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Article

A Multiclass Fault Diagnosis Framework Using Context-Based Multilayered Bayesian Method for Centrifugal Pumps

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Abstract: The notion of predictive maintenance is perceived as a breakthrough in the manufacturing and other industrial sectors. The recent developments in this field can be attributed to the amalgamation of Artificial Intelligence- and Machine Learning (ML)-based solutions in predicting the health state of the machines. Most of the existing machine learning models are a hybridization of common ML algorithms that require extensive feature engineering. However, the real time deployment of these models demands a lower computational effort with higher accuracy. The proposed Multi-labeled Context-based Multilayered Bayesian Inferential (M-CMBI) predictive analytic classification framework is a novel approach that uses a cognitive approach by mimicking the brain's activity, termed MisMatch Negativity (MMN), to classify the faults. This adaptive model aims to classify the faults into multiple classes based on the estimated fault magnitude. This model is tested for efficacy on the Pump dataset which contains 52 items of raw sensor data to predict the class into normal, broken and recovering. Not all sensor data will contribute to the quality of prediction. Hence, the nature of the sensor data is analyzed using Exploratory Data Analysis (EDA) to prioritize the significance of the sensors and the faults are classified based on their fault magnitude. The results of the classification are validated on metrics such as accuracy, F1-Score, Precision and Recall against state of art techniques. Thus, the proposed model can yield promising results without time-consuming feature engineering and complex signal processing tasks, making it highly favorable to be deployed in real-time applications.

Keywords: MisMatch Negativity; condition monitoring; fault diagnosis; centrifugal pumps; health state

Citation: Selvaraj, S.; Prabhu Kavin, B.; Kavitha, C.; Lai, W.-C. A Multiclass Fault Diagnosis Framework Using Context-Based Multilayered Bayesian Method for Centrifugal Pumps. *Electronics* **2022**, *11*, 4014. https://doi.org/10.3390/electronics11234014

Academic Editors: Xin Ning, Praveen Kumar Donta and Achyut Shankar

Received: 8 November 2022
Accepted: 30 November 2022
Published: 3 December 2022

1. Introduction

The health assessment of any type of equipment holds a profound place in the industrial sector. The terminologies such as condition monitoring, fault prediction and fault diagnosis are closely interrelated. The course of Condition Monitoring (CM) is shown in Figure 1. CM is the unceasing process of system surveillance, which can be decomposed into system monitoring, failure detection, failure diagnostics and failure prognostics. The real-time deployment of CM in industries is executed through monitoring critical variables that characterize the health state of the system under observation. Isolating the critical variables in any system can be completed by domain experts. The notion of CM is bifurcated into reactive and proactive strategies; the reactive strategies initiate the recovery actions after the occurrence of faults while the proactive strategies predict the faults before their occurrence [1]. The proactive fault diagnosis in industries is reinforced by exploring the domain of predictive analytics [2] that integrates the CM data and Artificial Intelligence algorithms to predict the health status of the machine to carry out equipment maintenance activities [3]. The reactive strategies are simple but are not cost-effective; they demand the scheduling of unnecessary maintenance activities. Nevertheless, the proactive CM strategies are initiated only when there is a demand, thus saving the maintenance costs.

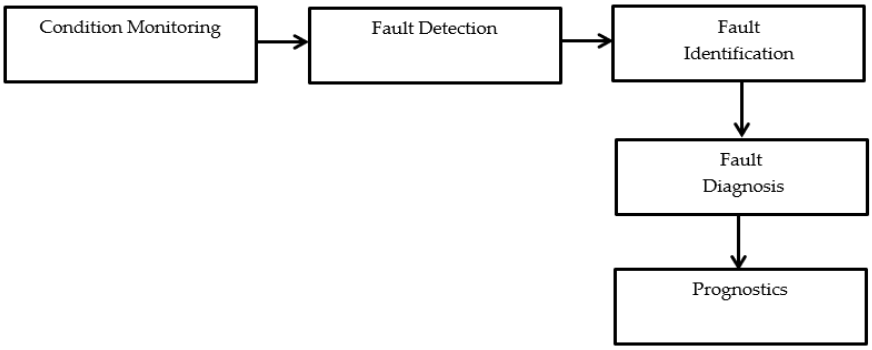

Figure 1. Steps in the process of Condition Monitoring.

Equipment maintenance is crucial for any organization. Nonadherence to proper maintenance policies can lead to adverse effects such as a decrease in production, a loss of equipment, labor overtime, an insufficient knowledge of machine life cycles, rescheduling work and a decline in overall performance. Industrial equipment maintenance strategies are classified into reactive and proactive strategies which are similar to the CM process. The proactive strategies are categorized into predictive and preventive maintenance. Preventive maintenance can be (1) usage-based in which the maintenance activities are performed after predefined running time of the equipment or (2) time-based in which the maintenance is completed after a specified duration from the time of equipment purchase [4]. Both strategies are the classical maintenance strategies adopted in most of industries because of their simplicity. On the other hand, Predictive maintenance uses AI-based learning algorithms and other computing technologies to predict the equipment failures so as to schedule the maintenance activities before the down time of the equipment. The complete taxonomy of equipment maintenance policies is provided in Figure 2.

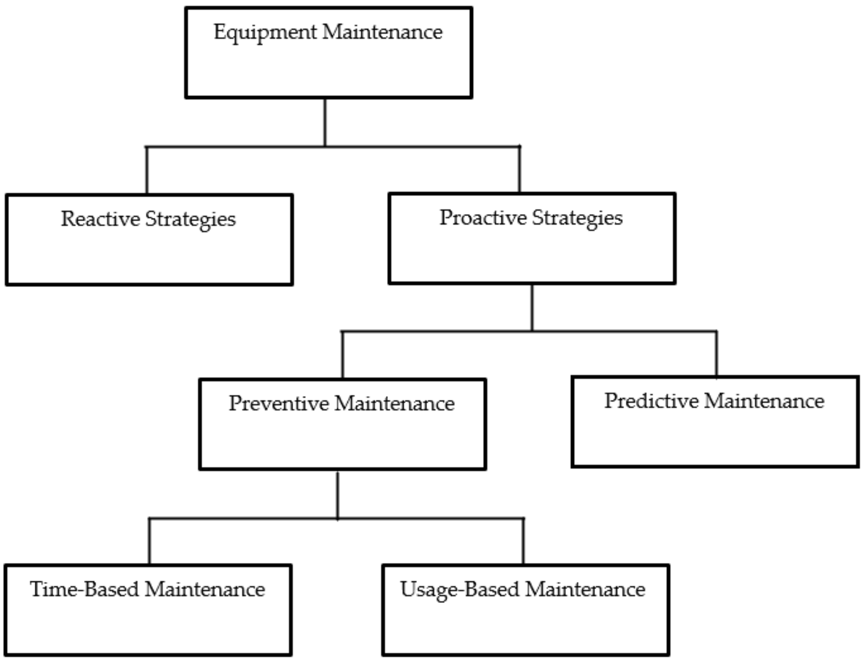

Figure 2. Taxonomy of equipment maintenance policies in industrial maintenance.

Implementation of a complete predictive maintenance framework in industries will substantiate uninterrupted equipment operation by learning the system characteristics through the critical parameters. Any deviation from the normal profile can be an early sign of the occurrence of faults. Thus, the AI-based systems will be able to forewarn the failures based on the past and present data that emanate from the system to facilitate the scheduling of maintenance activities. Techniques such as sensor technologies, intelligent robotic probes, commissioning of automatic plant monitoring, remote monitoring, telecommunication technologies, Big Data Analytics, Fuzzy logic [5], Predictive Analytics, Expert Systems [6] and other cutting-edge techniques are widely used in maintenance sectors with predictive maintenance as their foundation.

Industrial machineries are comprised of a multitude of small and large components for their operation. The condition monitoring of these components is vital for their proper functioning. Centrifugal Pumps are indispensable components that transfer liquids by exploring the rotational energy in a moving fluid. The fact that liquids are easy to contain but hard to control or manipulate compels the deployment of predictive maintenance of pumps in industries. Pump failures may occur due to a variety of reasons such as fatigue, lack of lubrication, contamination, corrosion, fouling, hydraulic imbalance and faulty installation. The pump failures may reduce the effective production time and may become a reason for unanticipated maintenance. Sometimes this failure may cause devastating effects such as the shutdown of an entire plant. A detailed analysis of the cause and effect of failures in Primary Loop Recirculating (PLR) in boiling water reactors can be found in [7]. The common parameters that are monitored in centrifugal pumps are vibration, temperature, fluid level and motor current. Any early sign of deviations from the normal operating profiles of these parameters is a warning of failure.

Modern condition monitoring through sensors has led to streaming online data, which are abundant and rich in features. The classical methods of extracting useful information from the data such as constructing physical models, statistical methods, etc., have become obsolete [8] because of their inherent limitations such as the inability to handle a greater number of parameters and assumptions made based on the physics of failure. This naturally led to the resurgence of data-driven models which extract useful knowledge from the voluminous sensor data, which are used to predict the occurrence of failures from early signs of deviant values. The existing models are supported by Artificial Intelligence (AI), Extreme Learning Machines (ELM), Machine Learning (ML) and Deep Learning (DL) techniques augmented by signal processing and feature engineering methodologies [9]. The literature in the domain of fault diagnosis and condition monitoring using these learning techniques highlight the fact that a considerable amount of time and effort are expedited in deriving information from the signals and figuring out the right features from the data. The proposed methodology labels the health state of the machine (centrifugal pumps) by learning the trends and patterns from the raw signals without tiresome feature engineering and signal processing tasks. The motivation for the proposed methodology is derived from MisMatch Negativity (MMN), a physiological phenomenon that makes the brain respond faster to the negative stimulus than the positive one [10].

The primary contributions of this article are:

- A Multi-labeled Context-based Multilayered Bayesian Inferential (M-CMBI) predictive analytic classification framework which leverages the MMN, a physiological activity happening in the human brain;
- The proposed framework is deployed in classifying surface-level defects in industrial steel plates;
- The work presents extensive Exploratory Data Analysis to learn about the sensors that contribute to faults apart from investigating the recovery time of industrial pumps.

The organization of the article is presented here. Section 2 briefs on the state-of-the-art in AI-based condition monitoring in pumps. Section 3 explains the proposed context-based multilayered Bayesian inferential predictive analytic framework for multi class fault classification of pumps. The experimental setup and significant results are discussed in Section 4. Section 5 concludes the work with the scope for future research.

2. Literature Survey

The domain of AI-based data-driven predictive maintenance has a very rich literature. It envisions all of the recent advancements such as the Internet of Things (IoT), Internet of Everything (IoE) and quantum computing to implement predictive maintenance in industrial components.

Fault diagnosis of ground-source heat pumps from multisource sensors was performed by Baoping Cai et al. [11]. This model was based on the cause–effect relationship that was implemented in two layers, namely, the fault layer and the fault symptom layer. The complete model was built by integrating the two Bayesian layers to achieve a higher fault classification accuracy. This model was able to diagnose multiple faults simultaneously by fusing the information from multiple data sources. This work focuses on only limited symptoms. Hence, there is room for expanding the set of symptoms from which faults could be identified.

Muralidharan et al. conceived the idea of detecting multiple faults such as impeller faults, bearing faults and cavitation in centrifugal pumps by using stationary wavelet transform to extract useful features form the vibration signals [12]. J48, a top-down inductive decision tree algorithm was used to classify the faults. This proved to have a decent classification accuracy but suffered with the limitation of model overfitting. The advent of ELMs reduced the intensity of tiresome feature engineering. Ye Tian et al. designed an ELM which processed the data extracted through Singular Value and Local Mean Decomposition [13]. A significant amount of accuracy has been improved by using ELM in classifying the pump fault state within a shorter time. This method demands extensive signal processing, which is very expensive. Another interesting application of ELMs is the diagnosis of slipper abrasion defects in axial piston pumps [12]. This method uses Wavelet Packet Transform (WPT), Empirical Mode and Local Mean Decomposition along with Local Tangent Space Alignment as signal processing techniques. ELM is used to recognize the fault patterns from the data extracted through the above-mentioned signal processing methods.

Rapur, J.S. et al. built an SVM-based model that could determine the severity of multiple faults occurring in centrifugal pumps from the motor current and vibration data [14]. The hyper parameters were chosen through fivefold cross validation, and a wrapper model was used to select the features. Though this methodology could isolate multiple faults with their severity, it suffered from tiresome parameter tuning. An amalgamation of wavelet transforms, fuzzy and neural networks for fault diagnosis was proposed by Fansen Kong et al. [15]. A more robust algorithm for fault classification in centrifugal pumps by hybridizing Artificial Neural Networks, SVM with genetic algorithms and Particle Swarm Optimization (PSO) proved to be more accurate than the state-of-the-art techniques [16]. This algorithm exhibited enhanced classification even with noisy data, thus making it more deployable in a real-time industrial scenario. The major limitation of this work is that integrating the algorithms increases the computational complexity.

Decision Trees (DT) attempt to select the significant features from the underlying data based on Gini index or entropy. This work leveraged Top-Down Inductive Decision Tree (TDIDT) to predict faults in monoblock centrifugal pumps. The purity of the class is preserved by pessimistic pruning of redundant and nonprominent sub trees [17]. Myeong-Seok Lee et al. examined the vibration signals, fluid pressure and flow rate, and deployed them to design a fault prognosis framework for gear pumps [11]. The notable feature of this work was the construction of a degradation index by augmenting the variance of data, predictability and stochastic significance of the statistical features extracted from the dataset through Kalman filters. These temporal data are tapped by Bidirectional Long Short-Term Memory to obtain accurate fault prediction.

A popular method of using an Inverse Gaussian (IG) process in the health management of hydraulic piston pumps is proposed by Bo Sun et al. [18]. This model considers the measurement errors as well as other random forces in the prediction process. The proposed model used the Expectation Maximization algorithm augmented with Monte Carlo integration to estimate the parameters. Industry 4.0 has witnessed the deployment of advanced manufacturing and computing technologies to improve productivity and reliability. One such concept is digital twin, which is gaining momentum in the creation of Electric Submersible Pump (ESP) systems [19]. The dynamics of physics, designing of ESP subsystems along with AI-based solutions are extensively used in pump-failure monitoring and prediction in industries.

The brief literature on fault classification in pumps shows that a wide range of signal processing, feature engineering, machine learning and deep learning techniques are used in classifying its health state. The challenges confronted during the study included expensive feature selection, complex computations in extracting information from the signals, overfitting, tuning hyper parameters and too much specificity of the models. Hence, the proposed model classifies the health state of pumps by learning the trends and patterns from the raw signals collected from multiple heterogeneous sources. In addition, this methodology highlights the duration in which the pumps were under a recovering stage to facilitate the maintenance engineers in gaining more insight.

3. Context-Based Multilayered Bayesian Inferential Predictive Analytic Framework

The proposed framework is a cognitive approach that mimics the human brain's potential to detect surprising or abnormal events. This phenomenon is called MisMatch Negativity (MMN) through which brains learn faster from abnormal elicited sensory signals. The theory of MMN is supported by Bayesian Brain (BB), which exhibits dynamic generative predictive coding to catalyze the convergence of the internal state of the brain.

3.1. MisMatch Negativity

MMN is based on Newton's free energy principle, which states that all biological systems maintain their equilibrium condition by suppressing their internal variation in free energy [17]. This postulate is confirmed by the Helmholtz agenda which aligns to the fact that this variational free energy is converted into work completed (momentum) by the biological system. This physiological process of the brain can be explored to detect the abnormal changes happening in the health state of the machine [20]. As given in Equation (1), the MMN can be quantified as the measure of variational free energy with error E':

$$\mathrm{MMN} = \mathrm{Free\_Energy} + \mathrm{E}' \tag{1}$$

3.2. Bayesian Brain (BB)

BB is perceived as an implementation of MMN with a cause–effect relationship. The probable causes for the elicited sensory signals are derived through BB [21]. The measure of elicited signals is a direct implication for the change in the internal state of the brain because of the deviation caused due to internal free energy. The steady state of the brain could be achieved only if there is no deviation in the internal free energy, which means that there is no change in the level of sensory inputs [22]. The entire process is shown in Figure 3.

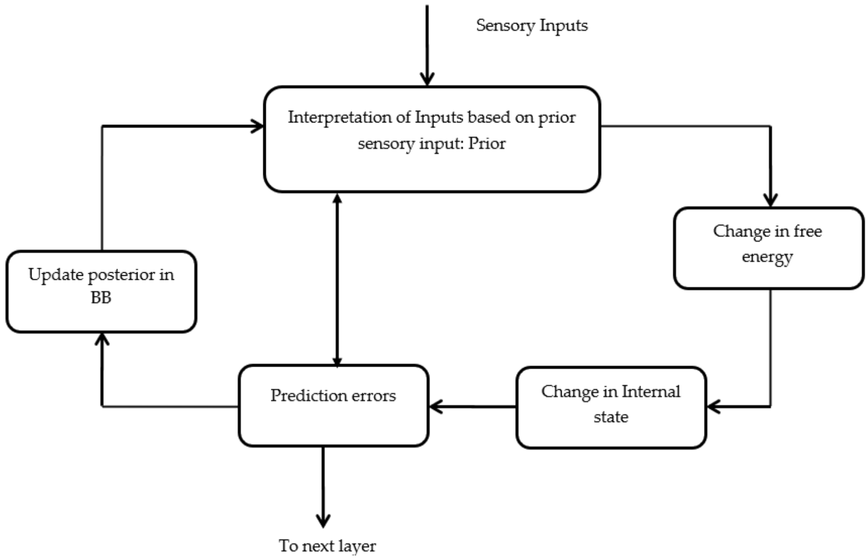

Figure 3. Relationship between Hierarchical BB and free energy principle.

3.3. Dynamic Hierarchical Predictive Coding

Dynamic Hierarchical Predictive Coding is the technique used to accumulate the causes of the sensor inputs and transfer them to the next level of neurons in a hierarchical fashion. The predictions are also passed in the same way. This is a faster method to aggregate the signals among various neuronal levels. Unlike the ANNs, the predictive coding communicates the prediction errors to the next level, thus hastening the process of convergence of the state. The brain adaptively learns the abnormal sensory signals and changes its state accordingly. There should be an inhibiting factor that controls the proposed model from learning the abnormal signals. In this view, a novel hyperparameter called Context (*C*) is introduced that mitigates the model from adaptively learning the abnormal signals. The input vector $\mathrm{f_i}$, with the present state $\mathrm{s_i}$, is treated as given in Equation (2) with the Context that helps in convergence:

$$g(f_i, s_i; C) = s_i \frac{1}{2\pi} \exp(-f_i/2)^2 \tag{2}$$

$$y_i \leftarrow g(f_i, s_i; C) + E_i,\ E_i \in \left[0, \pi\left(\lambda^{-1}\right)\right] \tag{3}$$

The fault magnitude (y_i) is estimated by Equation (3). The machine health state is classified into three classes through Equation (4). The threshold and context values are determined experimentally and $\mathrm{E_i}$ is the error component that is propagated hierarchically:

$$h(f_i, s_i; C) = \begin{cases} \text{Normal},\ y_i < \mu_1 \\ \text{Faulty}\ y_i = \mu_1 \\ \text{Recovering},\ \mu_1 < y_i \leq \mu_2 \end{cases} \tag{4}$$

The next state information (s_{i+1}) is predicted from the Equation (5):

$$s_{i+1} \leftarrow g(f_i, s_i; C) + E_i,\ E_i \in \left[0, \pi\left(\lambda^{-1}\right)\right] \tag{5}$$

Thus, the proposed methodology classifies machine states into normal, faulty and recovering based on the fault magnitude. The threshold values can be modified based on the equipment under study.

4. Experimental Procedure

The proposed methodology was used to classify the health status of 7 centrifugal pumps numbered from 0 to 6. The real-time temporal data were collected from multiple centrifugal pumps by installing 52 sensors at various locations. The parameters monitored were vibration, temperature and pressure at the site of the pump. The distribution of the data is given in Figure 4. The recovering status of the sensor is the duration in which the pumps are reported to be faulty but still under faulty state only.

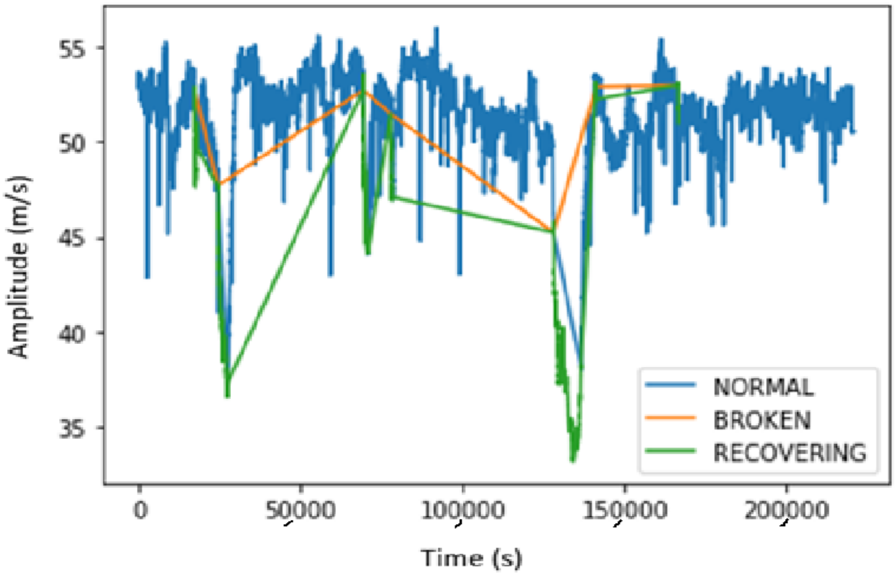

Figure 4. Distribution of sensor values of sensor 2.

The Exploratory Data Analysis (EDA) of the sensors is given in Figure 5. The EDA was conducted to find the sensors which had a deviation in the sensor values in due course of time. The number of units of a particular deviant value is given in the Y axis, and the exact sensor value is given in the X axis. From the EDA, it was evident that sensor 15 had null values, hence it was discarded. The time-based analysis of the pump dataset contained signals from pumps at three different health conditions, namely, normal, broken and recovering. The broken status indicated that the pump deviated from the normal range of signals. The recovering status indicated that the pump was still in a broken state and will remain in the recovering state until its signals fall under the normal operational range. The dataset contained values from heterogeneous sensors, namely, temperature, vibration and pressure. The Fused Input Vector (F_IV) was formed by the weighted variances (V_i) of Sensor values (S_i):

$$\text{F\_IV} = \frac{S_1 V_1 + S_2 V_2 + \ldots + S_n V_n}{{V_1}^{-1} + {V_2}^{-1} + \ldots + {V_n}^{-1}} \tag{6}$$

The sensor values were fused together to form a distinct metric, F_IV, which was used as the input vector. This metric considered the variances of the sensor values to decide the weight of the data. Hence, a sensor with a greater variance in data is the one with the potential to decide the occurrence of faults. This can be associated with the fact that the faults in machinery are sensed from the deviation or variance in sensor values. Table 1 shows the duration of pumps in the recovering stage with the time in hours. The occurrence of pump failures is shown in Figure 6. The comparative chart of the recovering time of the pumps is given in Figure 7. The pump failure at pump number 5 and 6 was recovered faster than the others. The Mean Time to Failure is an important metric that was be estimated from Figure 6, and was an important parameter in manual Failure mode and Effect analysis.

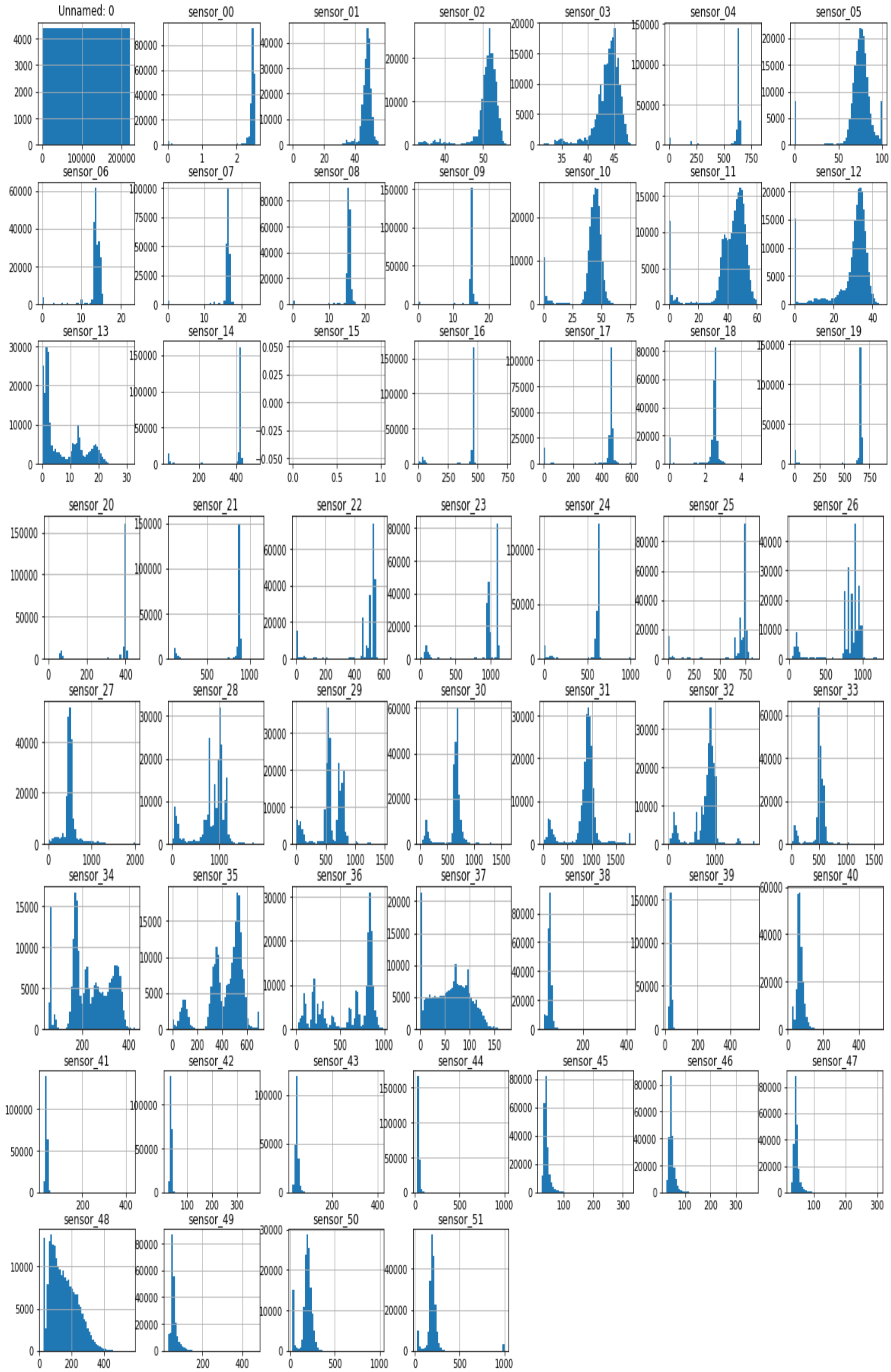

Figure 5. Exploratory data analysis.

Table 1. Pump recovery status.

Row Number with 'BROKEN' Status	Row Number in Which Pump Recovered	Duration of 'RECOVERY' (in hrs.)
17155	945	15.8
24510	3111	51.9
69318	1313	21.9
77790	606	10.1
128040	8391	139.8
141131	42	0.7
166440	76	1.3

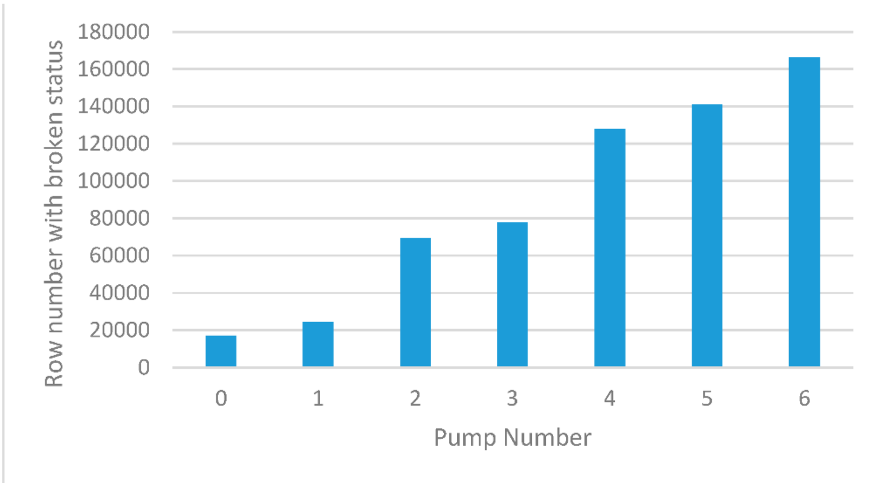

Figure 6. Pump failure status.

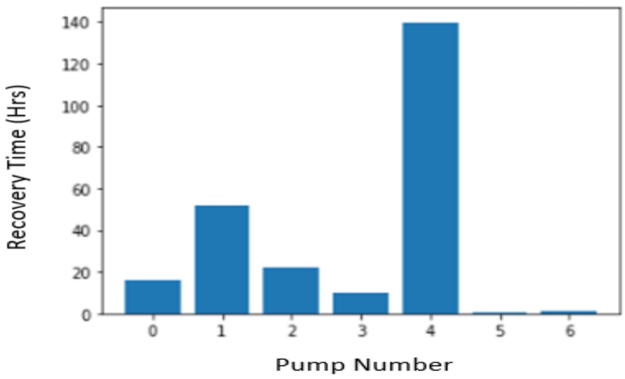

Figure 7. Duration of recovery phase for the 7 pump failures.

Analysis of the Health State Classification

The pump dataset with disproportionate data was taken from Kaggle. This dataset contains vibration data from 52 pumps across various time periods. This is a labeled dataset with three classes, namely broken, normal and recovering. The failure data are very scarce. Hence, the machine is considered to be in recovering state until it resumes normal operation. This is a measure to balance the distribution of data among multiple labels. The performance analysis of the classification using M-CBMI was validated using precision, recall, F-measure, AUC and accuracy.

The value of Context, the novel hyperparameter, was determined by empirical analysis as shown in Figure 8. The value of Context varied between 2 and 22. The best results of accuracy both in testing and training was 18, after which there was a decline in the results. This is due to the fact that the model started learning much of its previous value and began to overfit. Both the testing and training phases confirmed that the pump dataset overfit when the context value increased beyond 18.

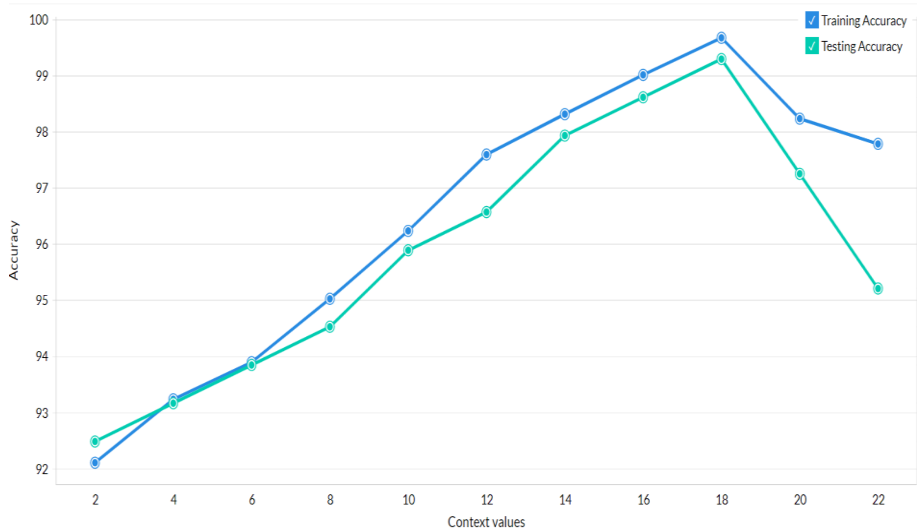

Figure 8. Determining the Context value.

The dataset comprises data from about 7 pumps with 52 sensors. The contribution of each sensor value is given in Figure 9. The vibration sensor labeled sensor_00 held higher prominence in the classification task. The Extreme Gradient Boost (XGBoost) was deployed to rank the features.

(i) Precision:

This is a measure of correctly classified samples in the right class, which corresponds to positive samples belonging to a positive class. Precision is an important metric, especially in critical tasks such as fault diagnosis where the False Positives have a greater impact on the classification.

The expression is given in Equation (7):

$$\text{Precision} = \frac{\sum_{i=1}^{n} \text{TruePositives}_i}{\sum_{i=1}^{n} \text{TruePositives}_i + \text{FalsePositives}_i} \tag{7}$$

(ii) Recall:

This is a measure of positive class samples out of all the samples classified as true positives and false negatives. Recall is the metric that gives more weight to False Negatives. In the domain of fault diagnosis, this holds higher importance, as a fault should not be left unpredicted. This could cause severe devastation to the industrial equipment and machinery. The expression is given in Equation (8):

$$\text{Recall} = \frac{\sum_{i=1}^{n} \text{TruePositives}_i}{\sum_{i=1}^{n} \text{TruePositives}_i + \text{FalseNegatives}_i} \tag{8}$$

(iii) F1-Score:

Neither precision nor the recall can precisely define the purity of the class. Hence, the F1-Score is the harmonic mean of precision and recall and is given by the formula in

Equation (9). This measure integrates the costs of False Negatives and False Positives, as both would affect the reliability of the systems:

$$\text{F1-Score} = \frac{2 \, * \, \text{Precision} \, * \, \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

(iv) Classification Accuracy:

This is the classical metric which determines how many samples are rightly classified among the entire dataset. The expression is given in Equation (10). This is a very generic metric that considers only the correctly classified samples:

$$\text{Accuracy} = \frac{\text{TruePositives} + \text{FalseNegatives}}{\text{Total number of samples}} \tag{10}$$

(v) Area under the Curve:

This is an indication of the potential of the developed model to distinguish between examples of different classes. In other words, it is a measure of inseparability.

The result of the proposed framework is given in Table 2.

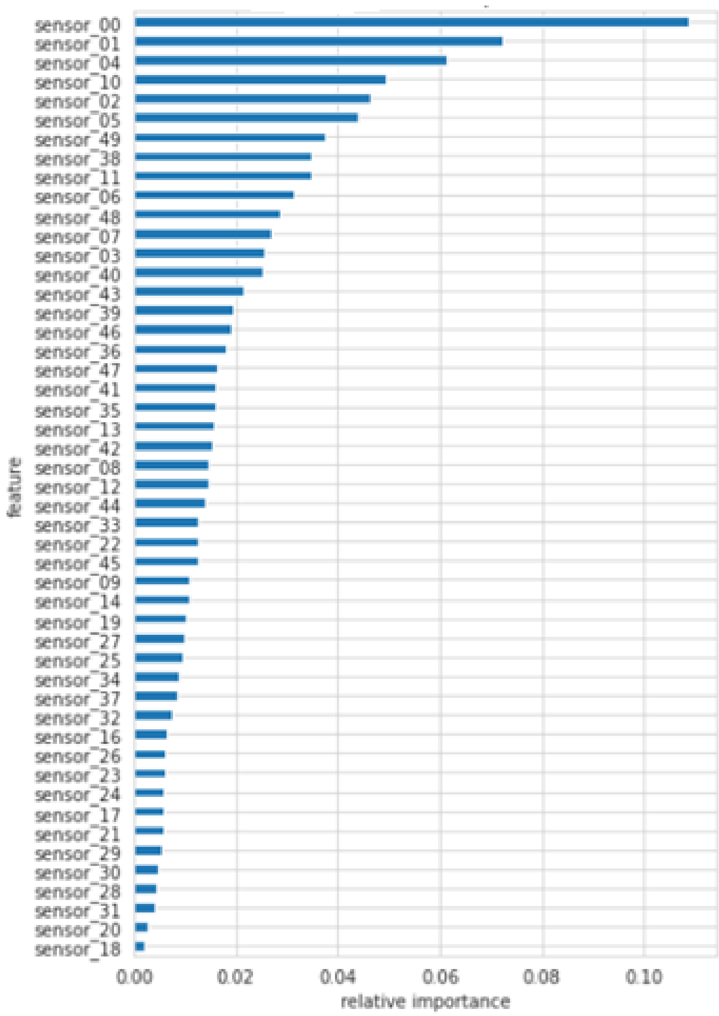

Figure 9. Ranking the features using XGBOOST.

Table 2. Results of classification.

Metric	Value (in %)
Accuracy	99.67
F1-Score	98.02
Recall	97.5
Precision	98.56
AUC	97

Figure 10 shows the comparison of the state-of-the-art techniques with the proposed methodology in terms of their accuracy [22–24]. The proposed M-CBMI showed improved accuracy of 99.67% because the Context hyperparameter augmented the previously classified health states, thus enhancing the model's performance. The other models were also competent enough with the proposed model in terms of accuracy. The Generative Adversarial Network with Sparse Auto Encoders (GAN-SAE) is a more popular algorithm for classification. The relatively low performance of this model is such that it could not effectively learn the data space.

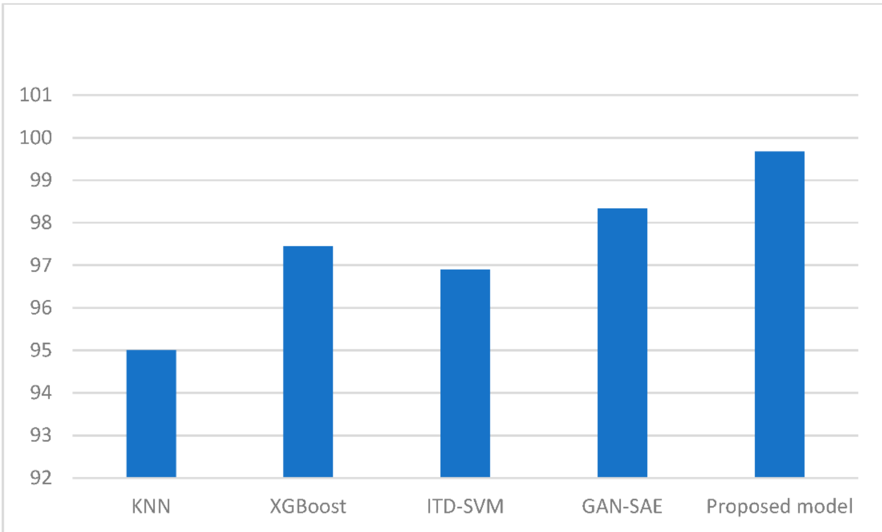

Figure 10. Comparison of Accuracy of some state-of-the-art techniques.

The precision and recall measures of the proposed model is better than its peers. The model can mitigate the rate of false positives and true negatives as any time-critical application would demand. Figure 11 illustrates the results of this comparison. The F1-score of the model also showed promising results. It is evident that the model's misclassification costs were lower than other state-of-the-art techniques. The comparative study of F1-scores of different models is portrayed in Figure 12. The AUC value of the model also confirmed that the proposed model outperformed others, which can be seen from Figure 13.

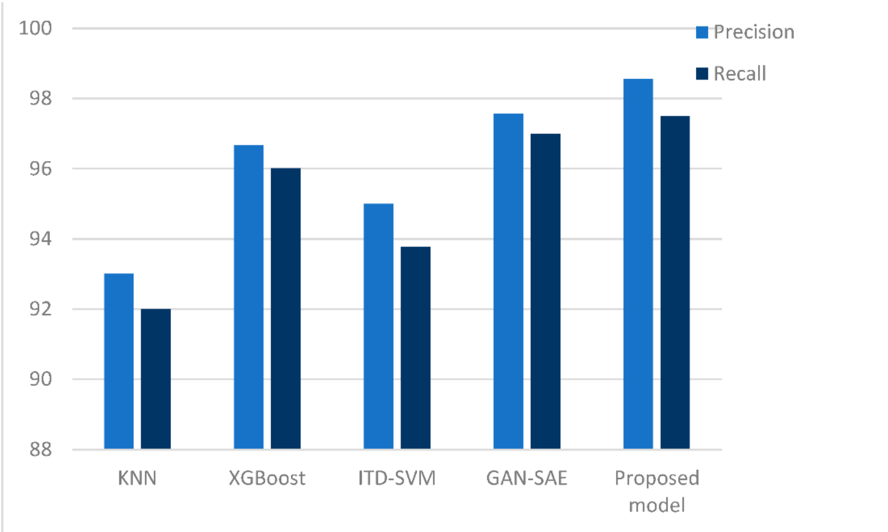

Figure 11. Comparison of Precision and Recall of some state-of-the-art techniques.

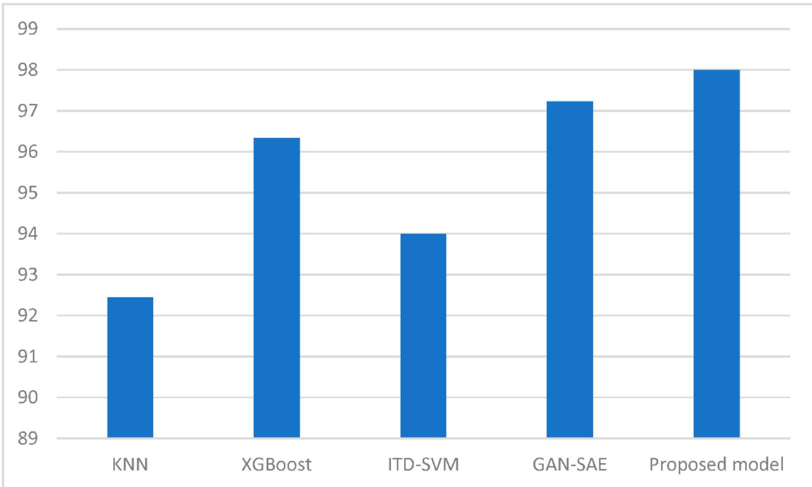

Figure 12. Comparison of F1-Score of some state-of-the-art techniques.

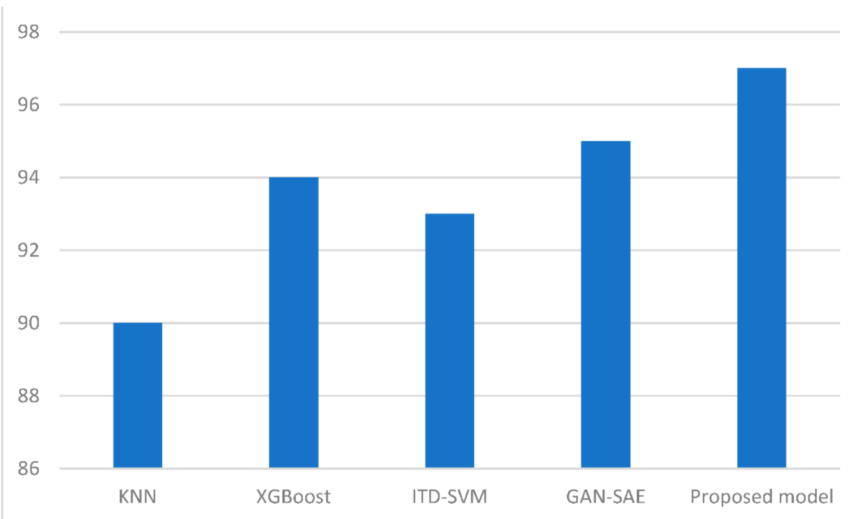

Figure 13. Comparison of AUC some state-of-the-art techniques.

5. Conclusions and Future Work

The domain of predictive maintenance demands the classification of the health state of machines to gain insight into scheduling maintenance activity. The proposed framework M-CBMI is a novel cognitive approach that eliminates the tiresome feature engineering and complex signal processing task. This method is very robust in that it can combine the multifaceted data by using the weighted variances method and then apply the proposed algorithm. This algorithm is one of the first of its kind to explore the MMN phenomenon in the human brain. The proposed methodology outshines some of the classical techniques such as SVM, GAN with SAE, XGBOOST and KNN. The proposed work assesses the performance of the model using the sensor values obtained from 52 sensors. However, the computational complexity of the model must be greatly reduced by deploying sensor fusion technology, which has not been examined in this work. The work can be extended by using more powerful ensemble classifiers. This work is competitive in the context of predicting the exact time of failure of the equipment under study.

Author Contributions: S.S. and C.K.: research concept and methodology, writing—original draft preparation; B.P.K.: Review and editing; W.-C.L.: Validation and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Yunlin University of Science and Technology, Douliu.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: https://archive.ics.uci.edu/ml/machine-learning-databases/mechanical-analysis/PUMPS-DATA-SET/ (accessed on 7 November 2022).

Conflicts of Interest: The authors declare no conflict of interest.

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