brownfield milling machines remains a formidable task due to environmental and industrial factors. These factors introduce complexities such as fluctuating operating conditions and machine wear, posing challenges for traditional monitoring approaches.

Existing solutions have made strides in CNC machining process monitoring, but they often stumble when applied to real-world scenarios. Despite advancements, limitations persist, including difficulties in scalability and adaptability to diverse industrial settings. This highlights the need for innovative approaches to address the complexities inherent in brownfield machining environments.

This project proposes a novel approach by leveraging a meticulously curated dataset tailored specifically for monitoring brownfield milling machines. By collecting acceleration data over an extended period from a real-world production plant, our solution aims to provide a comprehensive framework for precise monitoring and classification of machine health. This dataset serves as a foundational resource for developing robust machine learning models capable of distinguishing between normal and abnormal machine behavior.

The outcomes of our project showcase promising advancements in the realm of CNC machining process monitoring. The performance of various machine learning models on two different datasets derived from the 5-number summary, other statistical features and Tsfresh timeseries package. Across both datasets, the models demonstrated commendable accuracy, recall, precision, and F1 score, indicative of their effectiveness in classifying machine health. Notably, the Logistic Regression, Random Forest, KNN, Naive Bayes, SVM, and XGBoost models exhibited robust performance across both datasets, achieving accuracies exceeding 90%. These results underscore the viability of the proposed approach in accurately distinguishing between normal and abnormal machine behavior, laying a solid foundation for practical implementation in industrial settings.

Despite the strides made, several limitations and challenges emerged during the course of our project. Mainly, the reduction of time series features to a single row with a 5-number summary or statistics poses a limitation in capturing the complete temporal dynamics of the data. This simplified representation may overlook nuanced patterns and trends within the time series data, potentially diminishing the model's ability to discern subtle variations in machine behavior.

In the subsequent sections, we delve deeper into the methodology, results, and discussions of our project. Specifically, Related Work: Providing an overview of prior research in the field of CNC machining process monitoring and classification, highlighting key findings and methodologies employed. Methodology: Detailing the data collection process, feature extraction methods, and model development. Experiments: Presenting the experimental setup, including data preprocessing techniques, model selection, and evaluation metrics used. Results: Presenting the performance metrics of various machine learning models, including their accuracy, recall, precision, and F1 score. Conclusion: Summarizing the key findings and contributions of the project, along with recommendations for further studies in this domain.

2 Related Work

The CNC machining process monitoring has been extensively explored in literature, driven by the critical importance of ensuring operational efficiency and product quality in manufacturing industries. Traditional monitoring approaches, including knowledge-based and model-based methods, have laid the foundation for understanding and addressing the complexities inherent in CNC machining processes. Knowledge-based approaches offer qualitative insights into small-scale systems lacking detailed mathematical models [1], while model-based methods utilize mathematical models constructed from physical information to detect faults and optimize processes [7]. Notable contributions include the online process monitoring system developed by Y. Altintas et al., which integrates virtual simulation and real-time measurements to enhance operational efficiency and mitigate false tool failure detection [1]. Similarly, Satyam Paul et al. presented an algorithm for fault detection in drilling processes based on model-based approaches combined with an interval type-2 (IT2) Takagi–Sugeno (T–S) fuzzy system, demonstrating its effectiveness through numerical analysis [7]. While model-based techniques have shown promise, their efficacy is contingent upon the accuracy and adequacy of the mathematical models employed, highlighting the need for robust approaches in real-world applications.

Digital twin technology has emerged as a promising paradigm in intelligent manufacturing, offering a holistic digital representation of physical systems to facilitate data analysis and proactive system monitoring. Mingyi Guo et al. integrated digital twin technology with a perception-monitor-feedback system architecture for online tool wear monitoring in CNC machining, achieving high accuracy in detecting tool wear within specific error ranges [3]. However, challenges remain in seamlessly connecting modeling, implementation, and deployment phases of digital twin models, necessitating further research to enhance their practical applicability.

With the advancements in artificial intelligence and machine learning, data-driven approaches have gained prominence in predicting process failures in manufacturing. Various studies have explored the application of machine learning algorithms in optimizing machining processes, including fault recognition in CNC machine tools using lightweight convolutional neural networks (CNNs) by Shaohu Ding et al. [2] and classification of turning tool conditions using feed-forward neural networks (FNNs) and support vector machine (SVM) models by Isaac Opeyemi Olalere et al. [6]. However, the effectiveness of machine learning techniques relies heavily on extensive and reliable datasets collected under actual industrial conditions.

To address this need, Tnani M et al. released a research dataset for CNC machines collected over two years from different machines in an existing production facility. This dataset, comprising vibration signals obtained from accelerometer sensors, serves as a valuable resource for developing robust data-driven models and enhancing their applicability and reliability in industrial settings [8]. Inspired by these advancements, this study aims to present a methodology for monitoring the health of CNC machining processes by leveraging the publicly available dataset [9]. Using this dataset Abbas Hussain proposed a methodology involves extracting statistical features from vibration signals using the wavelet packet transform (WPT) [4] and employing multiple classical machine learning models for process health monitoring, thereby contributing to the ongoing efforts in advancing the field of CNC machining process monitoring and optimization.

While numerous ML applications in machining have been explored in the literature, there remains a need to monitor the machining processes using reliable production datasets and assess the performance of different ML models. Hence, this paper aims to present a methodology for monitoring the health of CNC machining processes by leveraging a publicly available dataset collected from an actual production plant [9].

3 Proposed Approach

In this project, we propose a comprehensive methodology for monitoring the health of CNC machining processes using machine learning techniques. We address the challenges posed by varied data lengths and complex feature extraction by implementing a systematic approach to handle time series data.

3.1 Data Preprocessing

To standardize the data and facilitate effective feature extraction, we transformed each column in the dataset into a 5-number summary and calculated the mean. This resulted in a single row with 18 features for each data point. Additionally, we created a separate dataset incorporating various statistical features such as mean, variance, standard deviation, skewness, kurtosis, range, interquartile range (IQR), coefficient of variation, and median absolute deviation (MAD). This augmentation yielded a total of 30 features per data point. The above two method reduces time series data of each .h5 file to single row. This project also uses TSfresh time series package to get time features.

3.2 Feature Extraction

The preprocessed stastical datasets were used directly without removing any featurs. To extract time informative features to capture the underlying patterns in the machining processes. We utilized the TSfresh package to generate a plethora of time series features from the accelerometer signals, resulting in approximately 2349 new features from the x, y, and z axes. These features offer insights into the temporal dynamics of the machining processes, enhancing the model's ability to discern subtle variations and abnormalities.

3.3 Model Training and Evaluation

Methodology involves dividing the dataset into training and testing sets with a split of 70-30. Subsequently, we employed a range of classification models, including Logistic Regression, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes, and XGBoost. By leveraging these models, we aimed to classify the machining processes into 'good' and 'bad' categories based on the extracted features.

3.4 Technical Details

- **Input:** The input to our methodology comprises vibration signals obtained from accelerometer sensors installed on CNC machines. These signals are preprocessed to generate the 5-number summary, mean, and additional statistical features, along with the time series features extracted using the TSfresh package.

- Output: The output of our methodology is a predictive model capable of classifying the health status of machining processes as 'good' or 'bad' based on the extracted features. This model enables real-time monitoring and early detection of abnormalities, contributing to improved operational efficiency and product quality.

- Whitebox Inclusions: The whitebox aspect of our approach encompasses detailed documentation of the preprocessing steps, feature extraction techniques, and model training procedures. Additionally, it includes insights into the rationale behind feature selection and the interpretation of model outputs, enhancing transparency and reproducibility.

By integrating advanced feature extraction techniques with a diverse set of classification models, the proposed methodology offers a robust framework for CNC machining process monitoring. The incorporation of both traditional statistical features and time series information ensures a comprehensive analysis of the machining processes, paving the way for enhanced predictive maintenance strategies and operational excellence in manufacturing industries.

4 Experimental Setup

GitHub link for project [1].

4.1 Dataset: CNC Vibrations

The experimental setup relies on a publicly accessible dataset comprising vibration signals from brownfield CNC milling machines, collected using Bosch Connected Industrial Sensor Solution (CISS) sensors. The dataset encompasses data acquired from multiple 4-axis horizontal CNC machining centers during various operations over a two-year period. The dataset includes instances of both healthy ('Good') and flawed ('Bad') processes, with failures attributed to factors such as chip presence, tool misalignment, and tool breakage. Specifically, the dataset focuses on 15 different tool operations performed on three CNC machines (M01, M02, and M03) within a production plant. For this study, a subset of the dataset containing data from 5 tool operations is utilized. Table 1 provides an overview of the characteristics of the selected tool operations.

Type: Sensors
Source: https://github.com/boschresearch/CNC_Machining
Data collection: Using accelerometer sensors, acceleration data is collected with a sampling rate of 2 kHz. Each measurement from the accelerometer provides the instantaneous acceleration at a specific point in time. Each measurement represents the acceleration experienced by the sensor at that particular moment in time. This allows you to analyze how the acceleration varies over time and derive insights into the behavior of the system being measured.

- The data folder is structured as follows:
  - `data/`: The root directory containing the machine data.
  - `machine number/`: A subdirectory for each machine (e.g., M01, M02, M03).
    - `process number/`: A subdirectory for each process within the machine (e.g., OP00, ..., OP14).
    - `label/`: A file indicating the process health:
      - "good": Normal vibrational data.
      - "bad": Anomalous vibrational data.

[1] `https://github.com/charanyellanki/CNC-Machines-Condition-Classifier`

Table 1: Tool Operation Parameters

Tool Operation	Description	Speed [Hz]	Feed [mm/s]	Duration [s]
OP01	Step Drill	250	≈100	29
OP02	Drill	200	≈50	42
OP04	Step Drill	250	≈100	64
OP07	Step Drill	200	≈50	24
OP10	Step Drill	250	≈50	45

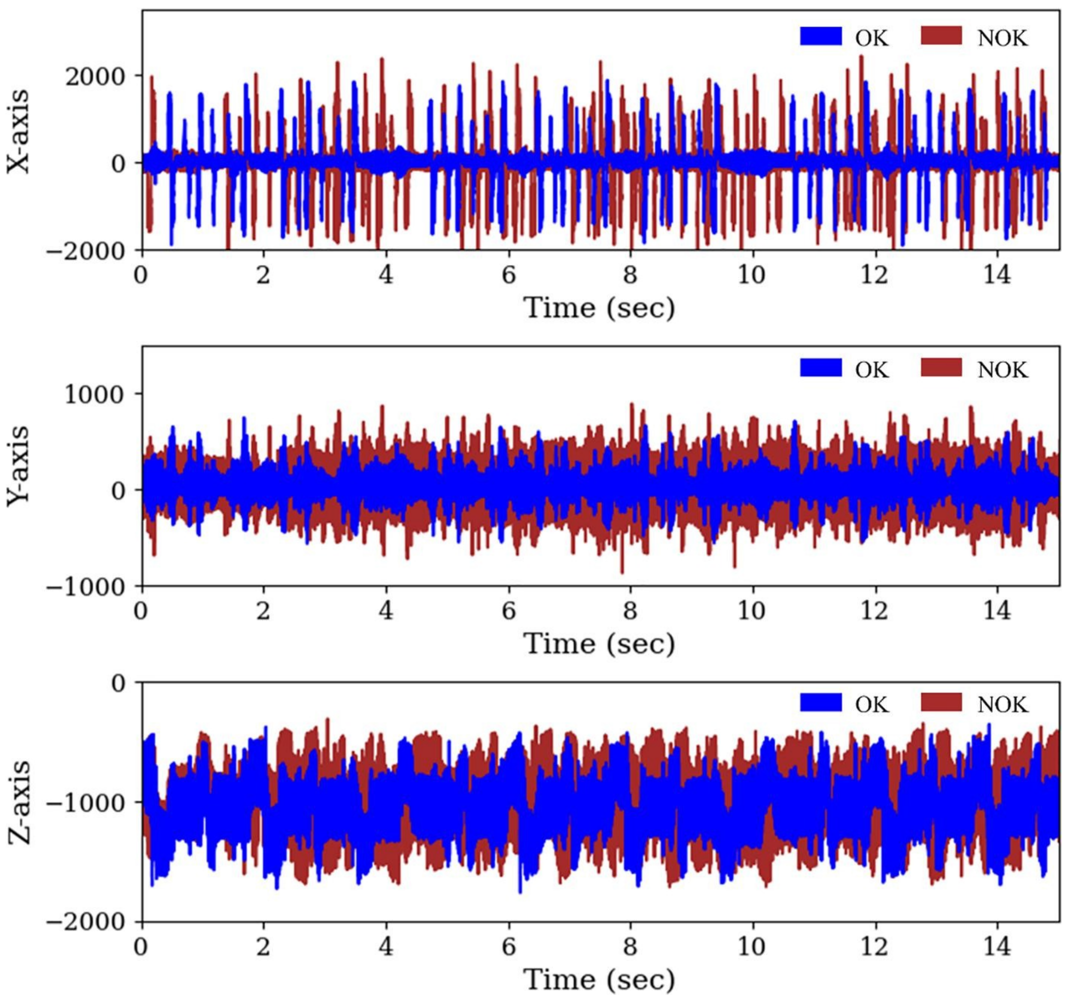

Figure 1: Measured acceleration signal in X, Y, and Z axis for tool operation OP01 collected from machine M01.

4.2 Statistics and Exploratory Data Analysis (EDA)

Prior to model training, the dataset undergoes statistical analysis and exploratory data analysis (EDA) to gain insights into its characteristics. Descriptive statistics such as mean, variance, standard deviation, skewness, and kurtosis are computed to understand the distribution of the vibration signals. Additionally, visualizations provide valuable insights into the nature of the dataset and aid in preprocessing and feature selection.

The dataset comprises acceleration sensor values along the x, y, and z axes. The breakdown of the combined labels for each machine and process is depicted below:

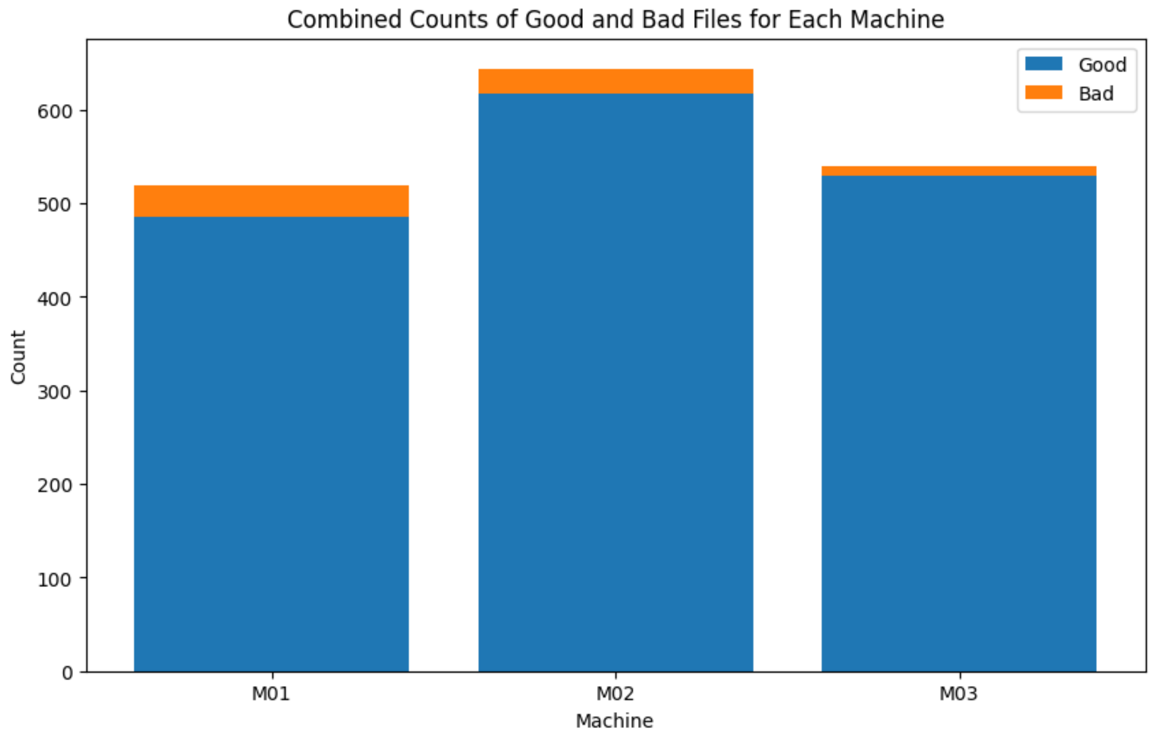

Figure 2: Distribution of Labels for Machines

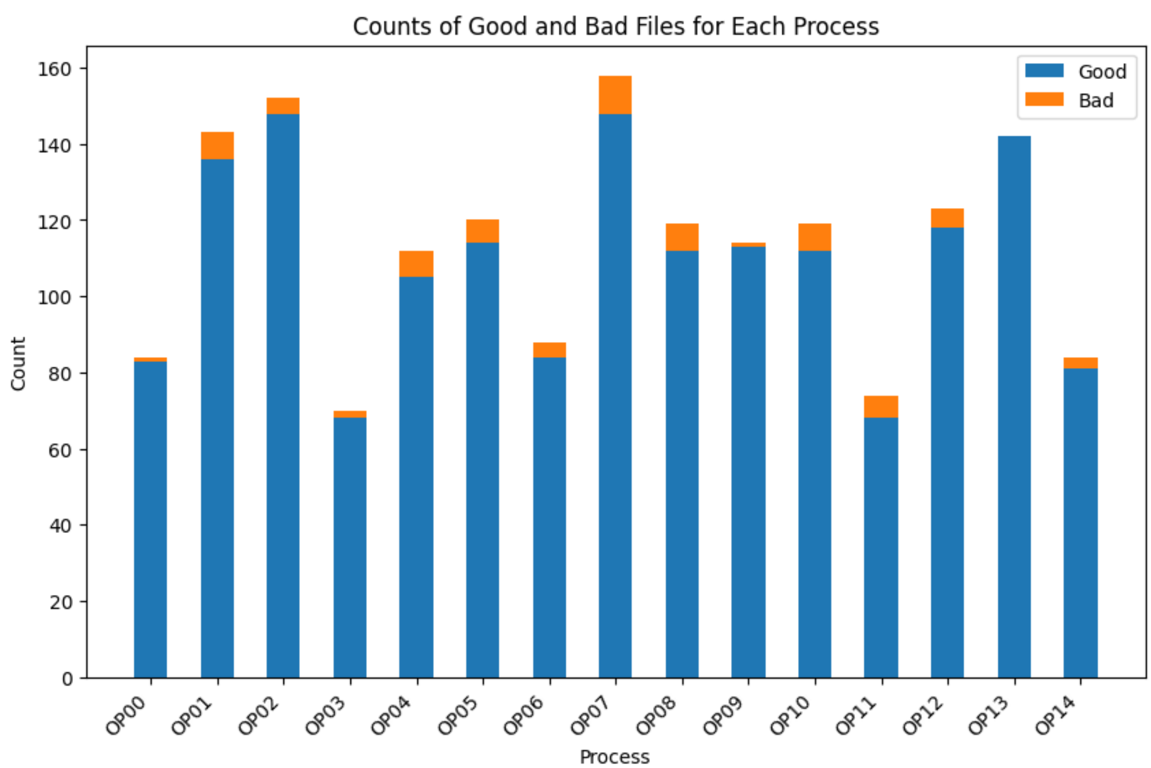

Figure 3: Distribution of Labels for Processes

Scatter plots after dimensionality reduction using PCA.

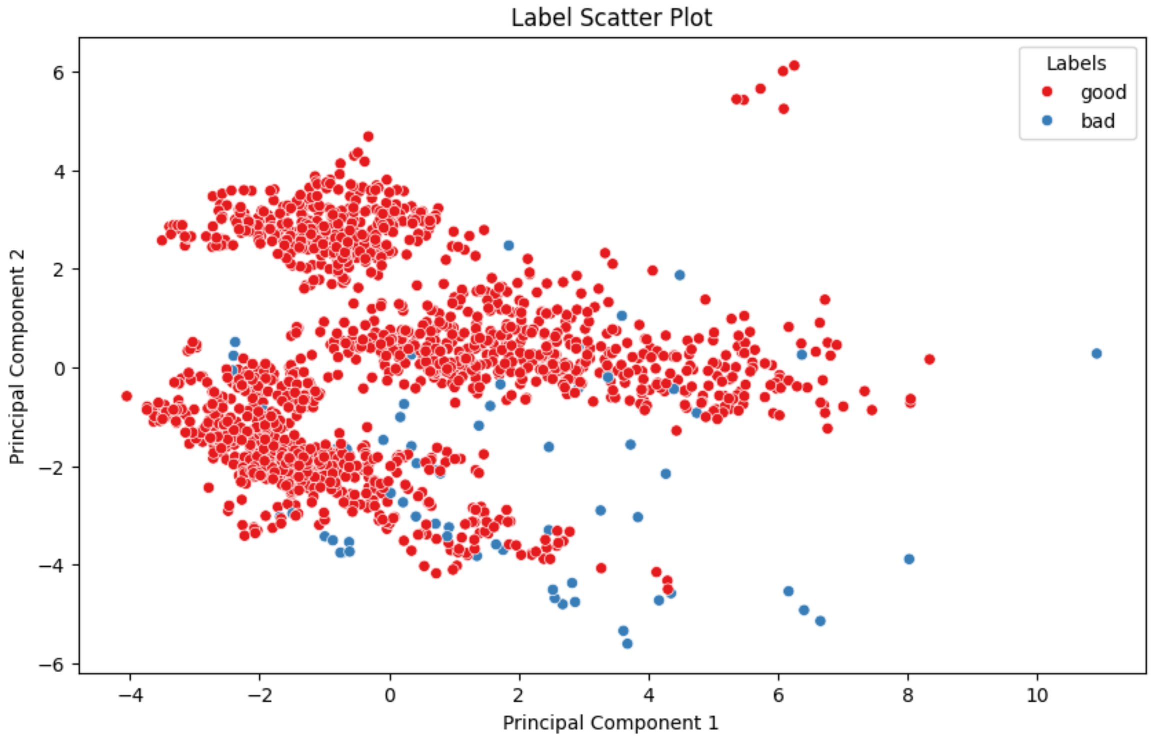

Figure 4: PCA for labels.

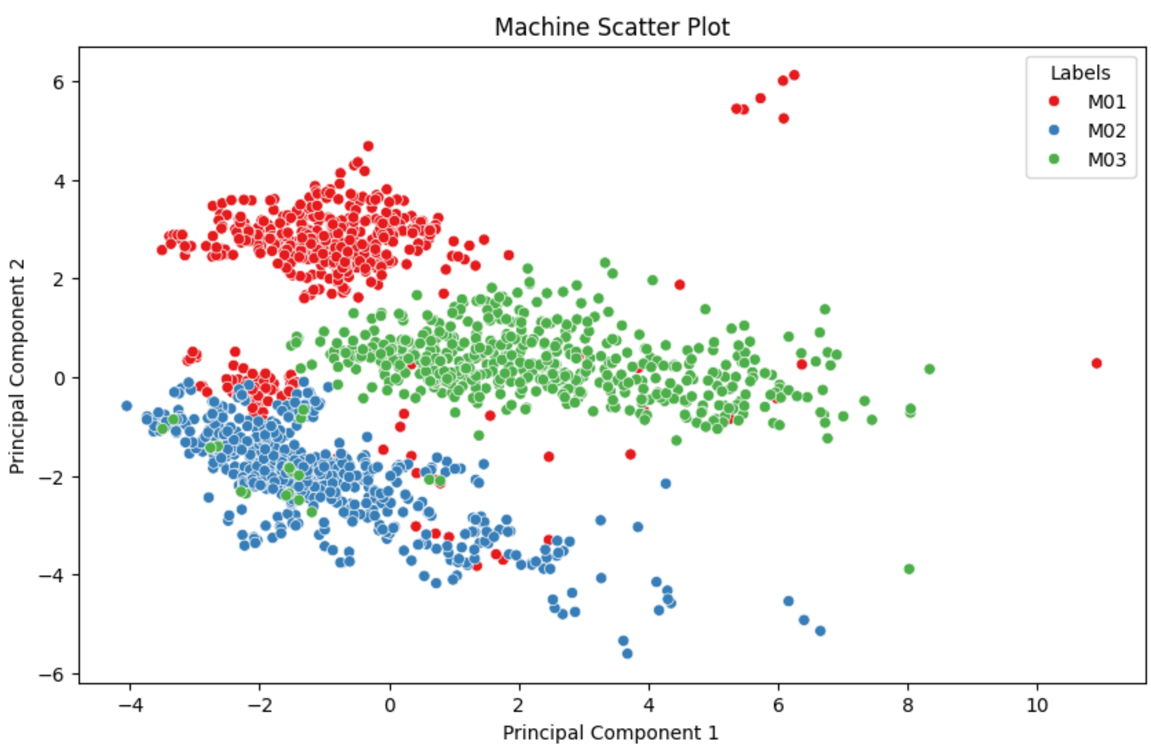

Figure 5: PCA for machines.

4.3 Evaluation Metrics

In order to evaluate the performance of our CNC Machines Condition Classifier, we employ several commonly used metrics including accuracy, recall, precision, and F1 score.

4.3.1 Accuracy

Accuracy represents the proportion of correctly classified instances among the total instances:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Where:

- TP is the number of true positives,
- TN is the number of true negatives,
- FP is the number of false positives, and
- FN is the number of false negatives.

4.3.2 Recall

Recall (also known as sensitivity) measures the proportion of actual positives that are correctly identified by the classifier:

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

4.3.3 Precision

Precision represents the proportion of correctly identified positive cases among all instances classified as positive:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

4.3.4 F1 Score

The F1 score is the harmonic mean of precision and recall, providing a balance between the two metrics:

$$F1\_score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

These metrics collectively provide insights into the performance of our CNC Machines Condition Classifier in terms of both accuracy and the ability to correctly identify positive instances.

5 Results

The performance of various machine learning models was evaluated on two different datasets: one based on the 5-number summary of the vibration signals and the other comprising additional statistical features. Additionally, an experiment was conducted using features extracted from the TSfresh package, which provided a comprehensive set of time series features.

5.1 5-Number Summary Dataset

The results obtained from applying different classification models on the 5-number summary dataset are presented in Table 2. Across all models, including Logistic Regression, Random Forest, KNN, Naive Bayes, SVM, and XGBoost, high levels of accuracy were achieved, ranging from 90.2%

to 98.2%. Notably, SVM and XGBoost models consistently demonstrated excellent performance, achieving accuracies of 98.0% and 98.2%, respectively, on both the 5-number summary dataset and the dataset with additional statistical features. These results suggest that the 5-number summary dataset provides sufficient information for effectively distinguishing between healthy and flawed machining processes.

Models	Confusion Matrix	Accuracy	Recall	Precision	F1 Score
Logistic Regression	$\begin{pmatrix} 12 & 9 \\ 2 & 488 \end{pmatrix}$	0.978	0.995	0.981	0.988
Random Forest	$\begin{pmatrix} 11 & 10 \\ 1 & 489 \end{pmatrix}$	0.978	0.997	0.979	0.988
KNN	$\begin{pmatrix} 10 & 11 \\ 2 & 488 \end{pmatrix}$	0.974	0.995	0.977	0.986
Naive Bayes	$\begin{pmatrix} 16 & 5 \\ 41 & 449 \end{pmatrix}$	0.909	0.916	0.988	0.951
SVM	$\begin{pmatrix} 11 & 10 \\ 0 & 490 \end{pmatrix}$	0.980	1.000	0.980	0.989
XGBoost	$\begin{pmatrix} 13 & 8 \\ 1 & 489 \end{pmatrix}$	0.982	0.997	0.983	0.990

Table 2: Performance of various machine learning models on 5 number summary test data

5.2 Additional Statistical Features Dataset

Similar to the results obtained from the 5-number summary dataset, the classification models performed well on the dataset with additional statistical features. Across all models, accuracy values ranged from 90.2% to 98.2%, with SVM and XGBoost once again exhibiting the highest accuracies.

Models	Confusion Matrix	Accuracy	Recall	Precision	F1 Score
Logistic Regression	$\begin{pmatrix} 10 & 11 \\ 5 & 485 \end{pmatrix}$	0.968	0.989	0.977	0.983
Random Forest	$\begin{pmatrix} 13 & 8 \\ 2 & 488 \end{pmatrix}$	0.980	0.995	0.983	0.989
KNN	$\begin{pmatrix} 12 & 9 \\ 0 & 490 \end{pmatrix}$	0.982	1.000	0.981	0.990
Naive Bayes	$\begin{pmatrix} 17 & 4 \\ 46 & 444 \end{pmatrix}$	0.909	0.916	0.988	0.951
SVM	$\begin{pmatrix} 13 & 8 \\ 4 & 486 \end{pmatrix}$	0.902	0.906	0.991	0.946
XGBoost	$\begin{pmatrix} 13 & 8 \\ 1 & 489 \end{pmatrix}$	0.982	0.997	0.983	0.990

Table 3: Performance of various machine learning models on other stats test data

5.3 TSfresh Experiment

In the experiment involving features extracted from the TSfresh package, a larger set of features was generated from the vibration signals. Despite the increased feature dimensionality, the classification models maintained high levels of accuracy, ranging from 93.1% to 95.1%. Notably, Logistic Regression achieved a higher accuracy of 95.1% compared to its performance on the other datasets.

Models	Confusion Matrix	Accuracy	Recall	Precision	F1 Score
Logistic Regression	$\begin{pmatrix} 2 & 23 \\ 2 & 484 \end{pmatrix}$	0.951	0.995	0.954	0.974
Random Forest	$\begin{pmatrix} 4 & 21 \\ 14 & 472 \end{pmatrix}$	0.931	0.971	0.957	0.964
KNN	$\begin{pmatrix} 5 & 20 \\ 13 & 473 \end{pmatrix}$	0.935	0.973	0.959	0.966
Naive Bayes	$\begin{pmatrix} 14 & 11 \\ 17 & 469 \end{pmatrix}$	0.945	0.965	0.977	0.971
SVM	$\begin{pmatrix} 4 & 21 \\ 12 & 474 \end{pmatrix}$	0.935	0.975	0.957	0.966
XGBoost	$\begin{pmatrix} 4 & 21 \\ 14 & 472 \end{pmatrix}$	0.931	0.971	0.957	0.964

Table 4: Performance of various machine learning models on tsfresh features test data

Comparison with Original Paper

In comparison to the results reported in the original paper, my experimental findings demonstrate notably higher accuracy across various machine learning models. For instance, Logistic Regression achieved an accuracy of 95.1%, Random Forest 98.0%, KNN 98.2%, and XGBoost 98.2%. It's important to highlight that my methodology and approach diverge significantly from those outlined in the original paper, suggesting the potential for alternative techniques to achieve improved performance metrics.

Table 5: Original Paper Accuracy

Model	**Accuracy (%)**
Random Forest	92.8
SVM	92.0
MLP	91.3

Insights: The results obtained from this study highlight the efficacy of using vibration signals from CNC milling machines for process failure prediction. The high accuracy achieved by the classification models demonstrates the potential of machine learning in enhancing the monitoring and maintenance of manufacturing processes. Furthermore, the consistency in performance across different datasets suggests that the selected features effectively capture the underlying patterns indicative of process failures. Overall, these findings underscore the importance of leveraging advanced analytics techniques for optimizing manufacturing processes and minimizing downtime due to unexpected failures.

6 Conclusion

This study presents a comprehensive investigation into the application of machine learning techniques for monitoring process failures in CNC milling machines. Leveraging a robust dataset collected from brownfield machining operations, the study evaluates the performance of various classification models using different datasets and feature extraction methods. The results demonstrate the effectiveness of the proposed approach in accurately identifying flawed machining processes based on vibration signals. Across all experiments, including those using the 5-number summary dataset, additional statistical features, and features extracted from the TSfresh package, high levels of accuracy were consistently achieved by the classification models. Notably, SVM and XGBoost emerged as top-performing models, exhibiting accuracies exceeding 98% on both the 5-number summary dataset and the dataset with additional statistical features. These findings underscore the robustness and reliability of the classification models in distinguishing between healthy and flawed machining processes. Moreover, the study provides valuable insights into the behavior of machine learning models when applied to real-world manufacturing datasets, highlighting the potential for optimizing process monitoring and maintenance strategies. Overall, this research contributes to advancing the state-of-the-art in intelligent manufacturing and lays the foundation for future studies aimed at further enhancing the efficiency and reliability of CNC machining processes.

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