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An IIOT Approach for Prediction of Machine Failure in Industries Using Edge Software via K Means Clustering

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Abstract

Internet of Things, in this technological era contributes for many applications particularly when we deal this technology in industry, we name it as Industrial Internet of Things (IIOT). In this paper one such application of Industrial Internet of Things, (i.e. by using Internet of things method) for predicting the failure of the machine with the audio signal generated from the machine. Predictive maintenance is a type of maintenance of the machine where the failure of the machine is predicted well in advance, so that the consecutive occurrence of the failure is eradicated by introducing appropriate maintenance measure. Generally, the traditional way of predictive maintenance is based on the statistical tool that is employed so far in many industries. Now a day the recent development of IOT applied for predictive maintenance of the machine can replace the traditional way in orders to increase the life time or operating hours of the machine in production line in a better way. The novelty of this study is by implementing the sensors to trap the audio signal of the machine operation. Now this signal is further fed to edge impulse software for anomaly detection using k means clustering using Edge impulse software. This way of predictive maintenance using IOT would be in line with real time data. The analysis could be further expanded to identify and analyses the type of machine error based on the application of machine learning algorithm.

Keywords: Audio Signal, Edge Impulse, Industrial Internet of Things, k means Anomaly Detection, Predictive Maintenance.

Introduction

One of the challenging task for machine maintenance in industry lies in identifying exactly when the machine fails and how frequent it fails. Generally, this possibility of machine failure is eradicated under predictive maintenance of the machineries in industries. Though its add-on cost, it avoids many repair and breakdown maintenance cost and increases the production by running the machines continuously. For such an important maintenance process, Internet of Things has also contributed its role by diagnosing the machine failure well in advance with recent trends in technology. In this article, Edge Impulse Software is used to predictive maintenance of the machine by tapping the machine sound (audio signal) and finding the point at which anomaly begins. Mihigo *et al.,* (1) developed predictive maintenance model using DNN and TinyML in Edge Impulse software. Fernandes *et al.,* (2) discussed on the existing machine, learning algorithm particularly rule based and partition based using for mechanical fault diagnosis. Vermesan *et al.,* (3) proposed a method in IIOT for temperature monitoring, vibration sensing, sound and ultrasound sensing with various ML and DL algorithms for intelligent edge processing maintenance in manufacturing industries. Nangia *et al.,* (4) proposed a case study on predictive maintenance in automobile industry from traditional system to modern way of diagnosing the machine failure. Him *et al.,* (5) proposed a model for IoT based predictive maintenance in smart manufacturing especially in welding machines. Farahani *et al.,* (6) proposed fog driven IOT architecture. Selcuk *et al.,* (7) proposed how to introduced IoT in predictive maintenance of machines. Rajendran *et al.,* (8) developed fault diagnostic method using FTA. Al-Sheikh (9) discussed on mobile healthcare monitoring system using internet of things for bio signals. Hasan *et al.,* (10) developed an android smart application for an Arduino based local meteorological data recording.

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Fault Tree Diagnosis

The machine failure in industries has greater impact on production output from industries which in turn affects the performance of the industry in global market. The fault tree dragonizes is shown in Figure 1. So, this issue has to be given high priority particularly when we consider production or manufacturing unit where production happens 24/7 x 365 days continuously. The entity like wear and tear which is deterioration of the machine when it runs for long run. Sometimes the machine may get fail due to random handling of inexperienced worker. There are few external factors like fire accident and other violation on safety aspect of machines may also fall as the reason for machine failure. Finally, the lack in proper maintenance policy will also remain as the reason for machine failures in industries. Most of the failures occur because of this lack in proper maintenance policy. Understanding all these reason for failures, it is important for us to predict the occurrence of failures by adopting the technology way of solution for implementing appropriate maintenance policy.

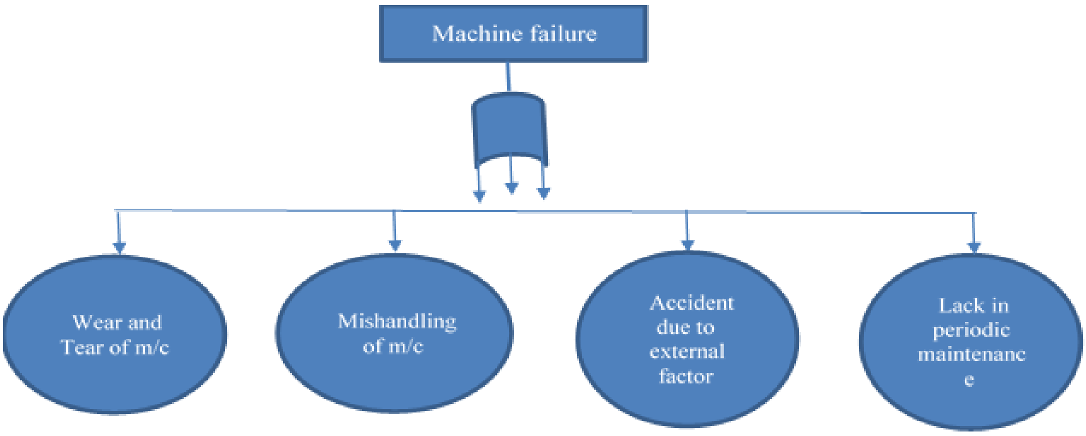

Figure 1: The Fault Tree Diagnosis for Machine Failure

Significance of IIOT

The IIOT plays a crucial role in contemporary industrial operations by integrating advanced connectivity, sensor technology, and data analytics. When combined with machine learning methods for predicting failures, IIoT becomes even more significant due to several synergistic benefits:

1. **Enhanced Predictive Maintenance**: IIoT sensors continuously collect real-time data from industrial equipment, such as temperature, vibration, and performance metrics. Machine learning algorithms analyze this data to detect patterns and anomalies that indicate potential equipment failures before they occur. By predicting failures in advance, maintenance can be scheduled proactively, minimizing downtime and reducing maintenance costs.
2. **Optimized Operations**: Machine learning algorithms can optimize operational processes based on IIoT data. For example, predictive analytics can optimize production schedules by predicting demand fluctuations or adjusting parameters to maximize efficiency and quality. This synergy improves overall operational performance and resource utilization.
3. **Data-Driven Decision Making**: IIoT generates vast amounts of data from various sources within industrial environments. Machine learning algorithms can sift through this data to uncover hidden insights and correlations that human analysis might overlook. This data-driven approach enables informed decision-making, from supply chain management to quality control to inventory optimization.
4. **Improved Safety and Reliability**: By predicting equipment failures in advance, IIoT combined with machine learning enhances workplace safety by preventing potential hazards. Predictive maintenance ensures that critical systems remain reliable, reducing the risk of accidents or disruptions that could impact safety and operational continuity.
5. **Scalability and Adaptability**: The scalability of IIoT solutions allows for the integration of machine learning models across diverse industrial sectors and applications. Whether in

manufacturing, energy, transportation, or healthcare, predictive maintenance powered by IIoT and machine learning adapts to various operational needs and scales effectively with growing data volumes.

6. **Continuous Improvement and Innovation**: The iterative nature of machine learning enables continuous improvement of predictive models over time. By feeding back data on actual performance and maintenance outcomes, these models can refine their predictions, leading to increased accuracy and efficiency in predicting failures.
7. **Competitive Advantage**: Organizations leveraging IIoT and machine learning for predictive maintenance gain a competitive edge by reducing downtime, lowering maintenance costs, and improving overall operational efficiency. This enables them to deliver higher-quality products and services while responding more swiftly to market demands.

In summary, the synergy between the Industrial Internet of Things and machine learning for predicting failures transforms industrial operations by enhancing efficiency, reliability, safety, and competitiveness. It represents a pivotal shift towards data-driven, proactive maintenance strategies that optimize resources and drive sustainable growth in the modern industrial landscape.

Edge Impulse Software

Data Collection and Pre-processing: Edge Impulse provides tools to gather sensor data (vibration, temperature, etc.) directly from IIoT devices. It also offers functionalities for data cleaning and pre-processing, which is crucial for training effective machine learning models.

Model Development with a Low-Code Approach: Edge Impulse offers a user-friendly, visual interface that minimizes the need for extensive coding knowledge. This allows engineers and technicians with domain expertise to build custom models for specific machine types and failure scenarios.

Training on Edge Devices: A key advantage of Edge Impulse is its ability to train models directly on the IIoT devices themselves. This eliminates the need to send data to the cloud, reducing latency and addressing security concerns.

Optimized Model Deployment: Edge Impulse generates lightweight models specifically designed for deployment on devices with limited processing power and memory.

Real-time Anomaly Detection: The trained models can analyze sensor data in real-time on the edge device.

Process of feature Selection: Edge Impulse simplifies feature selection for beginners by offering an automatic approach

The following are the steps involved in automatic feature selection

1. Processing Blocks
2. Calculate Feature Importance
3. Feature Explorer

Visualizing feature and disabling feature are the steps involved in manual selection of features

Reason for choosing k means clustering

There's no single "best" criterion for k-means clustering.

1 .For well-separated, spherical clusters, SSE might be sufficient.

2. For more complex cluster shapes or to assess overall cluster quality, consider silhouette score or Calinski-Harabasz Index.

3. The elbow method can be a helpful starting point to determine the number of clusters (k). The Sum of Squared Errors calculates the total squared distance between each data point and its assigned cluster centroid.

Unsupervised Learning Techniques (Anomaly Detection): These approaches can be used when labeled data for machine failure is scarce. They identify data points that deviate significantly from the norm, potentially indicating anomalies or impending failures.

K-Means Clustering: While primarily used for grouping similar data points, k-means can be used for anomaly detection. Points falling outside of the identified clusters could be flagged as potential anomalies. However, k-means assumes spherical clusters and might not be suitable for complex anomaly patterns.

Local Outlier Factor (LOF): This technique identifies data points that are significantly different from their local neighbors. It's a density-based approach that can be effective for various anomaly detection tasks.

One-Class SVMs: Unlike traditional SVMs that learn from labeled data for classification, one-class SVMs focus on modeling the distribution of healthy data. Points deviating from this learned distribution are considered anomalies.

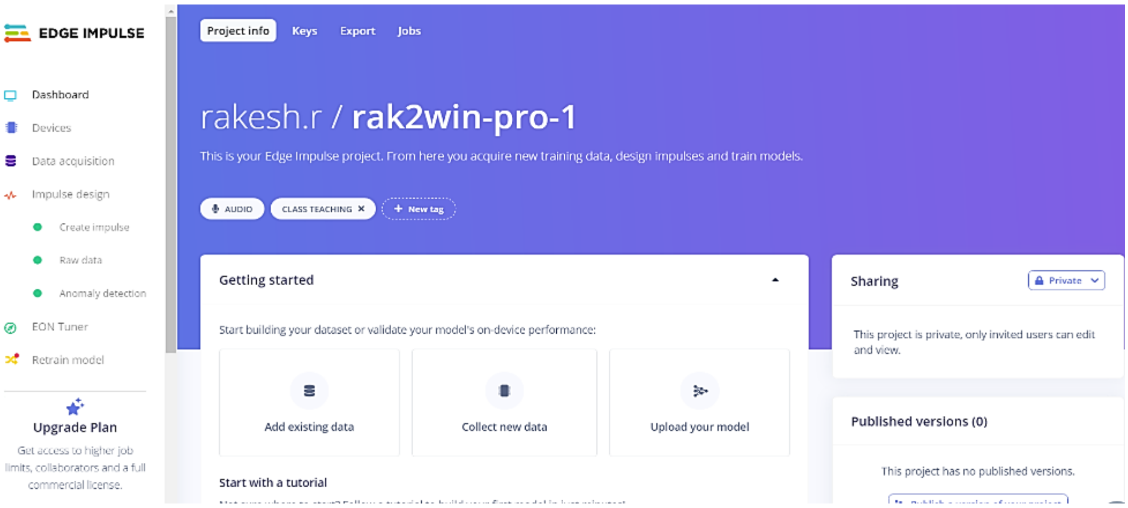

Figure 2: This Project Created in Edge Impulse Software

The audio signal trapped from gear spinning loop is considered as the reference signal. Similarly, the audio signal trapped from gear spinning loop with error is taken as the test signal. The Project is created with user login rak2win, the Figure 2 shows that the two audio signals (ie. Reference signal as shown in Figure 3 and test signal as shown in Figure 4) are given as input to the Edge impulse software (11). Now two spectrograms are considered in order to have accuracy in the anomaly detection method. Based on the feature generated, the reference signal is compared with the test signal twice for both the chosen different spectrum. The final graph obtained shows the anomaly detection between the reference and test signal. If there is no error (or anomaly), it means the life time span of the spinning machine is good in condition and there is no need for any predictive maintenance measure. Vice versa, if there is any occurrence of anomaly detected, then it means there is an immediate need of the predictive maintenance measure.

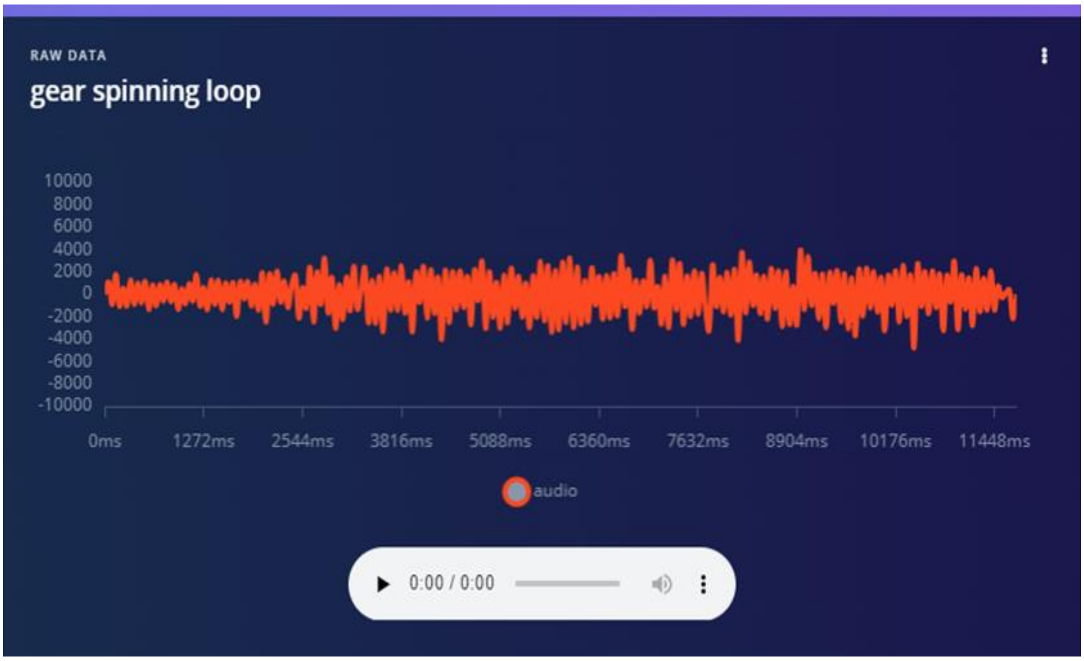

Figure 3: Reference Signal

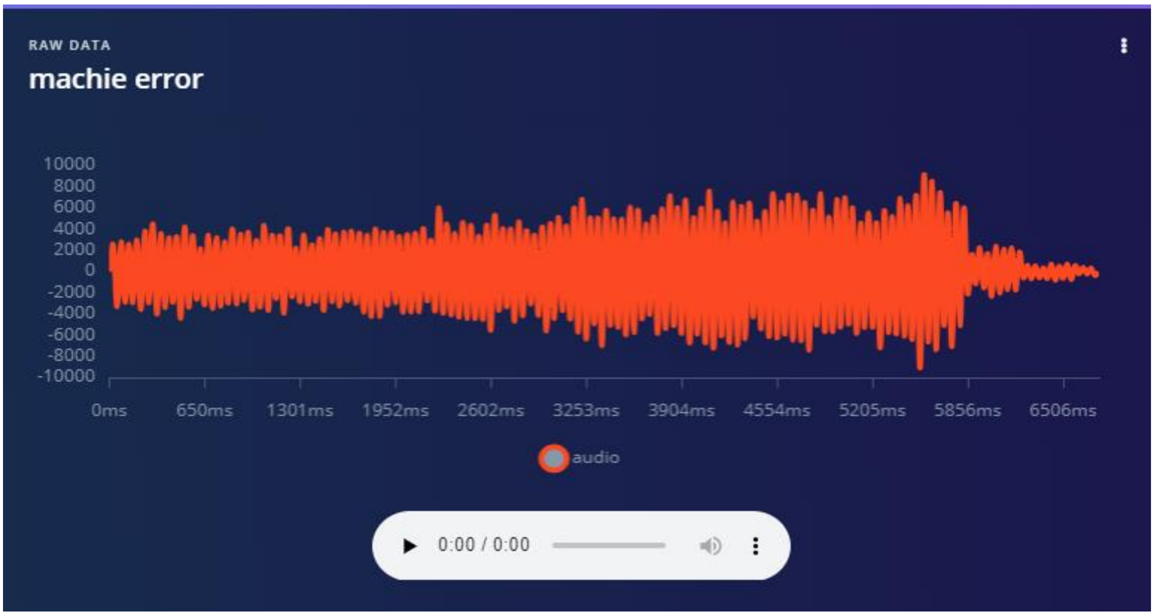

Figure 4: The Test Signal

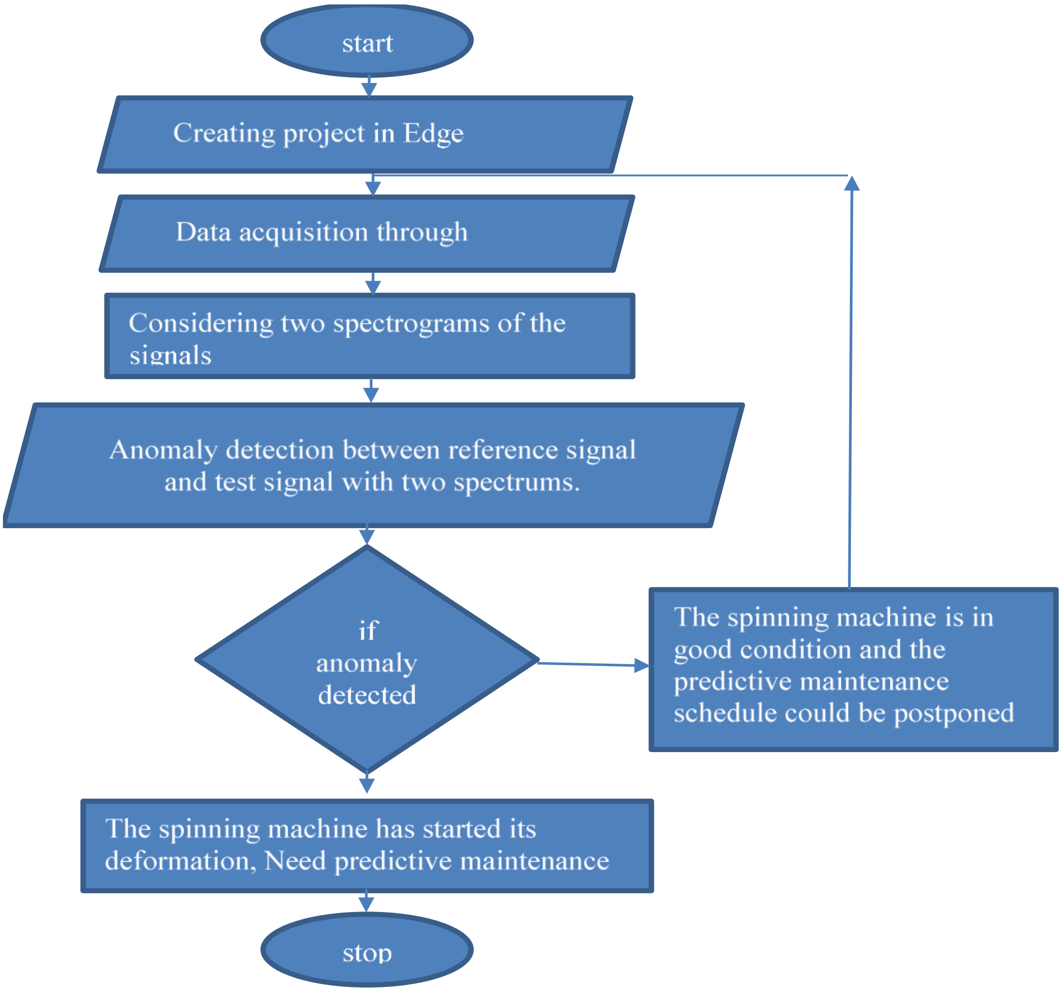

Figure 5: Flowchart Showing the Overall Methodology

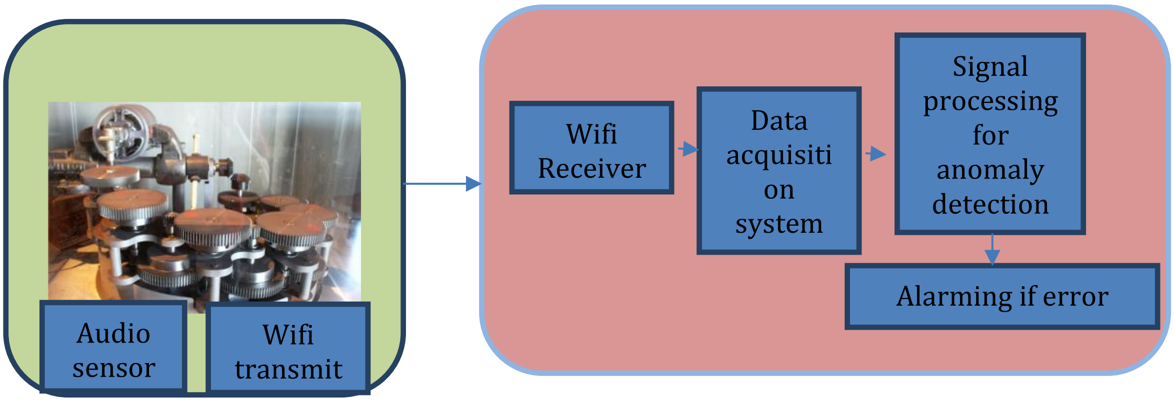

Figure 6: Block Diagram Showing the Online Monitoring of Machine Health Using Edge Impulse (Pic courtesy from https://www.instructables.com/Basic-Gear-Mechanisms/)

Methodology

The overall methodology of execution is as shown in flowchart Figure 5. The entire process starts with project creation in Edge impulse software.

Block Diagram

Figure 6 shows the overall block diagram of the online monitoring system of machine health using edge impulse software. The Gear spinning audio signals are trapped with sensors at the production line and is transmitted to the online monitoring software (Edge Impulse) where is further processed by creating impulse, sampling feature extraction and finally anomaly detection of the received test signal with already stored reference signal. This online monitoring is a continuous process which ensures the healthy status of machine operation by predicting the occurrence of failure at the earlier stage and alarming the situation for necessary precaution measures.

Impulse Creation and Spectrogram

As shown in Figure 7 the impulse is created by mentioning the spectrogram chosen detailing the mode of input (audio signal here) in processing block. Now in learning block, include the anomaly detection (k means) with input features of spectrogram. Figure 8 shows the spectrogram A with difference time series data and the Figure 9 shows spectrogram B with another different time series data.

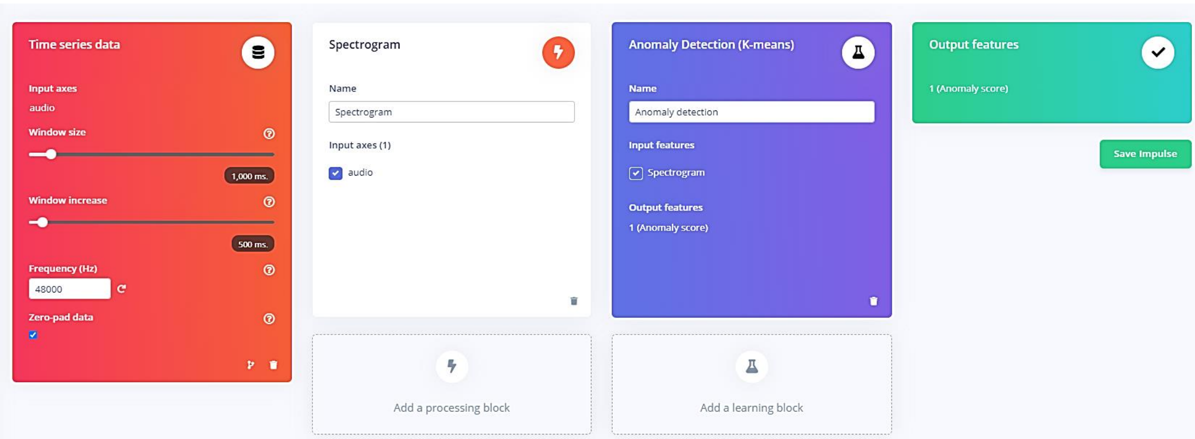

Figure 7: Impulse Creation

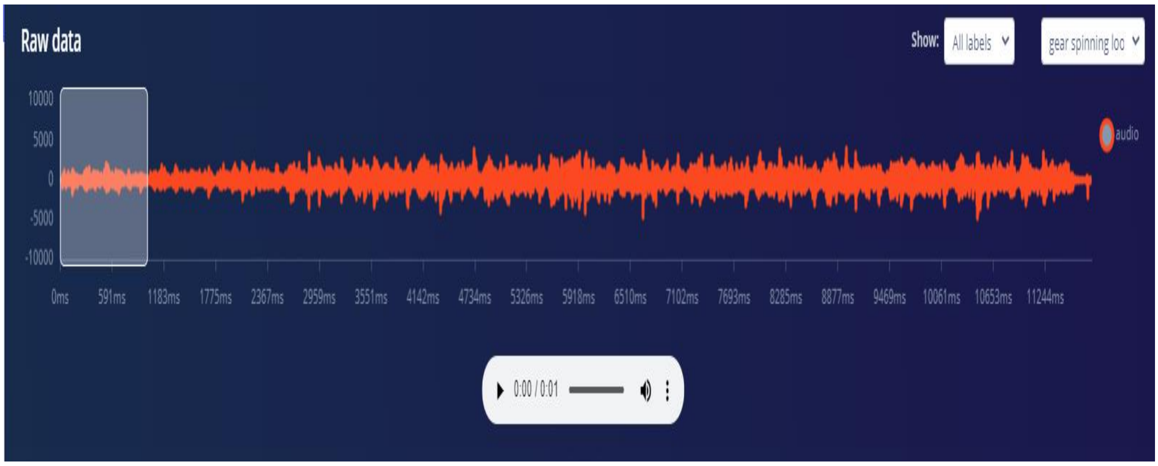

Figure 8: Spectrogram A

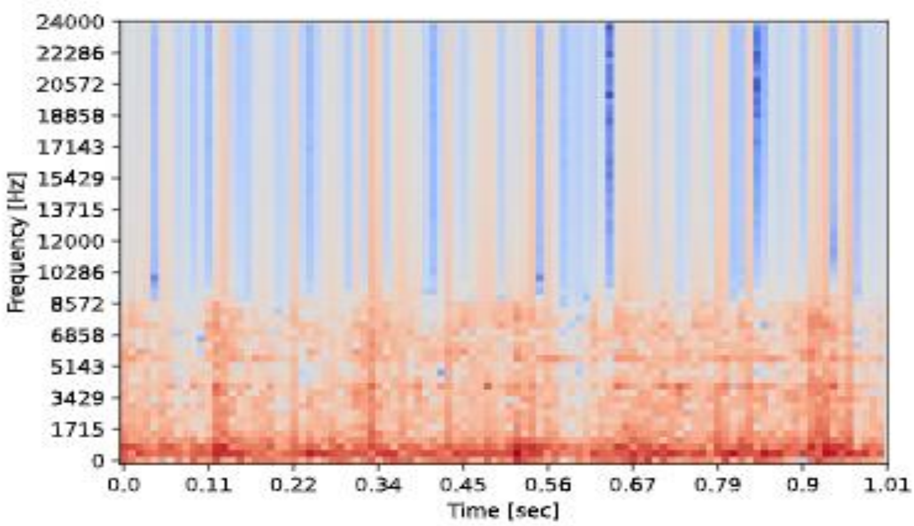

Figure 9: Spectrogram B

Results and Discussion

The anomaly is detected between the reference audio signal (from healthy machine) and the test audio signal (error machine). It is confirmed twice while considering the audio feature 3 and 3219 in x and y axis vice versa whiling comparing it with reference data (train data), which further helps us to confirm the prediction of occurrence of machine error as shown in Figure 10 and Figure 11 respectively. Analyzing the Figure 10 and Figure 11 it is clear that there is some deviation while comparing the test signal (test data) with reference signal (train data). This difference in comparison is called as anomaly. And it is clearly detected in both Figure 10 and 11. As discussed in Table 1 the presence of anomaly while comparing the test audio signal with reference signal is the clear indication for us to ensure the occurrence of failure. If the anomaly is less, that is the initial stage of occurrence of failure, if the anomaly is average, it means the deterioration or failure has been started and half way gone. If there are more anomalies, it means maximum failure of the machine has been reached. Thus an innovative method of utilizing internet of things helps in gathering the data and based on the application of Machine learning algorithm in identifying the presence of anomaly while comparing the test signal with reference signal helps us to verify the healthy status of the machine and early detection of the occurrence of the failure of the machine. This study can be further expanded in future to identify and analyze what type of error is about to occur in machine by applying machine learning algorithm. By this way we could eradicate the occurrence of failure of the machine by identifying it well in advance.

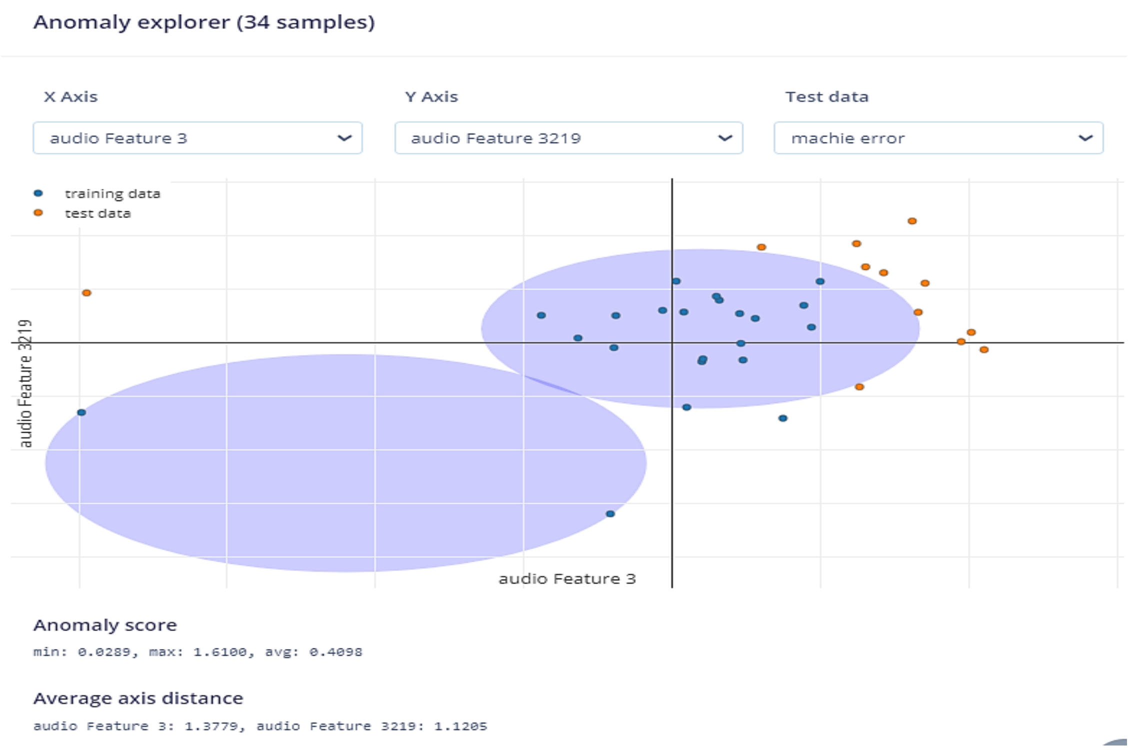

Figure 10: Anomaly Detection with Feature 3

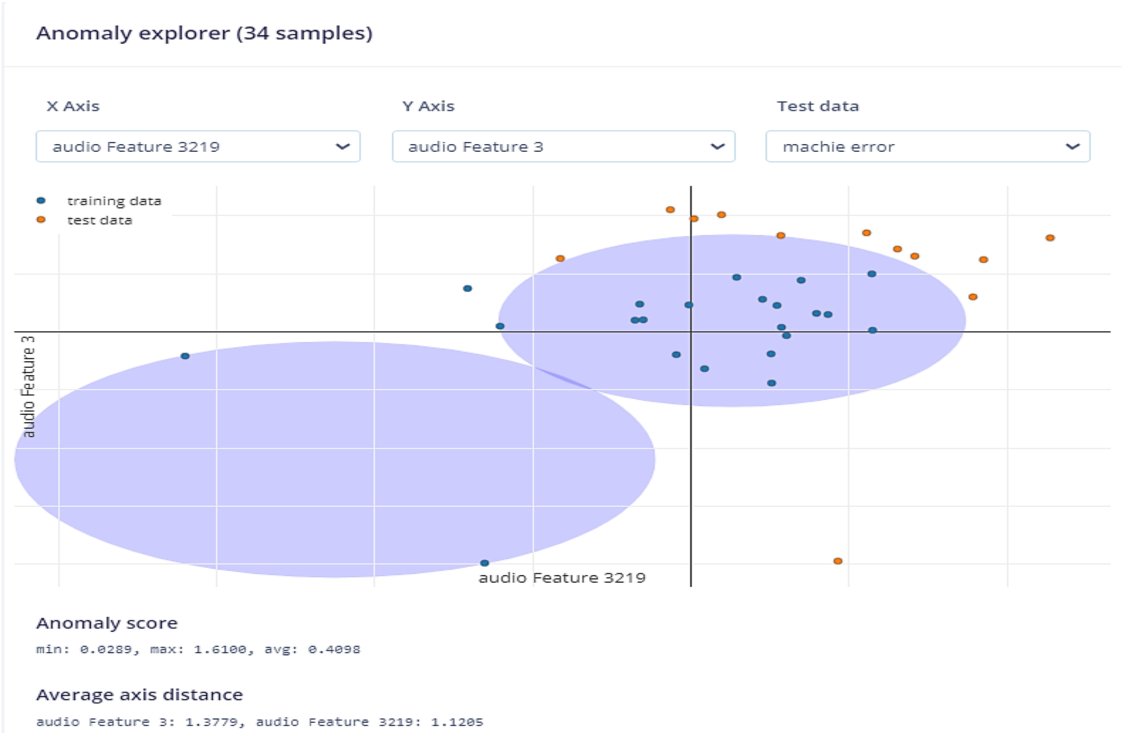

Figure 11: Anomaly Detection with Feature 3219

Table 1: Anomaly Vs Failure

Anomaly percentage	% of Anomaly	Failure level
	<25%	Less
	=50%	Average
	>75%	More

This study can be further expanded in future to identify and analyze what type of error is about to occur in machine by applying machine learning algorithm. By this way we could eradicate the occurrence of failure of the machine by identifying it well in advance.

Conclusion

Thus the research study helps us to understand the role of IoT in predicting the malfunctioning of machineries in industries. This would be an effective modern technological solution replacing the traditional statistical predictive maintenance. Hereby acknowledge the Edge Impulse Software for providing an online platform for data collection, impulse creation, feature classification and anomaly detection. There is no conflict of interest involved in this study

Limitations

The test audio signal considered here for the study doesn't include the noise which may be a part in real time case scenario.

Abbreviations

Nil.

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Author Contributions

All the authors have contributed equally to this research.

Conflict of Interest

None declared.

Ethics Approval

Not applicable.

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