International Innovative Research Journal of Engineering and Technology
Vol. 10, Issue. 3, March 2025, pp. 12~19
ISSN: 2456-1983, DOI: 10.32595/iirjet.org/v10i3.2025.216

AI-Assisted Predictive Maintenance in Smart Factories Using Vibration Signal Analysis

Dr. Sivaramakrishnan[1], Dr. Santhosh Kumar Chenniappanadar[2]
[1]Department of Computer Science and Engineering, School of Computing,
Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu - 600062, India.
[2]Department of Information Technology, Sona College of Technology, Salem-636005, Tamil Nadu, India.

Article Info

Article history:

Received Jan 10, 2025
Revised Feb 13, 2025
Accepted Mar 11, 2025

Keywords:

Predictive Maintenance
Smart Factories
Vibration Signal Analysis
Deep Learning
CNN-LSTM
Fault Diagnosis
Condition Monitoring
Industry 4.0

ABSTRACT

Due to Industry 4.0, smart factories require smart, data-based maintenance in order to be efficient and maintain a minimal amount of downtimes. It presented a robust predictive maintenance system, which is based on the knowledge of vibration signals to identify issues with the rotating equipment at a very early fault stage. Vibration signals are sensitive to machine changes, and hence they can be used to monitor the health of the machine without causing further damage to the machine. A suggested architecture consists of three large blocks: preprocessing the signals, time-frequency features extraction with STFT and CWT and faults classification with CNN-LSTM. It makes room to accommodate visual characteristics in addition to recording the sequencing of the vibration occurrences with time. Experiments were conducted by integrating CWRU bearing dataset with data in smart factory testbeds. Compared to the performance of CNN-LSTM, fault classification achieved 94.6 percent accuracy that surpassed the classification performance of typical machine learning or deep learning models. Moreover, the system performed effectively in various cases and the percentage of incorrect reports was less than 5%. Based on these findings, CBM reliability is enhanced because the structure identifies small problems before they evolve into significant defects. In all fairness, this study introduces a highly adaptable and successful model of predictive maintenance that could be effective in the case of smart manufacturing systems.

Corresponding Author:

Dr. Santhosh Kumar Chenniappanadar,
Department of Information Technology,
Sona College of Technology, India.
Email: sanscsk@gmail.com

1. INTRODUCTION

As the Industry 4.0 progresses, manufacture-as-usual is changing due to the introduction of new digitization technologies: artificial intelligence, the Internet of Things, cloud computing and cyber-physical systems. Factories can now adapt, monitor in real-time and are well connected and data-driven, all thanks to technology [1]. Here, maintenance of assets to be uniform and available is highly considerable in order to maintain frequent operation and maximum productivity. Nevertheless, regular breakdowns and downtimes are constant problems that generally lead to huge debts, rise of risks and reduction of the production of the company [2,3].

This issue has prompted firms to shift their attention to condition-based maintenance and predictive maintenance instead of addressing it in a reactive and pre-determined schedule manner. Although reactive maintenance addresses the failures after they become evident, preventive maintenance occurs according to the schedule regardless of the manner in which the equipment is performing and neither of them can predict the impending faults effectively [4]. Due to the adoption of the latest data and the most powerful tools, PdM is able to monitor the condition of equipment, locate a problem beforehand and react to it. Vibration signal analysis has become a common condition monitoring technique because the method is sensitive to such faults as misalignment, unbalance, loose joints and worn bearings. Vibration signatures allow identifying the abnormalities of rotating machinery earlier to prevent or resolve potential problems [5,6].

Even though traditional vibration analysis works well, it still involves much manual processing and expertise that is possessed by professionals. With AI, one can detect various faults in machines by simply using complicated vibration signals and with minimal human involvement [7,8]. It has been found that Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are adequate at discovering patterns both in time and location, making them applicable to the analysis of time-series signals in industrial scenarios.

A deep learning framework proposed in the paper combines the forces of CNNs and LSTMs to process vibration patterns extracted by rotating equipment. The framework steps include signal preprocessing, time-frequency transformation, and model training to identify the correct category of condition of the equipment. Due to the utilization of standard datasets and real smart factory data, this research demonstrates that the predicted system can perform credible, real-time fault diagnosis with high accuracy and stability. The key objective is to elevate the efficiency of condition monitoring systems and help to develop intelligent maintenance schedules of the new era of manufacturing.

2. LITERATURE REVIEW

Condition monitoring of vibration signals in industry has progressed well in the last years because of algorithms like Support Vector Machines, Random Forests and Autoencoders. Such models perform adequately in controlled testing, but they work less effectively in other real-world circumstances. Conversely, deep learning enables the utilization of huge and complex time-series data without extensive manual work.

This can be witnessed in the studies of [9] who investigated 1D Convolutional Neural Networks (CNNs) to identify bearing problems. Likewise in [10], the researchers propose a CNN-GRU based approach to gearbox fault prediction that can achieve better accuracy due to sequential learning. As was noted by [11], LSTM networks can capture changes in vibration that are far apart to effectively predict tool wear.

Nonetheless, currently, most models store spatial data and temporal data separately that lowers the overall performance during diagnoses. Many researchers [12] have not exhaustively combined the temporal and spatial features of vibration signals. To this end, a hybrid CNNs-LSTMs model is proposed in this paper, in which the proposed model can better identify and manage the faults in smart manufacturing.

3. METHODOLOGY

This section describes the entire configuration and procedure of the AI-assisted predictive maintenance system that identifies the issue in rotating equipment using vibration measurements in a smart factory environment. The methodology is consisting of two sections: the preparation of the entire system and the development of the CNN-LSTM hybrid model.

3.1. System Architecture

The structure developed here contains various steps which take the vibration data as input, processes the data in real time and provides the output. It is developed to be applied in the industries and includes the following five modules sequentially as represented in Figure 1:

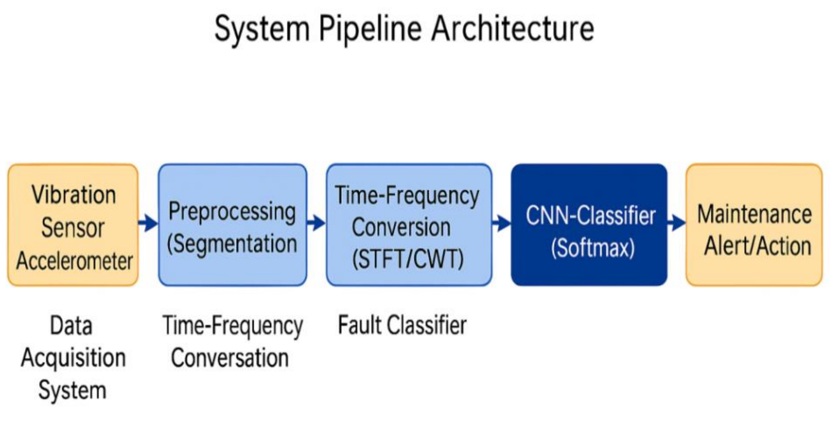

Figure 1. System Pipeline Architecture for AI-Assisted Predictive Maintenance

a) Sensor Layer:

Vibration signals are measured with tri-axial accelerometers located at critical locations (such as bearings and motors) on rotating machines. They continuously quantify the mechanical movement and transmit the information acquired to the computing system or the cloud. In the majority of cases, sampling rate of 12 kHz to 48 kHz is required in order to adequately capture fine details of the signal you are studying.

b) Preprocessing Layer:

The raw signal data feeds out of the vibrator, and is subjected to a sequence of processing stages, which serve to enhance signal quality, and reduce noise. To select the preferred frequency range and minimize noises and DC offsets, a Butterworth bandpass filter is inserted. The filtered data is divided into windows of fixed size (1024 or 2048 samples) with some overlap of each window. Each window is taken as a different observation to be treated further.

c) Feature Engineering Layer:

To extract meaningful representations from the time-domain signal, time-frequency transformations are employed. Two prominent techniques are used:

- **Short-Time Fourier Transform (STFT):** Converts time-domain signals into 2D spectrograms to reveal transient frequency components.
- **Continuous Wavelet Transform (CWT):** Provides high-resolution analysis of both low- and high-frequency signal components using wavelet basis functions.

These transformations yield time-frequency images that serve as inputs to the CNN-LSTM model, effectively capturing both local signal variations and temporal dynamics.

d) Deep Learning Layer (CNN-LSTM):

It is this layer that performs feature extraction and classification by itself. The CNN processes spatial dimensions of the spectrogram by splitting feature and the LSTM considers how the feature varies over time. The CNN-LSTM fusion is beneficial to guarantee that all notable changes in the signal as well as long-standing trends are identified accurately.

e) Decision Layer:

A dense fully connected layer and Softmax activation function that gives the possibility distribution over a set of predefined faults (including normal, inner race fault, outer race fault, ball defect and so forth) come next. A threshold is applied to determine whether the machine is healthy and also to set a value indicating the degree of reliability. The system has the capability to generate real-time alert and display dashboards on the overall factory control system.

Algorithm 1: AI-Assisted Predictive Maintenance Using CNN-LSTM

```
Input:
VibrationData ← Raw time-series signals from accelerometers
   fs ← Sampling frequency (e.g., 12 kHz to 48 kHz)
WindowSize ← Number of samples per segment (e.g., 2048)
   Overlap ← Overlapping stride between windows
   Model ← Pre-trained CNN-LSTM model

Output:
FaultClass ← Predicted fault type (e.g., normal, inner race fault, etc.)
ConfidenceScore ← Probability of prediction

Begin:

1. // Sensor Layer
  Acquire VibrationData from tri-axial accelerometers mounted on machinery

2. // Preprocessing Layer
FilteredSignal ← Apply Butterworth Bandpass Filter to VibrationData
SegmentedData ← Segment FilteredSignal into overlapping windows of size WindowSize

3. // Feature Engineering Layer
  For each Segment in SegmentedData:
     Spectrogram ← STFT(Segment)    // or use CWT(Segment) if preferred
     Append Spectrogram to FeatureSet

4. // Deep Learning Layer
```

```
  For each Spectrogram in FeatureSet:
SpatialFeatures ← CNN(Spectrogram)
TemporalFeatures ← LSTM(SpatialFeatures)
    Prediction ← Softmax(Dense(TemporalFeatures))
    Store Prediction

5. // Decision Layer
  For each Prediction:
FaultClass ← argmax(Prediction)
ConfidenceScore ← max(Prediction)
Display(FaultClass, ConfidenceScore)
    If ConfidenceScore> Threshold:
      Trigger Maintenance Alert

End
```

3.2. CNN-LSTM Hybrid Model Design

A deep learning model consisting of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks comprises the major component of the framework as illustrated in Figure 2. The purpose of this dual approach is to utilize maximum spatial and temporal learning that are essential in proper analysis of vibration signals in rotating machines. This component of the model takes two-dimensional spectrograms that are created by STFT or CWT. The time and frequency information contained input is run through a sequence of convolutional layers with ReLU activation to identify the variations throughout the signals and different edges. Max-pooling layers serve the main purpose of reducing the number of features and retaining the most significant ones, whereas Batch normalization layers stabilize the network and accelerate its training. Researchers turn high-level maps delivered by CNN into sequential vectors and pass them through layers of LSTM after receiving them. LSTM can identify trends in data, locate growing faults over time. Subsequently, the Temporal information extracted by LSTM is fed into a dense fully connected layer with Softmax activation function to provide the probability of each fault, namely normal, inner race fault, outer race fault and ball defect. This model is constructed upon categorical cross-entropy loss and its performance is enhanced with Adam optimizer, whose hyperparameters are modified through trial and error. The generalizability and robustness are obtained by dividing the data into groups according to the classes and regularization is performed by means of dropout and early stopping to avoid the case of model fitting an excessive amount of detail of the training set. The accuracy, precision, recall, F1-score and the confusion matrix that are part of the standard classification metrics are used to analyze the model workiness. In general, CNN-LSTM provides flexible, online, and accurate forecasting to maintain smart manufacturing systems operating efficiently.

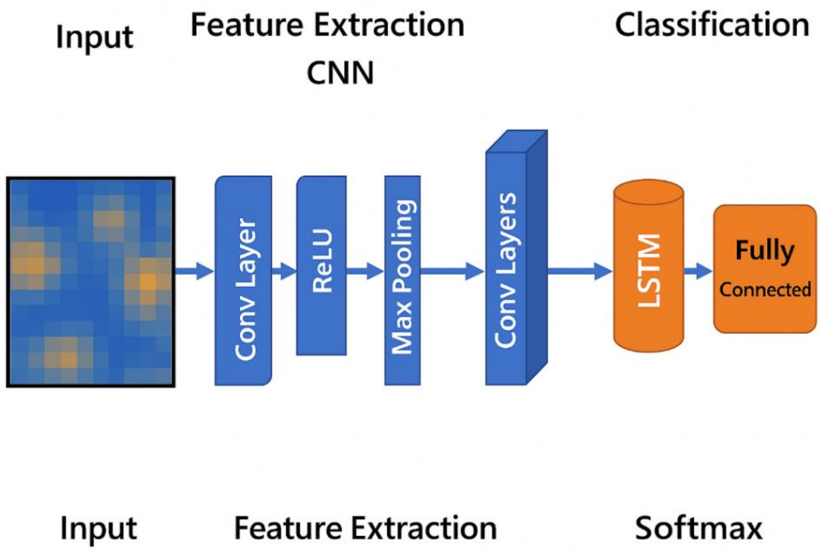

Figure 2. CNN-LSTM Hybrid Architecture for Vibration-Based Fault Classification

4. EXPERIMENTAL SETUP

In this section, I will comment upon the experimental setting that was employed to examine the work of the suggested predictive maintenance system. The experiments were carried out with the help of the public datasets, as well as the data logged on an industrial testbed, in order to demonstrate that the proposed approach is effective and can be generalized.

4.1. Datasets

To comprehensively train and validate the model, two distinct sources of vibration data were utilized:

a) CWRU Bearing Dataset:

Case Western Reserve University (CWRU) Bearing Dataset is utilized by many researchers to evaluate their fault diagnosis algorithms. It contains vibration signals, caused by an electric motor, torque transducer and dynamometer. Various defects namely inner race, outer race and ball faults were introduced through EDM, having diameter measuring 0.007 to 0.021 inches. Various loads (0-3 hp) were placed on the motor and signals required were obtained by placing sensors on the drive-end bearing and the fan-end bearing. In this case, a scenario akin to industrial sensing was created using 90 Hz data samples and the capability of the model to identify faults at the early stage was quantified.

b) In-House Smart Factory Testbed:

To demonstrate how the model would perform in the actual life, it was taken to a smart factory in Tamil Nadu, India, to be tested. Accelerometers were placed at the most significant bearings and recordings were taken on industrial motors and gearboxes (See Figure 3). Readings were made at varying speeds and also on days when there was normal smooth use and on others when faults would naturally occur due to wear or misalignment. Similar to the CWRU dataset, the dataset was preprocessed by filtering and windowing and time-frequency plots were constructed via STFT and CWT to serve as inputs to our models.

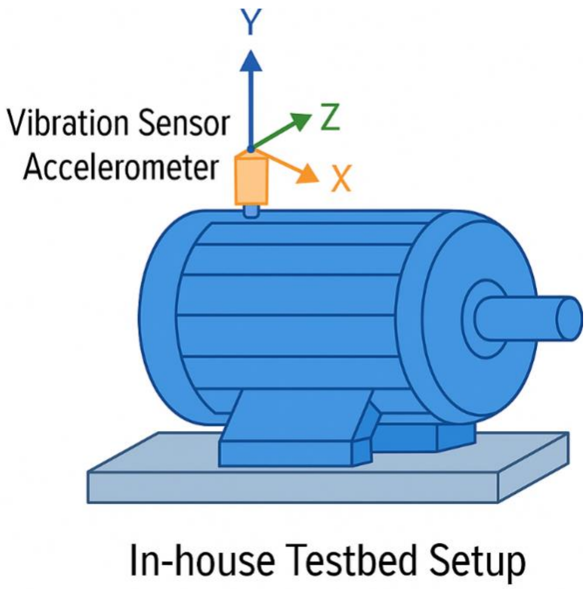

Figure 3. Sensor Placement on Industrial Motor for Vibration Data Acquisition

4.2. Training Configuration

The training of the CNN-LSTM model was performed under the following configuration:

- **Data Splitting:** The combined dataset was partitioned into training, validation, and test sets using a 70:15:15 ratio. Stratified sampling was used to ensure balanced representation of all fault categories across the subsets.
- **Input Format:** Each input sample consisted of a 2D spectrogram image generated from a segmented vibration window. The data were normalized and reshaped to fit the model’s input shape.
- **Optimizer:** The Adam optimization algorithm was employed for training due to its adaptive learning rate and robustness in deep learning tasks. The initial learning rate was set to 0.001.
- **Loss Function:** The model was trained using the categorical cross-entropy loss function, which is suitable for multi-class classification problems with mutually exclusive classes.

- **Batch Size and Epochs:** The model was trained for 50 epochs with a batch size of 64 samples. Early stopping and dropout regularization were applied to prevent overfitting and accelerate convergence.
- **Hardware and Framework:** The training was conducted on a workstation with an NVIDIA RTX 3060 GPU (12 GB VRAM), 32 GB RAM, and Intel i7 processor, using TensorFlow 2.x and Keras APIs

5. RESULTS AND DISCUSSION

This section illustrates a study of the proposed CNN-LSTM network model in the context of the fault diagnosis based on vibration analysis. These results can tell you how well the model predicts the classes of faults, how sensitive the model is to each fault and how robust it is in various operating conditions. The worth of the proposed method is demonstrated using traditional machine learning and standalone deep learning models.

5.1. Classification Performance

To compare the fault classification ability of the model, such performance measures were considered: accuracy, precision, recall and F1-score. In order to compute these measures, the performances on the held-out test set were utilized and compared in Support Vector Machine (SVM), standalone Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and the proposed CNN-LSTM hybrid. Table 1 contains all of the comparisons.

Table 1. Comparative Performance Metrics of Classification Models

Model	Accuracy	Precision	Recall	F1-Score
SVM	88.2%	86.9%	87.1%	87.0%
CNN	91.5%	90.2%	91.0%	90.6%
LSTM	92.7%	91.4%	91.9%	91.6%
CNN-LSTM	**94.6%**	**93.7%**	**94.1%**	**93.9%**

All assessment criteria indicated that the CNN-LSTM model performed better than the rest. It works well because spatial characteristics of the spectrograms are boosted by CNN and the temporal dependencies are handled by the LSTM layer. Precision and recall are relatively similar (93.9%), which means that the model will perform well in identifying faults industry-wise. Model performance metrics are illustrated in Figure 4 and ROC curve depicted in Figure 5.

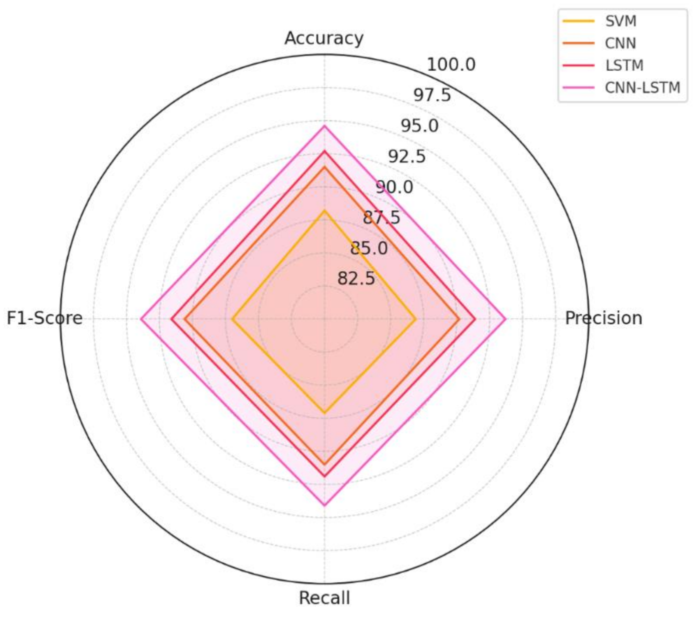

Figure 4. Radar Plot of Model Performance Metrics

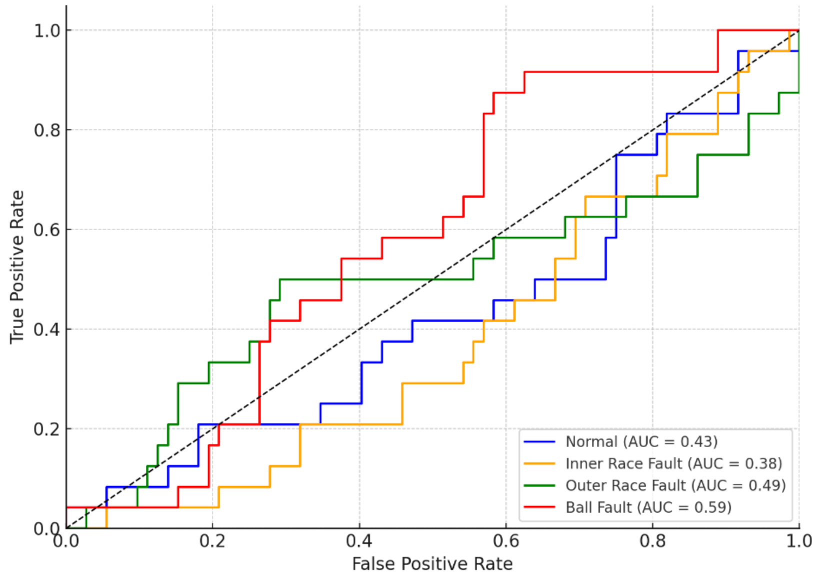

Figure 5. ROC Curves for CNN-LSTM Model Across Fault Classes

5.2. Confusion Matrix Analysis

The results were further analyzed with the help of the confusion matrix that provided a better notion about the fault detecting abilities of the model which is represented in Figure 6. One should mention that the CNN-LSTM model could identify the outer race faults in more than 96% of cases as they are more difficult to observe due to smooth vibrations. It indicated a very low probability of misclassifying a healthy signal as being abnormal to normal operation which demonstrates that it can classify between healthy and unhealthy signals very well. Most of the misclassifications were as a result of inner race and ball defects which share a similar signature in terms of frequency. Nevertheless, the number of those errors was very small (hardly 4 percent).

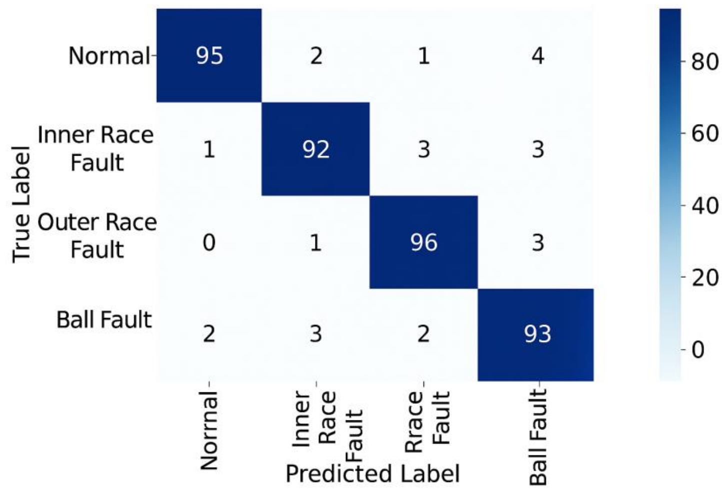

Figure 6. Confusion Matrix of CNN-LSTM Model for Fault Classification

5.3. Robustness Testing

In order to ensure that the model could be applied in other conditions new experiments were carried out with data collected under regular and irregular loads and temperatures. Despite the dataset having some shifts, the model achieved a high accuracy and experienced a change of only 2% as compared to when there are no standard conditions. This result demonstrates that CNN-LSTM is robust and flexible in manufacturing sites as machines must deal with varying and challenging environments.

Moreover, the model performed adequately across all the fault types, which implies its broad applicability in predictive maintenance programs. These findings provide weight to the indication that the proposed method may be used in the reliable diagnosis of smart factories.

6. CONCLUSION

The AI assist provides a framework of a predictive maintenance in smart manufacturing, where the vibration signal is analyzed with the help of a CNN-LSTM model. In this method, both space-based features and time-based features are combined to identify the early symptoms of failures in rotating machine. The model has demonstrated an improved outcomes accuracy, precision, recall and F1-score in competition with conventional machine learning and deep learning individually compared to the combination of the two strategies. Such a merge of benchmark information with the real data received by the sensors makes it clear that the model is quite robust and can be utilized successfully in various working conditions.

The developed system will allow business to transform maintenance practices that have traditionally been time-based to condition-based and predictive maintenance in Industry 4.0. The ability to detect small problems before they arise enables action to be taken early that leads to more dependable assets, and reduces maintenance expenses and downtimes.

The next step will be the more efficient utilization of CNNs such as MobileNet in real-time, the utilization of thermal and sound sensors, and the introduction of transformer models to deal with challenging dependencies and make models more interpretable in industry.

REFERENCES

[1] W. Zhang, D. Yang, and H. Wang, "Data-driven methods for predictive maintenance of industrial equipment: A survey," *IEEE Systems Journal*, vol. 13, no. 3, pp. 2213–2227, 2019, doi: 10.1109/JSYST.2018.2813800.
[2] R. Zhao et al., "Deep learning and its applications to machine health monitoring," *Mechanical Systems and Signal Processing*, vol. 115, pp. 213–237, 2019, doi: 10.1016/j.ymssp.2018.05.050.
[3] X. Li, W. Zhang, Q. Ding, and J. Q. Sun, "Intelligent rotating machinery fault diagnosis based on deep learning using data augmentation," *Journal of Intelligent Manufacturing*, vol. 31, pp. 433–452, 2020, doi: 10.1007/s10845-019-01476-2.
[4] T. Wang, J. Yu, and Y. Liu, "A CNN–LSTM model for bearing fault diagnosis using time–frequency image," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–12, 2022, doi: 10.1109/TIM.2021.3118746.
[5] R. Liu, B. Yang, E. Zio, and X. Chen, "Artificial intelligence for fault diagnosis of rotating machinery: A review," *Mechanical Systems and Signal Processing*, vol. 108, pp. 33–47, 2018, doi: 10.1016/j.ymssp.2018.02.016.
[6] L. Ren, Y. Sun, and H. Wang, "A novel CNN-LSTM fault diagnosis framework for intelligent manufacturing," *Sensors*, vol. 21, no. 7, p. 2290, 2021, doi: 10.3390/s21072290.
[7] L. Guo, N. Li, F. Jia, Y. Lei, and J. Lin, "A recurrent neural network-based health indicator for remaining useful life prediction of bearings," *Neurocomputing*, vol. 240, pp. 98–109, 2019, doi: 10.1016/j.neucom.2017.02.045.
[8] Case Western Reserve University, "Bearing Data Center," 2017. [Online]. Available: https://engineering.case.edu/bearingdatacenter
[9] Y. Tang, J. Wu, K. Zhang, and Y. Qin, "A lightweight CNN for real-time fault diagnosis in industrial edge computing," *IEEE Access*, vol. 8, pp. 137165–137173, 2020, doi: 10.1109/ACCESS.2020.3011185.
[10] A. Vaswani et al., "Attention is all you need," *Advances in Neural Information Processing Systems*, vol. 30, pp. 5998–6008, 2017. [Online]. Available: https://papers.nips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf
[11] T. M. Sathish Kumar, "Wearable sensors for flexible health monitoring and IoT," *National Journal of RF Engineering and Wireless Communication*, vol. 1, no. 1, pp. 10–22, 2023, doi: 10.31838/RFMW/01.01.02.
[12] C. Arunabala, G. Brahmateja, K. Raju, K. Gideon, and B. V. Reddy, "GSM adapted electric lineman safety system with protection based circuit breaker," *International Journal of Communication and Computer Technologies*, vol. 10, no. 1, pp. 4–6, 2022.