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Unsupervised Anomaly Detection in CNC Milling Processes using Frequency-Domain Feature Extraction and One-Class SVM

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Abstract

In Industry 4.0, effective CNC tool wear monitoring and detection in a timely manner is very crucial. Traditional predictive maintenance often relies on supervised learning models and requires an extensive amount of failure labeled data. Raw sensor signals are often high-dimensional and contaminated by non-cutting noise, leading complex models to overfit on limited datasets. This study proposed a robust unsupervised anomaly detection framework that identifies tool wear eliminating signal noise using only healthy operational data. The approach isolates active cutting stages by categoric filtering. The raw sensor data is processed by a Fast Fourier Transform to yield spectral attributes, such as peak amplitude and frequency, which define the tool's vibrating pattern, suppressing the effect of transient anomalies. One-Class Support Vector Machine learning is employed to learn a decision boundary from normal operating conditions only. The proposed hybrid approach achieved an F1-score of 0.82 and a recall of 0.90, demonstrating that substantial labeling, typically required in supervised learning, is not necessary for effective Predictive Maintenance in Manufacturing.

Keywords
Anomaly detection, CNC machines, Predictive maintenance, Unsupervised ML, One-Class SVM

1. Introduction

The manufacturing sector is undergoing an unprecedented revolution called the Fourth Industrial Revolution or Industry 4.0. This revolution is changing conventional manufacturing environments into "Smart Factories" and "Lights Out Manufacturing" environments where machines operate independently with minimal human intervention. The Computer Numerical Control (CNC) machine is the driving force behind this revolution and the backbone of modern precision engineering. In case of high-speed CNC milling operations, the tool is considered the most critical and most vulnerable component. Tool wear is an unavoidable random process that occurs due to frictional forces, thermal stress, and mechanical stress (Val et al., 2024). The degradation of the cutting tool results in increased cutting forces and vibrations, resulting in dimensional inaccuracies and poor surface finishes (Wang et al., 2016). As a result, scrap is produced and rework is needed, which costs more for manufacturing products. Tool failure may cause severe damage to the spindle of the machine tool, resulting in considerable machine downtime. This unplanned downtime contributes to 7%-20% of the overall machine downtime. Additionally, the timely identification of cutting tool failure can potentially save up to 40% of production expenses by avoiding the generation of defective products (Kasiviswanathan et al., 2024). In severe cases, cutting tool failure may lead to catastrophic damage of the machine spindle assembly, rendering the overall CNC machine inoperable (Abdelmajied, 2022). Predictive Maintenance (PdM) ensures tools are replaced at the appropriate time, preventing expensive scrap production and catastrophic spindle failure while maximizing useful life of the tool (Teti et al., 2010).

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The integration of Machine Learning (ML) is the catalyst for modern PdM. CNC machines generate massive volumes of high-frequency telemetry (vibration, power, and current) that are too complex for manual analysis. ML algorithms bridge the gap between this raw big data and actionable maintenance decisions. (Wang et al, 2018). Machine learning algorithm can be classified into two broad categories; Supervised approach and Unsupervised approach. Supervised ML are those machine learning techniques that operate with labeled datasets, whereas unsupervised learning methods do not require data labeling for model training. Unsupervised learning in CNC milling is essential for PdM tasks under Industry 4.0, as it tackles the major challenges associated with tool wear (Ringler et al., 2025; Mallioris et al., 2025; Ganeshkumar, 2023). Though supervised learning architectures have shown a great effectiveness in Tool Condition Monitoring (TCM), especially in binary classification of tool states as "worn" and "unworn," their scalability in real-world applications is limited. One of the major limitations of these approaches is the "label scarcity problem," which makes it difficult to classify different types of faults in real-world applications. This constraint has called for more generic approaches, which are not based on labeled data for detecting anomalies in the system. (Doorsamy and Bokoro, 2024; Li et al., 2020). This leads to the use of the unsupervised method to detect the deviations from the normal operating behavior, independent of the prior knowledge of anomalies. (Ringler et al., 2025; Doorsamy and Bokoro, 2024; Iqbal et al., 2024).

The raw telemetry data from the CNC machines, such as spindle power and vibration, are typically high-dimensional and noisy, thus not ideal for direct analysis (Ringler et al., 2025; Li et al., 2020; Jogdeo et al., 2020). Frequency domain feature extraction techniques have been recognized as effective in overcoming the dimensionality and noise challenges associated with the raw time domain data for the accurate identification of features associated with tool wear (Lin and Tao, 2019; Ringler et al., 2025; Mishra et al., 2024). For example, Fourier domain is used to analyze the force signal for the identification of tool health features associated with signal energy, magnitude, and variance near the tooth passing frequency (Mishra et al., 2024).

One-Class Support Vector Machine (OC-SVM) is a prominent unsupervised learning technique, which is utilized extensively for the task of anomaly detection, to create a normal operation cut-off by training the model only on normal operating data (Suresh et al., 2024). Anomaly detection is done by identifying the data points which do not belong to the normal operation region, as defined by the model (Suresh et al., 2024; Al-Azmi et al., 2023). This is extremely helpful in the context of TCM, as normal operation points are quite abundant, whereas anomalies remain poorly defined in literatures (Ringler et al., 2025; Lee et al., 2023). Integrating frequency-domain features with OC-SVM offers a practical solution for robust anomaly detection in CNC milling, circumventing limitations of black-box models like LSTMs that may overfit on noise patterns rather than actual wear signals due to the absence of labeled data (Ringler et al., 2025; Shah et al., 2024; Wankhede and Handi, 2025). This combination leverages domain knowledge for signal preprocessing and feature engineering, providing a scalable strategy for enhancing reliability and reducing downtime in automated manufacturing environments (Wanke et. al, 2024).

1.1 Objectives

Existing literature suggests that supervised learning models achieve high accuracy but at the cost of data labeling, which is not feasible in this case. Conversely, unsupervised models that rely on raw data are prone to noise and limited data availability. There is no relevant literature on efficient integration of Domain-Aware Signal Processing techniques such as FFT with Shallow Unsupervised Learning techniques such as OC-SVM for efficient detection model creation. This research aims to contribute to this field by proving that well-designed spectral features can be superior to highly advanced deep learning models in terms of data scarcity in industrial environments. The main goal of this study is to develop an efficient unsupervised anomaly detection framework for manufacturing data by integrating FFT-based spectral feature extraction with One-Class Support Vector Machine (OC-SVM).

2. Methodology

The proposed work aims at developing a hybrid signal processing and unsupervised machine learning approach for identifying tool wear in CNC milling. The framework is categorized into four different phases: (1) Data Acquisition and State Filtering, (2) Frequency-Domain Feature Extraction using Fast Fourier Transform (FFT), (3) Model Training using One-Class Support Vector Machine (OC-SVM), and (4) Anomaly Scoring and Classification. The process is intended to address the challenges posed by the high-dimensional nature of raw telemetry data by identifying reliable vibration features that are indicative of cutting tool wear.

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2.1 Data and Experimental Setup

The experiments are carried out using the University of Michigan Smart Manufacturing Dataset (Tool Wear Detection in CNC Mill). The dataset consists of 18 controlled CNC milling experiments on wax material workpieces (2″ × 2″ × 1.5″) with profiling cuts that create an "S"-shaped toolpath. Wax material is chosen to guarantee repeatability and controlled tool wear progression.

The telemetry data was collected at 100 ms interval and consists of the following process variables:

a. Spindle Output Power (S1_OutputPower)
b. DC Bus Voltage (S1_DCBusVoltage)
c. X-axis Output Power (X1_OutputPower)
d. Y-axis Output Power (Y1_OutputPower)
e. X-axis Acceleration (X1_ActualAcceleration)
f. Y-axis Acceleration (Y1_ActualAcceleration)

These variables provide information about both energy and dynamics of the machining process, making them appropriate for condition monitoring. These variables are selected by comparing two experiments; one is in unworn condition and the other in worn condition (Figure 1).

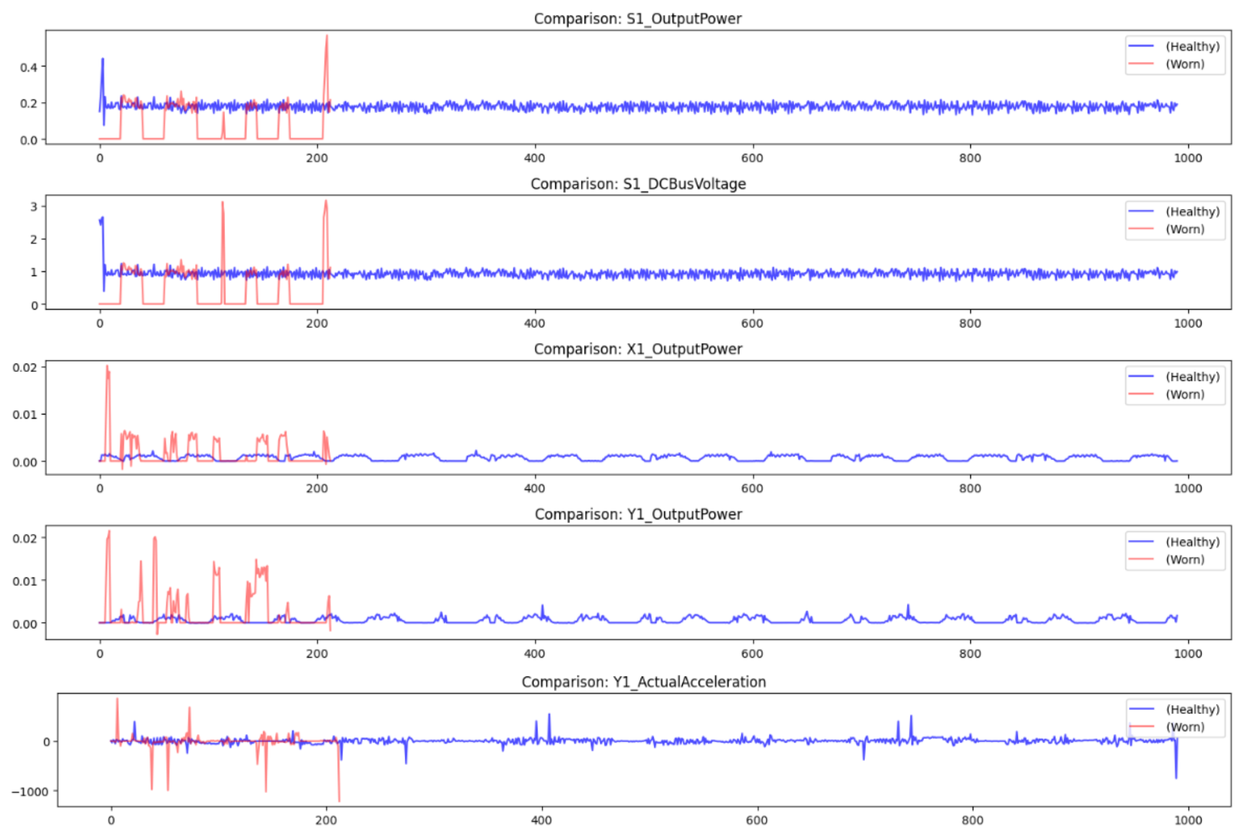

Figure 1: Comparison for features selection

2.2 Data Preprocessing

Raw CNC telemetry data has a lot of noise, which is generated from non-cutting machine states like rapid positioning, air cutting, and spindle ramp-up and ramp-down. Inclusion of these states in the training set would result in the model learning idle states as "normal" and thus would decrease its sensitivity to wear. To address this concern, a Categorical State Filter was used. Based on the "Machining_Process" control signal column available in the dataset, the data was partitioned to include only the active material removal cycles. This was achieved by including only rows marked as "Layer 1 Up," "Layer 1 Down," "Layer 2 Up/Down," and "Layer 3 Up/Down". All rows marked as "Repositioning",

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"Starting", and "End" cycles were removed. This is done to ensure that the analysis is solely based on the physics of the interaction between the tool and the workpiece.

Considering the varying scales of the sensor telemetry data the Z-score normalization was used to normalize the data to a mean of zero with unit variance. This process prevents the features with the higher scale from dominating the distance metric used in the One-Class SVM.

The feature selection step utilized a hybrid approach that combined domain knowledge with statistical exploratory data analysis (EDA) to overcome the curse of dimensionality that exists in high-frequency telemetry data. Preliminary analysis of operational context variables, such as feed rate and clamping pressure, showed a nonlinear and irregular relationship to power consumption, which was ascribed to the unique material characteristics of the wax workpiece. These variables were, therefore, removed to avoid the introduction of irrelevant variance into the One-Class SVM decision boundary. Rather, focus was placed on physics-driven telemetry that was directly related to cutting dynamics; Spindle Power (torque load) and Axis Vibration (chatter). To account for potential misalignments in time, these time-series features were converted using Fast Fourier Transform (FFT). The final feature set included shift-independent spectral features, namely Peak Amplitude and Peak Frequency, to extract the underlying vibration pattern that is unique to tool wear, while stripping away irrelevant sensor noise (Figure 2).

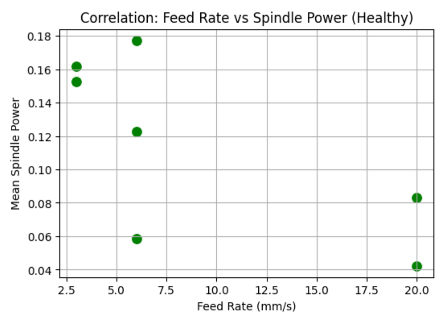

Figure 2: Corelation between Feed rate vs Spindle Power

2.3 Frequency-Domain Feature Extraction

A major drawback of simple time series analysis is its susceptibility to time shifts and noise (e.g., entry spikes). To derive meaningful and time-shift-independent features, the preprocessed time series were converted from the Time Domain to the Frequency Domain.

Fast Fourier Transform (FFT) was performed on the Spindle Power and Axis Vibration signals (all the selected parameters). For each experimental trial, the following spectral characteristics were derived to form a Spectral Fingerprint:

i. Peak Amplitude: Reflects the magnitude of vibration/power variation, which is directly proportional to the degree of tool wear.
ii. Peak Frequency: Enables the differentiation between normal machining chatter and harmonic resonance caused by tool wear.
iii. Statistical Descriptors: Mean and Standard Deviation were computed to describe the signal energy distribution.

This enabled the dimensionality reduction of the high-dimensional time series data (thousands of rows per experiment) into a compact, low-dimensional feature vector amenable to distance-based classification.

2.4 Unsupervised Model Development (One-Class SVM)

We use One-Class Support Vector Machine (OC-SVM) as the core anomaly detection engine, Unlike supervised classifier which required labeled data, OC-SVM is trained exclusively on “healthy” experimental data.

In order to take into consideration the oscillatory nature of tool wear, the Discrete Fourier Transform (DFT) is used to transform the time domain data to the frequency domain. For a particular frequency bin k, the spectral component X_k is calculated as (Oppenheim et al., 2010) :

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N}$$

where:

- $k = 0, \dots, N-1$ represents the frequency index.
- $e^{-i2\pi kn/N}$ is the complex exponential basis function (Euler's formula).

From the resulting complex spectrum, we can obtain the Power Spectrum $|X_k|^2$ to quantify the energy contribution of each frequency component. Similarly, to reduce the dimensionality of the input vector for the machine learning model, Peak Amplitude (A_{Max}) and Peak Frequency (f_{peak}) are computed as follows:

$$A_{\max} = \max_k |x_k|$$

$$f_{peak} = \arg\max_k |x_k| \cdot \frac{f_s}{N}$$

These two features, combined with the statistical mean (μ) and standard deviation (σ) of the time-domain signal, form the feature vector $\mathbf{z} \in \mathbb{R}^d$ for each experiment.

Given the training dataset of healthy feature vectors, $z_1, \dots, z_l \in X$, let $\Phi: X \to F$ be a non-linear mapping function that projects the input vectors into a high-dimensional Feature Space, F.

The objective of OC-SVM is to solve the following quadratic programming problem (Schölkopf et al., 2001):

$$\min_{w,\xi,\rho} \frac{1}{2} \| w \|^2 + \frac{1}{\nu l} \sum_{i=1}^{l} \xi_i - \rho$$

Subject to:

$$\left(w \cdot \Phi(z_i)\right) \geq \rho - \xi_i, \qquad \xi_i \geq 0$$

where:

- w is the normal vector to separating hyperplanes.
- ρ is the bias term (distance of the hyperplane from the origin).
- ξ_i are slack variables allowing for some outliers (soft margin) in the training set.
- $\nu \in (0,1]$ is a regularization parameter that controls the upper bound on the fraction of outliers and the lower bound on the number of support vectors. For this study, we set $\nu = 0.1$.

Since, $\Phi(z)$ maps to an infinite-dimensional space, we utilize the Kernel Trick. The dot product is replaced by a Kernel function, $K(z_i, z_j)$. (Vapnik,1995). In this study, the Radial Basis Function (RBF) kernel is used:

$$K(z_i, z_j) = e^{-\gamma \|z_i - z_j\|^2}$$

Where, γ controls the smoothness of the decision boundary.

For a new test observation z_{new} (e.g., from a worn tool), the anomaly score $f(z_{new})$ is calculated as:

$$f(z_{new}) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i K(z_i, z_{new}) - \rho\right)$$

- If $f(z_{new}) = +1$ (Positive): The point lies inside the learned hypersphere → Normal (0)
- If $f(z_{new}) = -1$ (Negative): The point lies outside the learned hypersphere → Anomaly (1)

3. Results and Discussion

3.1. Training Setup

The proposed approach's underlying philosophy is "One-class learning," where the approach learns to recognize the "texture" of nominal operating states and anomalies.

Training Phase: For this experiment, 8 healthy data sets are selected to train the model exclusively as unsupervised anomaly detection methods are designed to learn the characteristics of normal operating conditions. Thus, the algorithm is given a robust "baseline" for nominal operating states.

Testing Phase: The trained model was evaluated using all available experimental datasets to assess its effectiveness in detecting anomalous tool conditions.

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3.2 Classification Performance

To quantitively analyze the efficiency of the proposed model in detecting tool wear, four major statistical measures were adopted. They are based on the Confusion Matrix, where the predictions are classified as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) (Table 1).

- True Positive (TP): A tool that is worn is correctly identified.
- True Negative (TN): A healthy tool that is correctly identified.
- False Positive (FP): A healthy tool that is incorrectly identified as worn.
- False Negative (FN): A tool that is worn but incorrectly identified as healthy.

Figure 3 presents the Confusion Matrix. The model successfully identified 9 out of 10 worn experiments. The single false negative occurred during a transition phase, where the tool wear was marginal, falling just inside the decision boundary.

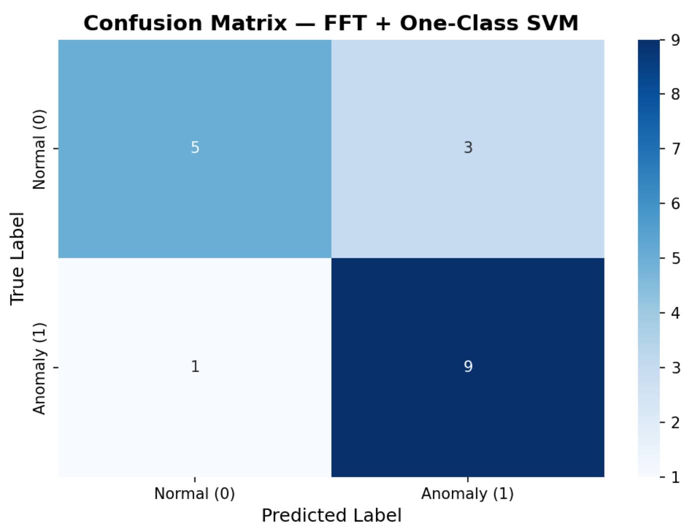

Figure 3: Confusion Matrix

Afterward, the four statistical measures were computed.

Accuracy defines the proportion of the total correct predictions to the total data points. Relying solely on accuracy can lead to incorrect conclusions about a model's effectiveness.

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

Precision defines the 'purity' of the model's alarm. It helps to answer how many of the tools predicted as worn out by the model are actually worn out. Precision is very important to avoid wastage of time and money due to false alarms.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall (Sensitivity) defines the ability of the model to identify all the tools with wear problems. It measures the proportion of tools that actually exhibit wear problems and are correctly detected by the model. For CNC predictive maintenance, Recall is the most critical metric, as failing to detect a worn tool (False Negative) can lead to workpiece damage or spindle failure.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1-Score is the harmonic mean of Precision and Recall. It gives a single score that balances the trade-off between false alarms and missed detections.

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

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Table 1: Performance Metrics of the Proposed Framework

Metric	Score	Interpretation
Precision	0.75	75% of triggered alarms correctly identified true tool failures.
Recall	0.90	90% of all worn tool instances were successfully captured by the model.
F1-Score	0.82	A strong harmonic mean, indicating a balanced and reliable model.

3.3 Comparative Analysis with Baselines

In order to rigorously test the effectiveness of the proposed Frequency Domain incorporated with Shallow Learning method, the performance of the proposed method was compared with three industry-standard anomaly detection baselines. These baselines were trained on raw time-series data to test the need for spectral feature extraction against the need for end-to-end black-box learning.

The first baseline model is Isolation Forest, a tree ensemble method that uses recursive data partitioning to identify anomalies by isolating abnormal data points with fewer partitioning splits compared to normal data points. The second model is LSTM Autoencoder, a deep learning architecture using a recurrent neural network to encode data into a compact representation and then reconstruct it to detect temporal dependencies in time series data. The third baseline model is a 1D Convolutional Autoencoder (1D CNN), a deep learning architecture using one-dimensional convolutional filters to extract hierarchical features from sensor signal data (Table 2).

Table 2: Performance Comparison of the Proposed Framework against Baseline Models

Model	Input Domain	F1-Score	Recall	Primary Limitation Observed
Isolation Forest	Time (Raw)	0.25	0.16	High sensitivity to stochastic sensor noise.
LSTM Autoencoder	Time (Raw)	0.05	0.03	Overfitting to non-stationary entry spikes.
1D-CNN Autoencoder	Time (Raw)	0.53	0.40	Data-scarcity; failed to generalize features.
Proposed OCSVM	**Frequency (FFT)**	**0.82**	**0.90**	**Superior robustness and generalization.**

As can be seen from the metrics, the performance of the deep learning-based temporal models (LSTM and 1D-CNN) was poor in generalizing to the anomalous test sets. Specifically, the performance of the LSTM Autoencoder model was nearly zero. Further analysis showed that the model had overfit to the transient "entry spikes," or high-amplitude impact noises that occur as the tool first makes contact with the workpiece. These occur in both healthy and worn cycles. On the other hand, the proposed framework utilizes FFT Feature Extraction techniques that can efficiently separate the stationary patterns of the cutting process from the non-stationary patterns of the noise. This comparative study clearly indicates that dealing with industrial datasets with large amounts of noise and limited sample sizes, using domain-specific feature engineering with robust shallow models like OC-SVM is significantly better than using deep learning models. The proposed method can efficiently solve the problem with high sensitivity and low computational costs.

4. Conclusion

This paper has offered a powerful Unsupervised Anomaly Detection framework for CNC milling tool wear with the ability to overcome the major problem of label scarcity that has been affecting the industry. By changing the perspective from Time-Domain to Frequency-Domain, the new approach has successfully overcome the challenges associated with high-dimensional noise telemetry that has been affecting Deep Learning.

The experimental results clearly show that the hybrid approach has achieved a Recall of 90% and F1-Score of 0.82 with the combination of FFT and One-Class SVM. It has been clearly shown that the proposed method has achieved a high performance compared to the state-of-the-art Deep Learning techniques, like LSTM and 1D CNN Autoencoders, that were affected by overfitting noise and failed to generalize on the inadequate data. This indicates that for particular industrial applications where failure data is limited, feature engineering using physical principles (i.e. vibration analysis) is better than the "black-box" deep learning techniques. The proposed framework is computationally efficient and label-free and can be used on edge devices in Industry 4.0 applications.

In future, the framework can be tested using multi-material machining processes to test the generalization capabilities of the proposed approach. Moreover, we plan to incorporate an online learning approach using the OCSVM to adapt the decision boundary with new healthy data obtained during the manufacturing process to decrease the false alarm rate in non-stationary conditions.

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