Real-Time Equipment Health Monitoring Using Unsupervised Learning Techniques

Nadeem Iftikhar[a] and Finn Ebertsen Nordbjerg
Centre for Industrial Digital Transformation, University College of Northern Denmark, Aalborg 9200, Denmark

Keywords: Equipment Health Indication, Real-Time Monitoring, Sensor Data, Unsupervised Learning, Anomaly Detection.

Abstract: Reducing unplanned downtime requires monitoring of equipment health. This may not be possible in many cases as traditional health monitoring systems often rely on the use of historical data and maintenance information which is not always available, especially for small and medium-sized enterprises. This paper presents a practical approach that uses sensor data for real-time equipment health indication. The methodology proposed consists of a set of steps. It starts with feature engineering which may include feature extraction to transform raw sensor data into a format more suitable for analysis. Anomaly detection follows next, where various techniques are employed to find any deviations in the engineered features indicating potential equipment deterioration or abrupt failures. Then comes the most important stages equipment health indication and alert generation. These stages provide timely information about the equipment's condition and any necessary interventions. These steps make it possible for such an approach to be effective even when there is little or no historical data available. The applicability of this approach is validated through a lab-based case study.

1 INTRODUCTION

Monitoring machinery and systems' health is very important through the equipment health indication (EHI). This enables early detection of issues based on real-time data, even when there are no predictive capabilities to forecast faults in future. The proposed approach, therefore, improves safety and reliability in production operations by reducing time for equipment repair and maintenance expenses. Typical methods employed for EHI usually requires lots of historical data, maintenance records, particular sensor types and expert advice for technical purposes. This can be a challenge to SMEs that might not have enough resources or expertise. This paper presents a contemporary approach of performing EHI using real-time data, which does eliminate the need for extensive historical data as well as maintenance details. The proposed methodology is divided into two main stages: unsupervised feature engineering that involves feature extraction; then proceeded by unsupervised anomaly detection. In cases where there's limited historical data available (with or without failure data), the entire process of feature engineering which includes feature extraction can be used. However, without historical data, the strategy is limited to feature engineering only with exclusion of the dimensionality reduction aspect involved in feature extraction. The main contributions of this paper can be summarized as follows:

- The paper discusses how unsupervised learning techniques can be used to analyze sensor data in order to identify complex patterns and anomalies that cannot be easily recognized without predefined labels, benchmarks, or failure data. This could enable SMEs to adopt early issue detection approaches thus bettering the maintenance strategies they use.
- A case study demonstrates the efficiency of this methodology. Specifically, this case study illustrates how adaptable the methodology is when traditional equipment health monitoring techniques are lacking as a result of which it has potential for optimizing operational effectiveness.

The rest of this paper is organized as follows: Section 2 presents an overview of the research question. Section 3 reviews relevant literature. Section 4 explains the adopted methodology. Section 5 provides the implementation details. Section 6 evaluates the methodology through a case study and discusses im-

[a] https://orcid.org/0000-0003-4872-8546

Iftikhar, N. and Nordbjerg, F.
Real-Time Equipment Health Monitoring Using Unsupervised Learning Techniques.
DOI: 10.5220/0012785500003756

In *Proceedings of the 13th International Conference on Data Science, Technology and Applications (DATA 2024)*, pages 401-408
ISBN: 978-989-758-707-8; ISSN: 2184-285X

plications for findings. Lastly, section 7 concludes the paper and suggests future research directions.

2 RESEARCH PROBLEM

This research is focused on the development of an EHI system that employs real-time sensor data for monitoring industrial equipment. To avoid costly breakdowns and ensure that equipment functions optimally, there is a need to come up with effective condition monitoring techniques for detecting anomalies in the machines' performance. In most cases, historic and maintaince data is used by traditional predictive maintenance systems. Nonetheless, such data may be limited or absent for many SMEs. Moreover, these predictive maintenance systems may not capture dynamic behavior and complexity of industrial equipment thus leading to false alarms.

This paper therefore introduces an unsupervised learning approach, which can analyze sensor data at real-time, extract/create relevant features and spot anomalies. The suggested approach could be effective in various situations. It could prove particularly useful when there is limited data, a lack of historical data, or even when there are no records of any failures. It makes this approach particularly useful for SMEs, who often lack resources and expertise to implement smart analytics solutions. Hence, the aim of this approach to achieve optimal equipment performance without depending too much on extensive historical data or failure incidents.

3 BACKGROUND AND RELATED WORK

Major progresses have been achieved in real-time equipment condition monitoring especially with the integration of unsupervised learning techniques. This was illustrated in a holistic study adopting such data-driven techniques as feature extraction, deep learning, novelty detection and cluster analysis as presented in the (Eltouny et al., 2023). Furthermore, a thorough study of 71 anomaly detection algorithms for the time series category on 976 datasets conducted by (Schmidl et al., 2022) delivered the necessary marks for technique choice and best practices. Unsupervised methods for detecting concept drift in machine learning were reviewed together with a taxonomy for these methods, and their importance in field scenarios where immediate class labels are not available was shown by (Gemaque et al., 2020).

In the anomaly detection research context, a literature review is outlined regarding the trend of unsupervised learning from 2000 to 2020, as presented by (Nassif et al., 2021). The superiority of Local Outlier Factor (LOF) and One-Class Support Vector Machines (OCSVM), reported by (Qasim et al., 2022), was one of the main focuses of an unsupervised anomaly detection algorithms comparison for predictive maintenance in SMEs. A real-time anomaly detection scheme for industrial automation through IoT and unsupervised learning was proposed by (Gultekin and Aktas, 2023). A novel infrastructure monitoring method using a hybrid semi-supervised approach combining Convolutional Autoencoder (CAE) and One-Class Classification (OCC) was described by (Saeedi and Giusti, 2022). An improved Autoencoder based method for unsupervised anomaly detection was presented by (Cheng et al., 2021).

Regarding the health monitoring, an industrial machine health prediction system was proposed, which was based on unsupervised learning and time series decomposition to compute the health index using sensor data as described by (de Lima et al., 2021). An unsupervised learning method based on Convolutional Autoencoder (CAE) for machine health assessment was presented by (Guo et al., 2022). Further, an unsupervised structural health monitoring approach that utilizes Autoencoder and Hidden Markov Model (HMM) was outlined by (Coraca et al., 2023). The role of data processing and machine learning model selection were examined in the context of condition monitoring in industry was revealed by (Surucu et al., 2023). Machine learning based approach for real-time monitoring and fault detection in industrial components was introduced by (Yang et al., 2019). An Long Short-Term Memory (LSTM) model for fault detection and health management of military vehicles was proposed by (Shukla et al., 2021). A Convolutional Neural Network (CNN) based model that can estimate the remaining useful life of machinery was introduced by (Wen et al., 2023). Moreover, a predictive maintenance framework for Industry 4.0 which employs machine learning for anomaly detection, demonstrating high recall levels across various scenarios, was introduced by (Morselli et al., 2021).

To expand on the previous research which points out the importance of advanced analytics in managing industrial equipment data, this paper demonstrates a practical data-driven method for SMEs. The use of this method that combines real-time sensor data and unsupervised learning techniques, is well placed in situations where SMEs may have no historical data, limited historical data, or only operational data with no fault data available. This approach connects the monitoring of equipment health to the improvement of operational performance, reducing downtime and maximizing overall efficiency. In addition, it has been presented in the paper that this proposed method can be implemented easily as well.

4 METHODOLOGY

The methodology for real-time EHI encompasses several steps, each of which is elaborated upon subsequently. The process (refer to Fig. 1) commences with raw sensor data, which is subjected to preprocessing. This is followed by an unsupervised feature engineering step that generates features from the cleansed data. As part of this step, there exists an optional process for reducing dimensionality to further refine these features. The features are then utilized in unsupervised anomaly detection and to compute the EHI score. Ultimately, based on the EHI score, alerts are generated if the scores surpass critical thresholds.

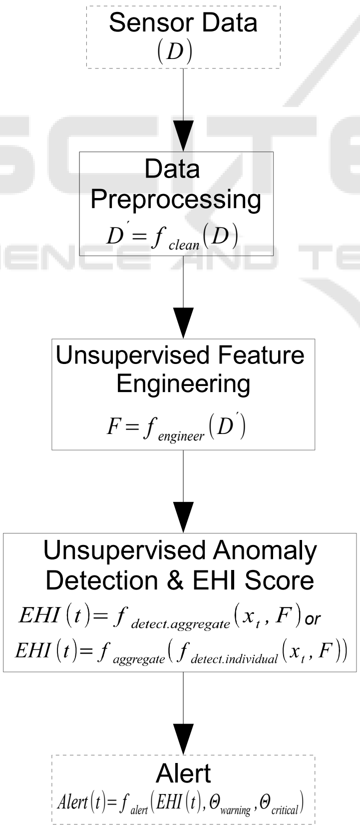

Figure 1: Distinct components of the equipment health indicator (EHI) system. The input for this proposed solution comprises a dataset containing raw sensor data, typically in the form of time series, while the outputs include EHI scores and a variety of alerts.

4.1 Data Preprocessing

The first step is raw sensor data preparation which is represented by D. This data passes through a cleaning function that can be written mathematically as follows:

$$D' = f_{\text{clean}}(D) \tag{1}$$

This equation represents that the cleaned data, D' results from applying the cleaning function denoted as f_{clean} to raw sensor data, D. The cleaning function, f_{clean}, usually involves several steps. There exist noise reduction approaches used in eliminating distortions caused by additive noise in true signal. Sensor data may have different measurement scales. Normalization can thus be performed on all data to ensure uniformity but at the same time maintaining original differences in value range. Missing values may occur in the sensor data due to malfunctioning of sensors or errors while transmitting data. Various methods are used for missing value handling like imputation where missing values get replaced with substitutes values. Furthermore, outliers can distort real underlying patterns in the information contained within a dataset being analyzed for any kind of research purpose. Thus, determination and treatment of such outliers are accomplished through various outlier detection methods for the relevant analysis purposes.

4.2 Unsupervised Feature Engineering

This process transforms the cleaned data, denoted as D' into F, a set of features that capture the dynamic nature of the equipment. This transformation can be stated mathematically as:

$$F = f_{\text{engineer}}(D') \tag{2}$$

Here, f_{engineer} denotes the function of feature engineering that is applied to D'. Feature engineering is a very important part of this process since it extracts useful information from sensor data. The goal is to change preprocessed data such that it becomes easier for analysis, thus exposing hidden patterns. One common method used in feature engineering involves windowing whereby continuous streams of data are divided into discrete windows for which features can be extracted after they have been computed and stored as window features. This helps to capture temporal relationships between various numerical values recorded over time on one hand and others taken at different intervals on the other hand. The function for feature engineering can incorporate multiple methods. Examples include statistical measures like mean, median among others which summarize the data distribution; frequency domain features can also be created showing periodic components within the dataset. The option to use feature engineering or extraction techniques depend on whether there is enough data. If there is limited historical data, both methods can be used. Feature engineering will convert the preprocessed data into a more useful form while feature extraction will help in identifying which features are most important for anomaly detection. Unsupervised learning techniques could help a lot in this regard, particularly for feature extraction. Such techniques may include clustering, dimensionality reduction strategies such as *Principal Component Analysis (PCA)* or autoencoders based approaches among others. In presence of no historical data at all, feature engineering might still be used to convert any new incoming data in a format, suitable for further analysis.

4.3 Unsupervised Anomaly Detection and Equipment Health Indication Score Calculation

The process of unsupervised anomaly detection and the calculation of an EHI score is the main element of equipment condition monitoring. This process locates such data points that do not follow the usual pattern of behavior by the system, without the need for prior labels or knowledge. This often occurs in cases where a sudden failure or degradation of equipment may not have occurred or been documented previously. The anomaly score of every data point is computed, in which case the corresponding input feature x_t in the feature set F is computed as the degree of difference. Each higher score suggests the point is considered as more unusual and the probability is less likely to be equal to the normal.

An array of machine learning models can be used for this task. Predominantly, each model has its particular strengths and some scenarios where they can be utilized effectively. There are cases where historical data is absent, unsupervised anomaly detection could be carried out with *Isolation Forest*, being just one of the many potential algorithms. This algorithm aims to detect the unusual nature of abnormal data rather than common patterns. With this feature in place, the model is well-equipped to face data with many complex dimensions and also provide a great amount of efficiency. In the case when there is limited historical data which includes both the normal and the fault data, the *Autoencoders*, which is a type of artificial neural network, can be used for anomaly detection. During the training using a normal and fault data set, the autoencoder with be able to adopt some of its weights and filters to learn and reconstruct the frequencies parts of it and mostly, it will reconstruct the normal operating conditions with greater accuracy as compared to the least frequent patterns that may between faults or anomalies. After training, reconstruction error is computed that is just the difference between the input and the output generated by the algorithm. It is called anomaly score. The point data that have greater reconstruction errors has high probability to be anomalous. In cases in which only a limited amount of historical data is available and fault data is missing, *One-Class Support Vector Machine (OCSVM)* can be utilized. This model will learn a boundary around the normal data, and any data point beyond this boundary will be detected as an anomaly by the model. This makes it a powerful tool for anomaly detection especially when there is a small dataset with only good or normal data.

The EHI score at a given time point t is then obtained through the use of the actual scores. This task can be implemented via two detection methods: an aggregate or an individual detection method. The aggregate detection method finds already aggregated anomaly scores for each data point, represented as:

$$EHI(t) = f_{\text{detect.aggregate}}(x_t, F) \tag{3}$$

Conversely, the individual detection method finds individual anomaly scores for each data point and then aggregates them, represented as:

$$EHI(t) = f_{\text{aggregate}}(f_{\text{detect.individual}}(x_t, F)) \tag{4}$$

This EHI score is considered to be a health condition of the equipment, and the lower the score, the greater the chance of a problem.

4.4 Real-Time Alert Generation

The final stage of the process is the generation of real-time alerts mechanism. These alarms are triggered based on the EHI scores reaching the corresponding threshold levels. The predetermined threshold values are set in advance, denoted by θ_{warning} and θ_{critical} in order to classify the equipment state as normal state, warning state and critical state. There is an issuance of alerts that are based on those standard thresholds. The alert generation function is represented mathematically as:

$$\text{Alert}(t) = \begin{cases} \text{Normal} & \text{if } EHI(t) \leq \theta_{\text{warning}}, \\ \text{Warning} & \text{if } \theta_{\text{warning}} < EHI(t) \leq \theta_{\text{critical}}, \\ \text{Critical} & \text{if } EHI(t) > \theta_{\text{critical}}. \end{cases} \tag{5}$$

In this equation, 'Normal' signifies a normal operational state, 'Warning' indicates a warning level alert, and 'Critical' denotes a critical level alert. The function $\text{Alert}(t)$ generates an alert at time t based on the EHI score and the predefined thresholds θ_{warning} and θ_{critical}.

5 IMPLEMENTATION

The proposed methodology has been effectively implemented, comprising several stages: data collecting, preprocessing, storing, extracting features, anomaly detection, alerting system setup and real-time monitoring dashboard creation. Real-time data has been continuously collected from the sensors and transmitted. A light-weight, scalable and efficient communication protocol (*Message Queuing Telemetry Transport (MQTT)*) is used for data transmission from the sensors to a central server. After, the sensor data is pre-processed, which is done using the *Python* scripts, it is then stored in a highly efficiently and flexible relational database, *PostgreSQL*. A data processing web steaming mechanism has been built using *Node-RED*, a effective flow-based development platform to ease the integration and flow in the data processing pipeline. Such a script start off by using Python's native libraries like *NumPy* and *Pandas* and then exploring for example, *Isolation Forest* algorithm in Scikit-learn's collections. Node-RED is additionally used as a tool to create the alert system. The last thing that has been employed is *Grafana*, which basically creates dashboards that are interactive in real time that show sensor data, deviation results and EHI scores and provide an immediate picture of the condition of the system.

6 EXPERIMENTAL RESULTS

This section describes the outcomes derived from the deployment of a real-time monitoring system, specifically designed to evaluate the performance and health status of robotic arms (refer to Fig. 2). The analytics procedure encompasses data pre-processing, engineered features to improve data representation, unsupervised anomaly detection methodologies and alert generation in real time based on EHI scores.

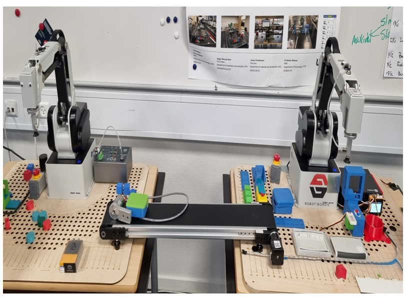

Figure 2: Robotic arms to run lab experimental assembly line.

6.1 Data Understanding

Data Understanding is the initial step of this research. The data used was sensor data from two different operating states of robotic arms: "gradual failure" and "sudden failure". The fact that the proposed monitoring systems has not encountered this type of data before is rather noteworthy. It is this states' data that is believed to be streamed in a near real-time, which is one of the key assumptions that depict an operational environment in which the monitoring system is deployed without a historical data or failure records to support it. This case is one of the challenges that SMEs usually confront. The research methodology employed here is developed to evaluate the efficiency of the proposed system against the scenarios where the conventional predictive maintenance models based on the historical data may not be applicable. This method, thus, reinforces the effectiveness and reliability of unsupervised learning approaches. These techniques can analyze time-series or incoming sensor data to find unusual data patterns and deviations which indicate equipment health issues at the moment without the need for pre-processed training data.

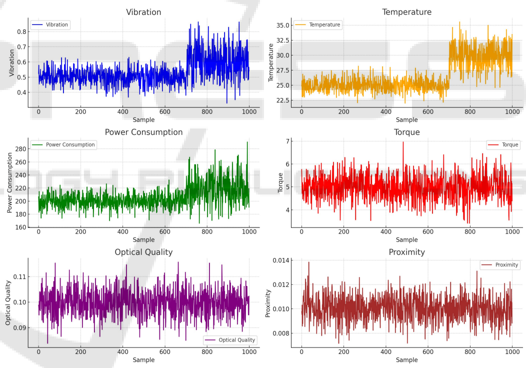

Figure 3: Subdivided plot displays each of the six sensors in the gradual failure scenario separately, with each subplot dedicated to one sensor.

The datasets are given here with an intention that they would simulate the type of data that the system might face in the real-world settings. The *gradual failure dataset* (refer to Fig. 3). These variations, particularly in the vibration, temperature and power consumption sensors after the 700th data point, can serve as indicators of approaching equipment failure and must not be neglected. The demonstration of these gradual alterations intensifies the significance of prior monitoring to avoid a continuous deterioration. On the other hand, the *sudden failure dataset* (refer to Fig. 4) is a situation where the system must rapidly respond to changes that are a sign of instant equipment failure. The dataset is comprised of the suddenly in-

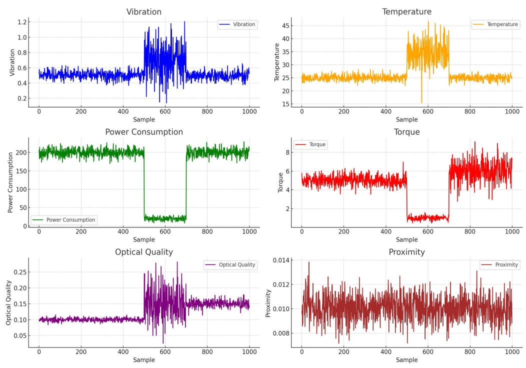

Figure 4: This visualization presents each of the six sensors for the sudden failure scenario, with each subplot dedicated to one sensor.

troduced fault, for example, sudden drops in power consumption and torque in a short span of time and elevated values for vibration and temperature readings together with the optical quality readings, especially evident between the 500th and 700th data point. These datasets, after generating the failures synthetically, will act as a base for validation of the given technique.

6.2 Data Preparation

The first step of the analysis is the data preparation phase, carried out on the incoming data. It is a pivotal part of the real-time operation because it enhances the data quality due to the fact that data comes in a steady, real-time stream. It includes the operations like noise reduction, filling of missing values, removal of outliers and so on. After the calibration process, the sensor data was adjusted to a uniform scale using normalization procedure. Normalization empowers a comprehensive approach to the processing of sensor records through data homogenization. In this manner, data is prepared for the following analytical tasks.

6.3 Feature Engineering

This phase has been perhaps rather crucial in turning cleaned sensor data into a format that has been more representative of all the dynamic conditions the monitored equipment has been going through. This paper use aggregation of the sensor data to determine the mean value for every operational condition, like gradual failure or sudden failure. On the other hand, other statistical measures may be employed depending on the analysis needs. The rolling windowing technique was used as a tool for effective feature engineering, and the data was segmented into blocks of 50 observations each. Inside each window, the average of the sensor readings were extracted. This step is the key for defining and modeling all temporal patterns signifying the abnormal operation or normal functioning of the equipment. Disclaimer- in this case, feature extraction was not applied for the lack of historical data. This unsupervised feature engineering process formed a solid basis for subsequent anomaly detection and equipment health assessment, thus demonstrating its potential use in real-time monitoring.

6.4 Anomaly Detection

The paper implemented Isolation Forest, a kind of unsupervised anomaly detection algorithm. This model is very applicable for the cases in which the historical data is either limited or nonexistent. It operates by detecting anomalies in high-dimensional datasets, which usually occur in sensor data for the equipment health monitoring. These anomalies, efficiently pinpointed by the model (refer to Fig. 5), could be an early warning or alarm suggesting faulty equipment functions and promptly the corrective actions. The models' output associated each observation with a normal (1) or anomalous (-1) status created the foundation for the development of EHI scores. EHI score represents a generated number from the results of anomaly detection and provides a numerical measure of equipment status. The visualization of EHI scores over time for both gradual failure and sudden failure scenarios provided insightful views on equipment health (refer to Fig. 6). For the case of gradual decline, the EHI scores showed considerable succession periods of stability were followed by visible health drops. In the sudden failure case, the scores of EHI that were stable earlier showed a noticeable drop that is usually related to the multiple abnormalities occurs within a short span of time. In general, EHI scores could be used in early failures identification, therefore would permit fast response to the potential equipment problems and minimizing of the downtime.

6.5 Real-Time Alert

This phase permits proactive maintenance interventions and helps to convert the insights obtained from EHI scores to actions. The paper featured visualization techniques that enabled straightforward presentation of equipment's performance over a given time period, as shown as condition status: *good condition*, *gradual failure condition* and *sudden failure condition*, each indicating an EHI score with corresponding real-time alerts. Visual indicators, represented by yellow and red vertical lines, represent the warning and critical alert zones, respectively (refer to Fig. 6). The

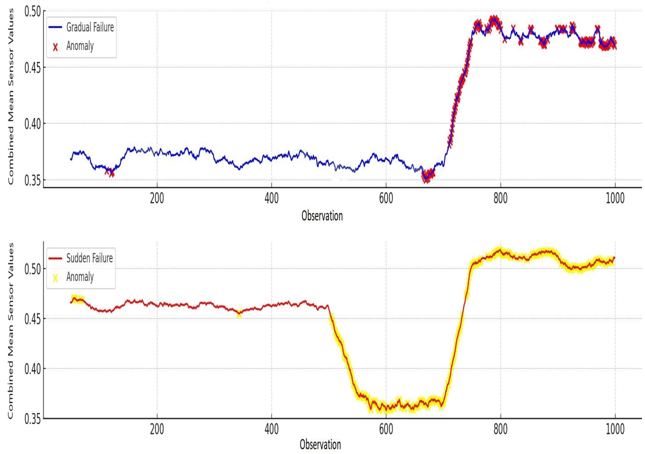

Figure 5: These visualizations highlight where the isolation forest algorithm detected anomalies within each dataset based on the combined mean of all sensor features, distinguished by color: gradual failure in blue and sudden failure in red.

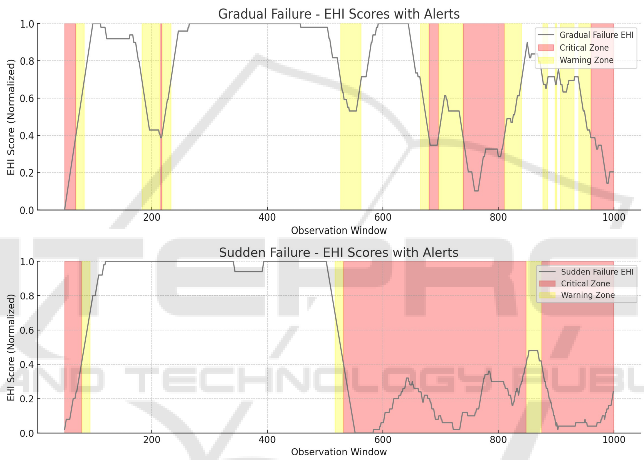

Figure 6: The visualizations display the EHI scores and the corresponding real-time alerts together for each condition, separately.

zones defined by predefined threshold levels signal that immediate action is required. In the case where everything works as planned, the device is demonstrated by stable EHI scores, for example, from 200th to 500th data point. Furthermore, the gradual failure condition (refer to Fig. 6 - upper) displays fluctuations in the EHI scores, indicating presence of drops where the scores have slipped into the danger or critical zones between 700th and 1000th marks. These alerts are the transitional ones which tell about the current state so that maintenance activities could be taken immediately to maintain smooth functioning. With respect to the sudden failure condition (refer to Fig. 6 - lower) where EHI scores suddenly drop from the 500th data point to lower levels, generating critical alert and suggesting catastrophic failure.

6.6 Discussion

The methodology suggested in this paper viewed the dynamics of operation and the conditions of equipment for good health also under different operational circumstances. The transformation of sensor data into a structured format by applying the feature engineering process was the next step in the process, and it captured the dynamic states of the equipment. The anomaly detection algorithms highlighted deviations from standard working patterns, thereby signaling possible equipment health problems. EHI score assessed the equipment health as a qualitative measure over time. The combination of EHI and real time alerts can give a holistic view of the equipment's health status. This strategy could provide a reasonable mechanism for maintaining workplace efficiency. Similarly, this real-time alerting system could be used as the core of the maintenance team's work as the team members can receive notifications about the possible issues in a timely manner, so it can guarantee greater efficiency and reduce production delays.

7 CONCLUSIONS AND FUTURE WORKS

The paper proposes a practical application of real-time equipment health monitoring. The approach eliminates the need for extensive historical data and maintenance records, which provides a considerably advantageous avenue for the SMEs. The core contributions of the research involve the implementation of an unsupervised learning system and a real-time notification system. This framework incorporates unsupervised learning algorithms, which helps analyze sensor data and highlight any abnormalities, which is useful for implementing efficient machine monitoring system. The real time alert system ensures the equipment reliability and durability and so it leads to the further improvement of the operation efficiency. It is worth mentioning that this approach is not only beneficial for SMEs but also simple to implement, making it a practical solution for real-time equipment health monitoring.

The future task will be devoted to increasing the system's capability to handle various IoT devices. Different unsupervised learning algorithms shall be tested to find out those best performing ones for anomaly detection. Furthermore, a variety of feature engineering techniques will also be studied in order to further improve the performance. The adaptability and scalability of the system through the use of real data, comprising real failures instances, will be tested in real production environments.

REFERENCES

Cheng, Z., Wang, S., Zhang, P., Wang, S., Liu, X., and Zhu, E. (2021). Improved autoencoder for unsupervised anomaly detection. *International Journal of Intelligent Systems*, 36(12):7103–7125.

Coraca, E. M., Ferreira, J. V., and Nobrega, E. G. O. (2023). An unsupervised structural health monitoring framework based on variational autoencoders and hidden markov models. *Reliability Engineering and System Safety*, 231:109025.

de Lima, M. J., Crovato, C. D. P., Mejia, R. I. G., da R. Righi, R., de O. Ramos, G., da Costa, C. A., and Pesenti, G. (2021). Healthmon: An approach for monitoring machines degradation using time-series decomposition, clustering, and metaheuristics. *Computers and Industrial Engineering*, 162:107709.

Eltouny, K., Gomaa, M., and Liang, X. (2023). Unsupervised learning methods for data-driven vibration-based structural health monitoring: A review. *Sensors*, 23(6):3290.

Gemaque, R. N., Costa, A. F. J., Giusti, R., and Santos, E. M. D. (2020). An overview of unsupervised drift detection methods. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 10(6):e1381.

Gultekin, E. and Aktas, M. S. (2023). Real-time anomaly detection business process for industrial equipment using internet of things and unsupervised machine learning algorithms. In *International Conference on Computational Science and Its Applications*, pages 16–31. Springer Nature Switzerland.

Guo, L., Yu, Y., Duan, A., Gao, H., and Zhang, J. (2022). An unsupervised feature learning based health indicator construction method for performance assessment of machines. *Mechanical Systems and Signal Processing*, 167:108573.

Morselli, F., Bedogni, L., Mirani, U., Fantoni, M., and Galasso, S. (2021). Anomaly detection and classification in predictive maintenance tasks with zero initial training. *IoT*, 2(4):590–609.

Nassif, A. B., Talib, M. A., Nasir, Q., and Dakalbab, F. M. (2021). Machine learning for anomaly detection: A systematic review. *IEEE Access*, 9:78658–78700.

Qasim, M., Khan, M., Mehmood, W., Sobieczky, F., Pichler, M., and Moser, B. (2022). A comparative analysis of anomaly detection methods for predictive maintenance in sme. In *International Conference on Database and Expert Systems Applications*, pages 22–31. Springer International Publishing.

Saeedi, J. and Giusti, A. (2022). Anomaly detection for industrial inspection using convolutional autoencoder and deep feature-based one-class classification. In *International Conference on Computer Vision, Theory and Applications*, pages 85–96.

Schmidl, S., Wenig, P., and Papenbrock, T. (2022). Anomaly detection in time series: a comprehensive evaluation. *Proceedings of the VLDB Endowment*, 15(9):1779–1797.

Shukla, I., Silas, A., Dozier, H., Hansen, B. E., and Bond, W. G. (2021). Data driven hybrid approach for health monitoring and fault detection in military ground vehicles. In *International Conference on Data Science, Technology and Applications*, pages 300–307.

Surucu, O., Gadsden, S. A., and Yawney, J. (2023). Condition monitoring using machine learning: A review of theory, applications, and recent advances. *Expert Systems with Applications*, 221:119738.

Wen, L., Su, S., Wang, B., Ge, J., Gao, L., and Lin, K. (2023). A new multi-sensor fusion with hybrid convolutional neural network with wiener model for remaining useful life estimation. *Engineering Applications of Artificial Intelligence*, 126:106934.

Yang, C., Liu, J., Zeng, Y., and Xie, G. (2019). Real-time condition monitoring and fault detection of components based on machine-learning reconstruction model. *Renewable Energy*, 133:433–441.