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CONVOLUTIONAL NEURAL NETWORK–BASED APPROACH FOR EARLY FAULT DETECTION IN INDUSTRIAL MACHINES.

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ABSTRACT

This study presents a Convolutional Neural Network (CNN)–based approach for early fault detection in machines using multi-sensor data. Vibration signals acquired from accelerometer sensors are analysed to capture mechanical behaviour, and frequency-domain features such as power spectra and Fourier analysis are extracted to identify abnormal frequency components associated with developing faults. In parallel, temperature sensors are used to monitor abnormal thermal rise in electric motors, while current sensors provide insight into the electrical operating condition and load variations of the machine. Sensor data are collected continuously over several months to capture both normal and abnormal operating states. The processed vibration, temperature, and current data are used to train a CNN model capable of automatically learning discriminative features and classifying machine conditions as normal or abnormal. The proposed multi-sensor framework aims to improve the reliability of early fault detection and support effective condition monitoring of industrial machines.

KEYWORDS

Early fault detection, convolutional neural network, condition monitoring.

INTRODUCTION

Industrial machines such as electric motors, pumps, and rotating equipment play a crucial role in manufacturing and production systems. Unexpected machine failures can lead to unplanned downtime, increased maintenance costs, and potential safety hazards. As a result, early fault detection and condition monitoring have become essential for ensuring reliability and efficiency in industrial operations (Jardine et al., 2006).

Traditional fault detection techniques often rely on manual feature extraction and threshold-based analysis of sensor signals such as vibration or temperature. While these approaches have been widely used, their effectiveness is limited in complex operating conditions where fault patterns are subtle and nonlinear. Moreover, conventional methods typically require expert knowledge to design features capable of capturing early-stage fault characteristics (Lei et al., 2020).

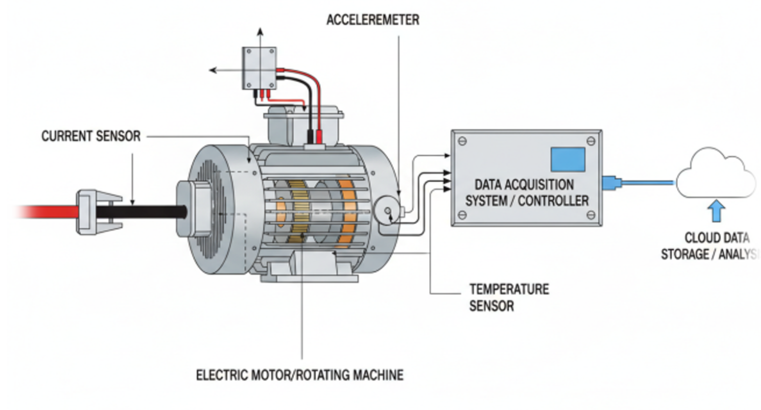

Figure 1: Typical machine condition monitoring system using vibration, temperature and current sensors.

Recent advances in machine learning, particularly deep learning, have provided new opportunities for intelligent condition monitoring. Convolutional Neural Networks (CNNs) have demonstrated strong capability in automatically learning discriminative features from raw or transformed sensor data. Although CNNs were originally developed for image processing, their application has been successfully extended to one-dimensional and multi-dimensional sensor signals, including vibration, current, and temperature data (Ince et al., 2016; Chen et al., 2019).

In machine fault diagnosis, vibration signals provide valuable information about mechanical defects such as bearing wear and imbalance, while temperature and current measurements offer insight into thermal and electrical abnormalities in motors and machines. The fusion of these complementary sensor modalities enables a more comprehensive representation of machine health (Lei et al., 2020). Motivated by these considerations, this study proposes a CNN-based multi-sensor framework for early fault detection in machines using vibration, temperature, and current data.

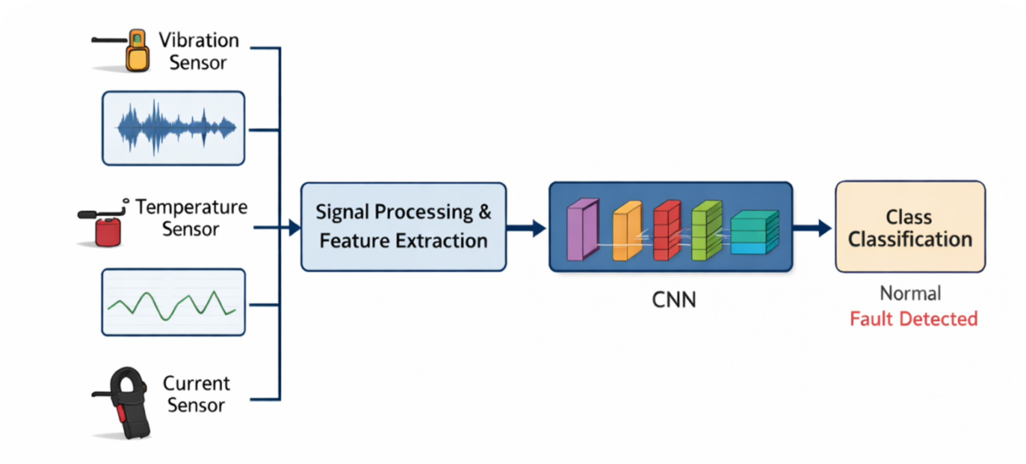

Figure 2: CNN-based framework for early fault detection using multi-sensor data.

MATERIAL AND METHODOLOGY

Data acquisition

Machine condition data are acquired from an electric motor or relevant machine part using multiple sensors installed at strategic locations. An accelerometer mounted on the motor casing is used to measure vibration signals associated with mechanical behaviour. A temperature sensor monitors thermal variations on the motor surface, while a current sensor placed on the power line captures electrical operating conditions. Data are collected continuously over an extended period to represent normal operation and abnormal conditions. All sensor outputs are logged using a data acquisition system and stored for offline and online analysis

Table1: Summary of sensors used for data acquisition.

Sensor	Measured Parameter	Installation Location	Purpose
Accelerometer	Vibration	Motor casing	Detection of mechanical abnormalities
Temperature sensor	Temperature	Motor surface	Monitoring abnormal thermal rise
Current sensor	Electrical current	Power supply line	Detection of electrical and load variations

Data pre-processing

The acquired sensor signals are pre-processed to improve data quality and ensure compatibility with the CNN model. Vibration signals are segmented into fixed-length sequence and transformed into the frequency domain using power spectral analysis to capture characteristic frequency features (Yan et al., 2014). Temperature and current signals are synchronized with vibration data and normalized to eliminate scale differences. Noise reduction and outlier handling are applied where necessary. The processed data are labelled according to machine condition and organized into training and testing sets.

CNN-based fault detection model

A Convolutional Neural Network (CNN) is employed to automatically extract discriminative features from the multi-sensor data and classify machine conditions due to ability to learn hierarchical representations in sensor data (Kiranyaz et al., 2021) . The network consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The input to the CNN includes vibration spectral features combined with temperature and current measurements. The model is trained to classify machine states into normal and abnormal categories using supervised learning.

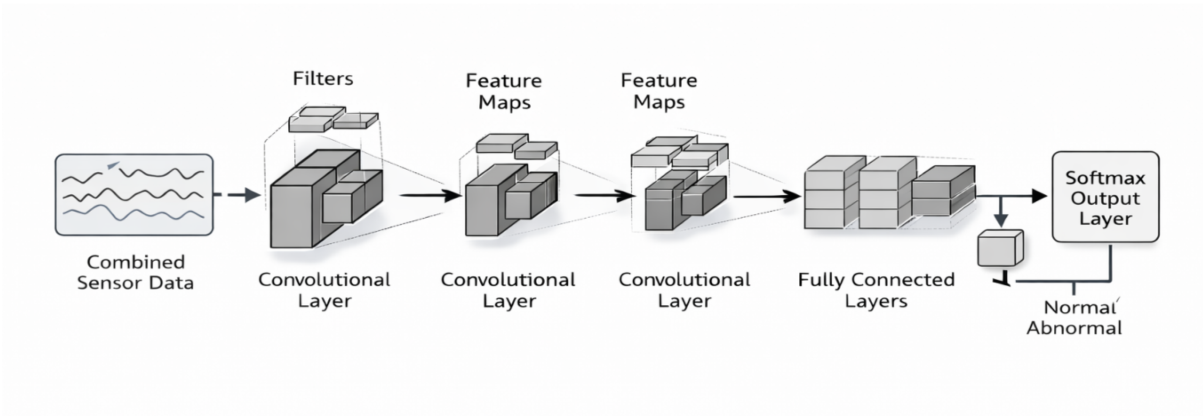

Figure 3: Detailed CNN architecture for fault detection.

Performance evaluation strategy

The performance of the CNN-based fault detection model is assessed using standard classification metrics commonly adopted in machine condition monitoring studies. These metrics include accuracy, precision, recall, and F1-score, which provide insight into the model's ability to correctly identify normal and abnormal machine states. Confusion matrix analysis is also employed to evaluate classification behavior across different operating conditions. Such evaluation metrics ensure an objective assessment of the effectiveness of the proposed fault detection framework.

RESULT AND DISCUSSION

The CNN-based fault detection model was evaluated using vibration, temperature, and current data obtained under different operating conditions. The model was able to distinguish between normal and abnormal machine states by learning characteristic patterns from the multi-sensor inputs (Ince et al., 2016; Chen et al., 2019). Vibration spectral features captured mechanical irregularities, while temperature and current measurements provided complementary information related to thermal and electrical behaviour.

The integration of multiple sensors enhanced the robustness of fault detection compared to single-sensor analysis. Accelerometer data were effective for detecting early mechanical degradation, whereas temperature rise and current variation supported the identification of abnormal operating conditions. The CNN's automatic feature learning capability reduced dependence on manual feature extraction and enabled effective modelling of nonlinear relationships in the data.

Model performance was assessed using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provided an objective means of evaluating the effectiveness of the proposed approach for early fault detection and machine condition monitoring.

CONCLUSION

This study presented a CNN-based approach for early fault detection in machines using vibration, temperature, and current sensor data. The integration of multi-sensor information enables effective monitoring of mechanical, thermal, and electrical conditions, while the CNN automatically learns discriminative features from the data. The proposed framework demonstrates the potential of deep learning–based multi-sensor fusion for machine condition monitoring. Future work will focus on extended experimental validation, advanced multi sensor fusion, and the development of multi-class fault diagnosis models

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