Smart Machine Health Prediction Based on Machine Learning

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In an industrial setting, consistent production and machine maintenance might help any company become successful. Machine health checking is a method of observing the status of a machine to predict mechanical mileage and predict the machine's disappointment. The most often utilized traditional approaches are reactive and preventive maintenance. These approaches are unreliable and wasteful in terms of time and resource utilization. The use of system health management in conjunction with a predictive maintenance strategy allows for the scheduling of maintenance times in such a way that device malfunction is avoided, and thus the repercussions are avoided. IoT can help monitor equipment health and provide the best outcomes, especially in an industrial setting.

Decision Tree algorithm | IoT | KNN algorithm | machine health prediction

1. Introduction

To avoid equipment failure, it is important to forecast system failure ahead of time. The importance of a well-functioning maintenance system cannot be overstated because it is critical to lean manufacturing [1]. Many businesses and organizations nowadays rely on sophisticated and advanced technology. Using naïve approaches might result in massive economic, human, and productivity losses. If the organization's methods for dealing with equipment failure are inadequate, the cost of failure might be excessive [2]. As a result, a company must pick a superior approach to help them overcome these dangers. Traditional equipment maintenance approaches such as reactive and preventative maintenance are still in use. Repairing equipment after it has failed is referred to as reactive maintenance [3]. Periodic inspections are performed while the equipment is still operational as part of preventive maintenance [4]. However, this is not the best strategy because the equipment is maintained even when it isn't needed. However, these methods need human interaction and equipment monitoring from afar.

2. Smart Machine Health Prediction Based on Machine Learning in Industry Environment

Daeil Kwon et al. [5], examines the advantages and disadvantages of PHM for industrial usage, with an emphasis on the Internet of Things (IoT). The primary goal of this article is to accelerate the development of PHM based on IoT since IoT offers a flexible and accessible framework. Human resources continue to be a key barrier in building, verifying, and maintaining the models necessary for prognostics, as shown by numerous examples of businesses successfully implementing IoT-based PHM. The fundamental assumption is that IoT-based PHM will have a significant influence on deployment quality review, analysis, and early detection, as well as the development of new business opportunities. It additionally examines the inaccessibility of real-time datasets as they will empower the advancement of new calculations. Moreover, the greatest concern is regarding the security of information as the IoT stages center around open design where open access stages empower improvement of utilization by third parties. The key premise is that IoT-based PHM will have a significant influence on quality deployment review, analysis, and early detection, as well as the exploitation of new opportunities [6], the authors assess four machine learning algorithms and put them to the test in order to characterize seven common steel plate defects. Multi-layer perceptron neural network (MLPNN), C5.0 decision tree, Bayesian system (BN), and ensemble model are the four machine learning models chosen. When compared to other models, the C5.0 choice tree delivered exceptional results, with 95.56 percent accuracy for the training data and 95.66 percent accuracy for the testing data. Van Tung Tran and other authors [7] mention the use of univariate time series techniques and regression models in this work to offer a methodology for estimating prospective system conditions. The recommended method is carried out by predicting future situations. The peak acceleration and the envelope acceleration are investigated in the low methane compressor condition. This method produced a forecast error of 1.43 percent in peak acceleration and a prediction error of 6% in envelope acceleration. The findings support the hypothesis that the proposed approach technique with one-step-ahead prediction has potential for machine health management. Predictive maintenance (PdM) in Industry 4.0 using machine learning approach [8] presents a machine learning engineering for predictive maintenance. By constructing the information framework inquiry, implementing the machine learning technique, and comparing it with the re-enactment instrument examination, the framework is tested on a real-world industry model. Another PdM technique based on PdM, the AI approach on a cutting machine, is described in this study. The proposed PdM philosophy allows for dynamical choice guidelines to be received for executive upkeep, which is achieved using Azure Machine Learning Studio and a random forest approach. Jimenez-Cortadi et al. [9] presents technique for carrying out information-driven predictive maintenance (PdM) in a dynamic system, which is described in this article. They demonstrated that preventive maintenance (PM) done in a real-time machining process could be converted to a PdM method. A dynamic application was built to provide a visual study of the machining apparatus's remaining useful life (RUL). This study demonstrates that the technique proposed in one process may be replicated for a significant amount of the procedure for sequential component production.

Machine health monitoring using knowledge-based systems [10] is a study to offer a framework for assessing machine well-being. Machine health monitoring is surveyed using an application based on knowledge-based systems' artificial intelligence (AI) approach. The framework's outputs are tested for passable characteristics using vibration standards and found to be worthy. The present framework is designed for disconnected situations in which the client physically transports machine vibration data to the information framework. Yan et al. [11] covers the development of a machine health management system that uses the machine's vibration and temperature as metrics for monitoring the machine's health condition. putting your health to the test the entire approach for improving the computer health monitoring system is described in this article. The assumption is that the most intense permitted vibration measurements are in the ranges of 0–20 Hz@210 rpm, 0–15 Hz@175 rpm, and 0–10 Hz@135 rpm. A Self Aware Health Monitoring Architecture for Distributed Industrial Systems [12] proposes Self-Aware Wellbeing Monitoring and Bio-Propelled Coordination for Disseminated Automation Frameworks (SAMBA)

(CPPS). The Framework's ability to react intelligently to quickly changing conditions and possible CPPS states is enhanced by SAMBA. This article suggests using mechanically conveyed CPPS engineering to build the framework's ability to adapt to changing events and conditions. The design's main emphasis elements are wellness assessment and social deviance correction. Lee et al. [13] presents the management of machine health for bright industrial facilities, which is also the subject of this study. The research also looked at several types of machine sensors, as well as the different types of computations and PHM devices used for machine wellness administrations. As a result, the current research aims to provide a broad overview and point of view of machine wellbeing administrations in smart processing plants and Industry 4.0. Machine Condition Monitoring System using a smart phone [14] is a framework for machine condition monitoring created using sophisticated smartphone functionalities in this article. This article offers a machine condition checking architecture that despite some equipment limitations tends to protect information. The accuracy of error identification is provided in this study, which validates the suggested system's capabilities in future condition checking administrations.

Chen et al. [15] offer a new technique for machine health status prediction based on Neuro-Fuzzy Systems (NFS) and Bayesian algorithms in their article. After training using system data, NFS is used as a predictive model to anticipate the reaction of the system failure state over time. Chen and colleagues tested the established procedure using two separate experimental cases: a damaged carrier plate and a faulty bearing. The experiment's efficiency is compared to three popular predictors: recurrent neural networks (RNN), NFS, and recursive neural networks (RNN) (RNFS). Monitoring machine health status and diagnosis of fault using SVM algorithm [16] are crucial for machine status monitoring and problem identification; this study primarily uses a support vector machine. The findings of the current research in machine condition monitoring are reviewed and presented in this publication. Artificial neural networks (ANN), fuzzy expert systems, random forests, and condition-based reasoning have all been employed. Despite the fact that SVM implementation is uncommon, it provides great performance and accuracy. Machine health monitoring with deep learning and its applications [17] is proposed by Zhao et al. to assess and summarize the recent fieldwork on machine condition monitoring using deep learning algorithms. Zhao et al. examine the implementation of deep learning from the perspectives of restricted Boltzmann machines, auto-encoders, and convolutional neural networks (CNN). Eventually, several important advances in computer state analysis approaches focusing on deep learning are discussed. Binding et al., discusses the predictive maintenance of a superior printing machine. Various metrics such as cross-entropy, AUC, ROC, PRC, decision thresholds, calibration curves were used to determine the best model. Random forest and XGBoost outperformed logistic regression in terms of decision thresholds [18][19][20]. In terms of ROC, all techniques outperformed random classifiers significantly. Motor failure time prediction is carried out using ANN [21][22], artificial neural networks, and this research presents an approach for predicting the status of the equipment. The model was trained to make predictions on the devices that imitated a motor using vibration readings obtained from an accelerometer. The algorithms used were ANN, regression tree, random forest, and support vector machine, with ANN providing the best results. Moreover, model generalization and k-fold cross-validation were performed.

Biswal et al. [23] discusses the methodology to monitor the condition of a wind turbine using ANN. To simulate the functioning of a real wind turbine, a bend-top test rig was created. Time-domain vibration signatures were investigated for essential aspects and vibration signatures were obtained depending on the state (healthy, malfunctioning, etc.,). The predictive model correctly classified the machine's status 92.6 percent of the time. Predictive maintenance system for refrigeration using case temperature data, demonstrates an ML-based approach [24][25][26][27] for detecting faults in refrigeration systems. Seasonality-based decomposition, pattern discovery employing dynamic time warping, and clustering were used to extract features. The collected features are utilized to train a binary classifier built using random forest. This approach was validated using real-world data from 2265 refrigerators. The precision of 89 percent was achieved with a 7-day lead time. When tested on unseen cases, it had a recall of 46%. Fernandes et al. outlines the work titled “A Machine-Learning Approach for Predictive Maintenance for forecasting appliances failures”, which outlines a mechanism for predicting boiler malfunctions as well as future failures up to a week in advance. LSTM was primarily utilized as a prediction model with various topologies. Results indicate that LSTM with three hidden layers of 50 neurons and LSTM with one hidden layer of 25 neurons gives the best performance. Along with this, a random stratified classifier, random tree, and neural networks were evaluated. It was observed that weighted neural networks performed poorly when compared to NN models. In [28][29][30], Gopi Krishna and Selvaraj use ML techniques to classify the type of fault in the bearings. Data were acquired using torque, displacement, accelerometer, and velocity sensors after which vibrational signal analysis [31][32] was carried out to extract the features. Machine learning models involving KNN, SVM, K-Means, CRA (collaborative recommendation approach) were used. Among all, CRA has given the best results with 93% accuracy in identifying a fault [33][34]. Arias et al. [35] gives an overview of how to forecast failures in power transformers using ML techniques including SVM, decision tree, random forest, and LSTM. Dataset of insulating oil test was used. Among all the techniques evaluated, SVM had given the best result, with a recall rate of 77%. As the data were gathered at such a low frequency, the LSTM could not provide a better outcome.

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