High Accurate Smart Device for Real-Time Monitoring Electric Motor Conditions Based on IoT Technology and Artificial Intelligence

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Abstract

In the study, the authors developed a portable, non-invasive smart device for real-time monitoring of electric motors' working conditions based on IoT technology and artificial intelligence. The device collects vibration data of an electric motor, predicting anomalies using deep learning algorithms. Additionally, an application was built to track the real-time working conditions of the electric motors. Whenever an anomaly is detected, an alert message is immediately sent to the user via their smartphone. For anomaly prediction, two types of vibration data were utilized in the deep learning algorithms: one in the time domain and the other in the frequency domain, obtained through a discrete Fourier transform. Various feature extraction models in deep learning algorithms were employed to assess the accuracy of each model in predicting electric motor anomalies. Experiments were conducted on a grinding machine operating under various grinding conditions to evaluate the accuracy of the developed device in predicting anomalies. The results indicate that predicting the working condition of an electric motor using time-domain vibration data is more accurate than using frequency-domain data. It was found that the Serenest26d_32x4d and Reset 34 feature extraction models achieved better training results with time-domain vibration data compared to other models. The Reset 34 feature extraction model achieves the highest accuracy, with an F1-score of 1, when predicting the working condition of the grinding machine. The running time for all prediction models is under 0.02 seconds, demonstrating the capability for real-time monitoring of the electric motor's working condition using the developed device.

Keywords: Motor condition monitoring, non-invasive monitoring, smart device, deep learning algorithms, real-time monitoring.

1. Introduction

Electric motors have played a crucial role in providing motion sources across various fields, including transportation, aerospace, machine tools, robotics, injection molding, production lines, and home appliances [1-3]. Particularly in the manufacturing sector, electric motors drive most devices and machines. A market study indicates that the global electric motor industry was valued at approximately 145.14 billion in 2022 and is projected to reach 292.23 billion by 2032. This growth is expected to occur at a compound annual growth rate (CAGR) of 7.3% from 2023 to 2032.

Regular monitoring of the working conditions of electric motors is essential and characterized by several critical needs. First and foremost, it ensures operational efficiency by early detecting potential issues, such as excessive vibration, overheating, or electrical imbalances. These early warnings can prevent costly downtime, as they enable maintenance teams to address problems before they escalate into significant failures that could halt operations and incur substantial repair costs. Secondly, it enhances safety by identifying potential hazards, such as mechanical failures and/or electrical faults, that could lead to serious accidents. Moreover, tracking the electric motor's performance metrics helps to optimize motor efficiency, thereby facilitating energy management, optimizing energy consumption and reducing operational costs. Finally, it aids in predictive maintenance strategies, allowing for timely interventions or maintenance that prolong the motor's lifespan. Overall, effective monitoring of the working condition of electric motors is neccessary for ensuring reliability, safety, and cost-effectiveness in motor-driven systems.

Monitoring the working condition of electric motors can be accomplished by two approaches. The first one is the invasive monitoring techniques, and the other one is non-invasive techniques. Invasive monitoring involves installing sensors directly on or within the motor to measure parameters such as temperature, vibration, and electrical signals [4]. These methods provide highly accurate and detailed data, enabling precise diagnostics and early detection of potential issues. However, it often requires motor

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disassembly or significant modifications, leading to higher installation costs and potential downtime. Moreover, the invasive nature can sometimes interfere with the motor's normal operation, potentially affecting its performance.

On the other hand, non-invasive monitoring techniques rely on external sensors or meters to measure and analyze the electric motor's operation conditions [5, 6]. Non-invasive monitoring is generally easier and cheaper to implement since it does not require physical alterations to the motor. Therefore, it minimizes downtime and avoids any risk of interfering with the motor's operation. However, the accuracy of non-invasive methods may be lower than invasive techniques. This is because they rely on indirect measurements and complex data processing and analysis. Additionally, non-invasive monitoring may struggle with many noises from the surrounding enviroment or nearby working machines which potentially results in less precise diagnostics.

Recently, alongside the growth of the internet, artificial intelligence (AI), and wireless communication technologies (WCT), the development of internet of things (IoT) devices is flourishing across various fields such as home appliances and healthcare services [7-9], and industrial manufacturing sectors [10]. The advancements in AI and WCT not only enhance the performance and accuracy of non-invasive systems for monitoring electric motors but also enable real-time monitoring. The integration of these non-invasive monitoring systems with IoT platforms facilitates effective real-time monitoring and remote control of electric motors. Furthermore, artificial intelligence techniques like machine learning (ML) can be utilized to analyze the collected data and provide improved assessments of electric motor performance.

Many efforts have been made to develop non-invasive monitoring systems or devices for electric motors based on IoT and/or AI. Magadán *et al*. [11] created an IoT system for wireless monitoring of electric motor conditions using wireless multi-sensor modules and single-board computers as gateways. It was reported that the system could monitor electric motors in real-time by collecting their vibration data. However, the use of the Bluetooth Low Energy (BLE) communication protocol between the sensors and the gateways limits the communication range. Additionally, obstacles typically exist in a practical production environment. Consequently, the data transfer speed between the sensors and the gateway is reduced, resulting in high latency. Furthermore, the analysis of the collected data for predicting anomalies in the electric motor was not addressed.

Similarly, Firmansah *et al*. [12], Mykoniatis *et al*. [13], Muhammad Sidik *et al*. [14], and Kunthong *et al* [15] also reported on IoT systems for monitoring electric motors. It was noted that the vibration of an electric motor is measured and displayed on a mobile application without predicting anomalies during the motor's operation [12]. Furthermore, the prediction of anomalies in an electric motor relies on the vibration magnitude and/or the case temperature of the motor exceeding a predefined limit [13, 14]. This leads to inaccurate predictions of anomalies when the electric motor operates under varying loading conditions (for instance, a driving motor for interrupted cutting or cutting at different depths). In such cases, the vibration magnitude of the electric motor fluctuates significantly depending on the depth of cut, yet it continues to function effectively. However, the monitoring system may alert the user frequently, resulting in false predictions. This creates inconvenience for users. Furthermore, relying on a fixed motor case temperature threshold to predict anomalies in electric motors based on temperature is not always reliable. This is due to the significant temperature variations that can occur between day and night or across different seasons, such as winter and summer. Consequently, the motor case temperature threshold should be a dynamic value that is continuously updated according to the actual operating conditions of the motor. Conversely, predicting anomalies in an electric motor by comparing its operational vibration data and temperature with that of a motor with a faulty ball bearing [15] is both inaccurate and challenging to implement in practice. This is because the fault associated with a ball bearing in an electric motor is not quantifiable, and a faulty ball bearing represents only one specific case among numerous types of motor malfunctions. Therefore, using faulty ball bearing data to predict anomalies in electric motors may lead to inappropriate applications for other types of motor failures. Additionally, the developed system necessitates that users observe and compare the collected vibration data from a functioning motor with that of a faulty motor. This process is time-consuming and poses challenges for practical applications.

Therefore, it is highly desirable to have an IoT system to monitor the working conditions of an electric motor, capable of autonomously predicting anomalies based on the collected operational data. In this study, the authors present an innovative system for monitoring the working conditions of an electric motor using IoT technology and artificial intelligence (AI). The collected vibration data from the electric motor is analyzed by deep learning algorithms to predict motor anomalies.

2. Development of IoT System for Monitoring Working Conditions of an Electric Motor

Fig. 1 illustrates the IoT system developed in this study for monitoring the working conditions of electric motors. The system's infrastructure resembles a standard IoT system, comprising four elements: devices, gateway, IoT platform, and a user application.

Each monitoring device is attached to an electric motor (as shown in the accompanying photo in Fig. 1) to measure its operating signals (such as vibration data and the motor's frame temperature) and subsequently sends these signals to the cloud (IoT platform) through a local computer (gateway) via wireless communication. The signals are then analyzed using deep learning algorithms to detect any abnormal signs or malfunctions of the electric motor. The working condition of the electric motor is tracked in real-time on the user application running on a smartphone. Any anomaly detected in the electric motor will be immediately communicated to the user. Consequently, any abnormal operating signs are detected at an early stage, minimizing the risk of serious malfunctions in the motor.

Fig. 2(a) illustrates the design of the electric motor condition monitoring device developed in this study. The vibration sensor and central processing unit are integrated onto a printed circuit board (referred to as the control PCB). A lithium battery serves as the device's power source. Both the control PCB and the lithium battery are housed in a hard plastic case composed of two halves (i.e., upper case and lower case). The entire device is mounted on a plate designed for optimal contact with the cover of an electric motor. The overall dimensions of the device are 70mm × 55mm × 50mm.

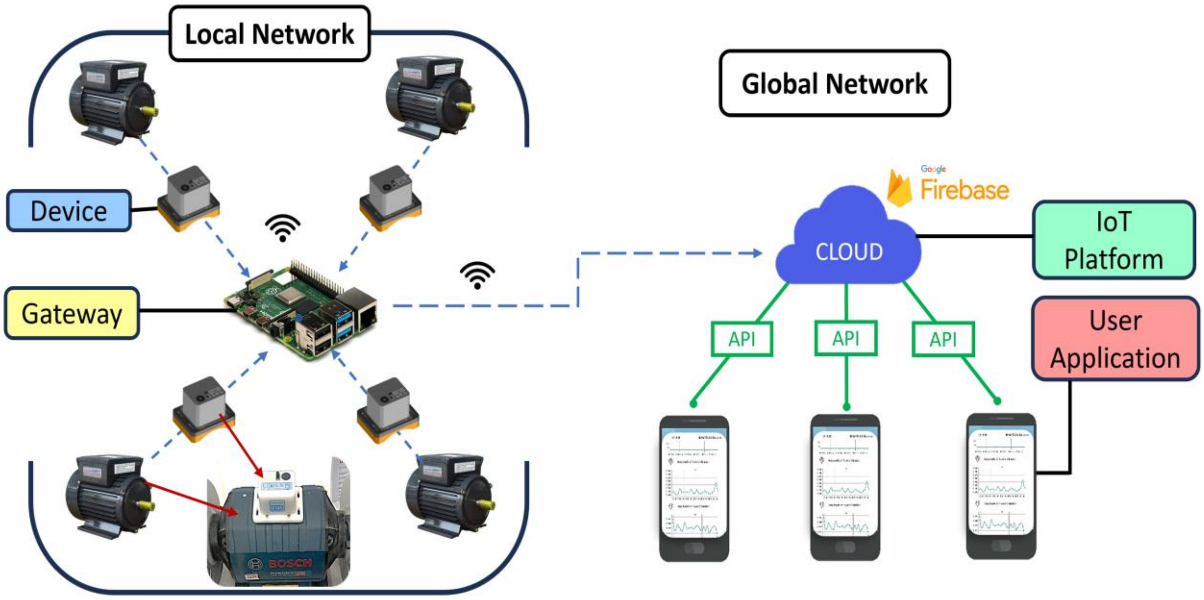
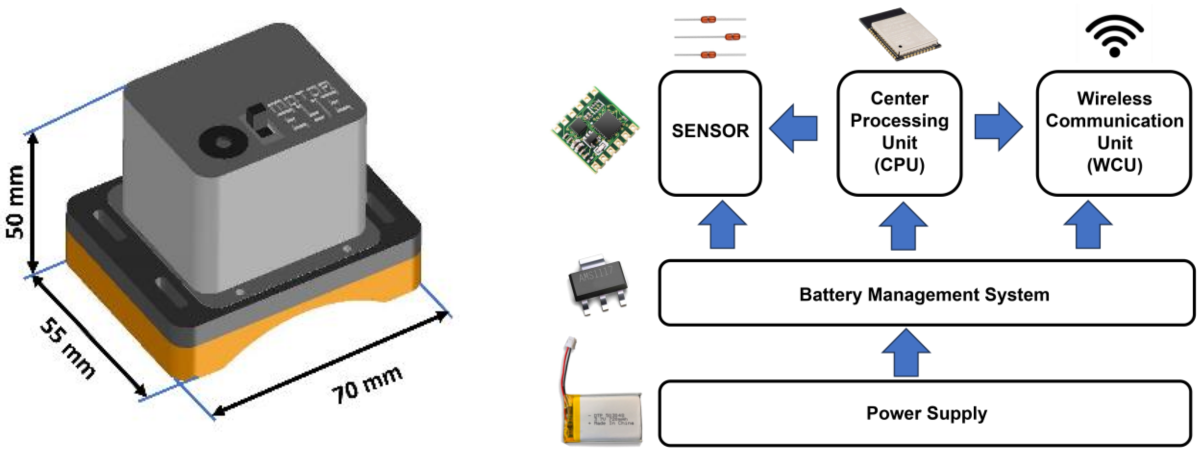


Fig. 1. IoT infrastructure of rotational speed and vibration measuring device system



(a) 3D design model of the device

(b) Block diagram of monitoring device

Fig. 2. 3D design model and block diagram of monitoring device

Fig. 2 (b) illustrates the block diagram of the electric motor working condition monitoring device. The control principle of the device aligns with several IoT systems previously presented [5, 7], which comprises the following units.

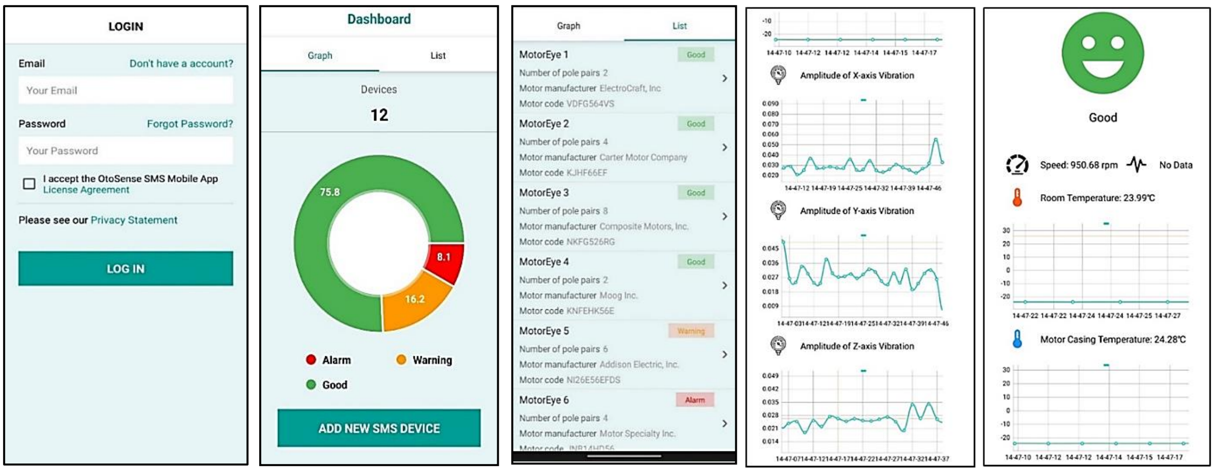
- Central Processing Unit (CPU): This is the most crucial component of the device, often referred to as its brain. The CPU contains the circuits necessary to process raw data gathered from sensors, store information, and transmit output control signals.
- Wireless Communication Unit (WCU): This WCU enables the CPU to communicate with the cloud server platform and/or smart devices via a Wi-Fi network. The sensing signals from the electric motor (i.e., the vibration data and motor frame temperature) are collected in real-time and synchronized with the cloud server and a user application through the WCU.
- Sensor Unit: This unit comprises a 6-axis accelerometer-magnetometer sensor (GY-511 LSM303DLHC) and temperature sensors (NTC MF 52 thermistors). The accelerometer-magnetometer sensor is a type of micro-electro-mechanical system (MEMS) that operates based on the principles of the piezoresistive accelerometer and Hall Effect Magnetometer. The GY-511 LSM303DLHC sensor measures the vibration accelerations of the motor in the *x*, *y*, and *z* directions, as well as the magnetic field. It then converts these measurements into electrical signals.
- Power Supply Unit: This unit consists of a rechargeable lithium battery and a battery management circuit. It provides appropriate power for the entire system. In addition, the battery is charged using a dedicated charger for the device. This charger ensures a consistent power supply for the device to operate continuously.

To access the monitoring device via the IoT platform, an application (app) has been developed for smartphones using Kotlin and the Android Studio IDE. The app displays various operational parameters of the electric motor, including vibration accelerations in the *x*, *y*, and *z* directions, rotation speed, the motor's frame temperature, and ambient temperature.

It is important to note that the device used for measuring rotation speed is specifically designed for induction motors, as previously reported [5]. In the app, the operational parameters of each electric motor are organized into specific tabs, as illustrated in Fig. 3. Whenever an anomaly or malfunction in an electric motor is detected, a warning message will be promptly displayed on the application screen to alert the user.

3. Measuring Vibration Data of an Electric Motor

Fig. 4 illustrates the flowchart diagram for predicting anomalies in an electric motor using artificial intelligence. A Deep Learning (DL) algorithm was employed to analyze the vibration data of the electric motor, which was measured by the developed IoT device in this study. Firstly, the raw vibration data of an electric motor was collected from the accelerometer-magnetometer sensor inside the device (i.e., vibration accelerations of the motor in the *x*, *y*, and *z* directions). The data collection process is detailed as follows.



(a) (b) (c) (d) (e)

Fig. 3. User interfaces of the mobile application: (a) Login interface; (b) Dashboard interface; (c) Devices list interface; (d) Motor vibration data interface; (e) Rotational speed and motor's frame temperature

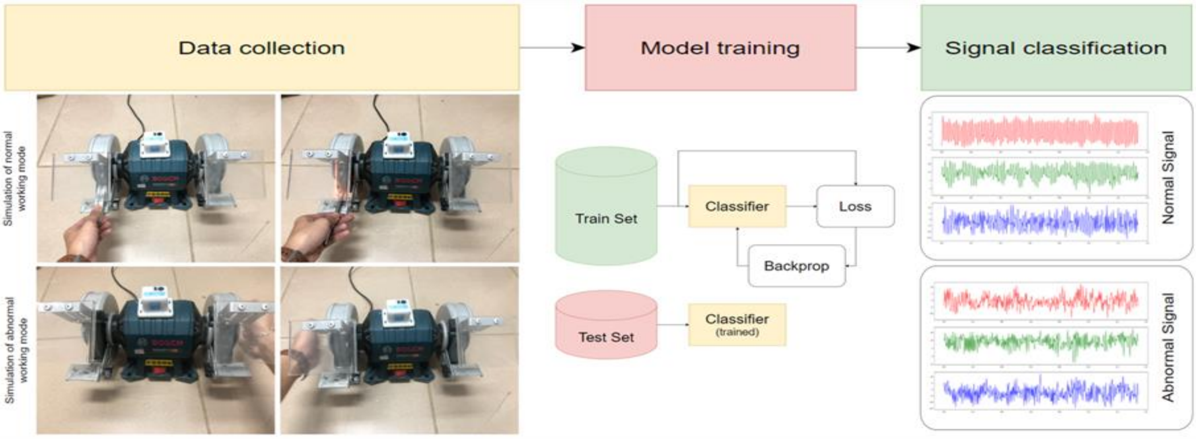


Fig. 4. Flowchart for predicting abnormal vibrations in electric motors using a deep learning algorithm

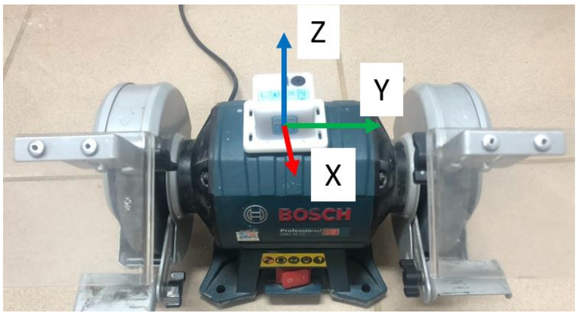


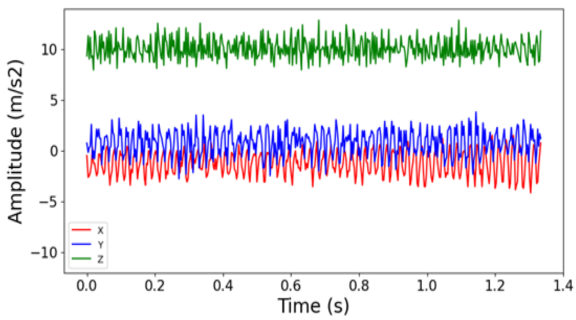
Fig. 5. Experiment setup for measuring the vibration of an electric motor

Fig. 5 illustrates the experimental setup for measuring vibration data from an electric motor using the developed device. The device is affixed to the electric motor of a grinding machine (Bosch GBG35-15 double-wheeled bench grinder). Vibration data was collected under two scenarios: the first under normal working conditions, and the second under abnormal working conditions (artificially induced impact forces).

Fig. 6 (a) illustrates the experimental setup for measuring the vibration data of the grinding machine under normal working conditions. Grinding experiments were performed on two types of workpiece materials. The first involved grinding aluminum, while the second focused on S50C steel. Throughout the grinding process, the feeding force was manually adjusted to gather vibration data from the grinding machine at various material removal rates. In total, 450 vibration data samples corresponding to different material removal rates were collected for both aluminum and steel grinding. Each sample was recorded over 1.5 seconds, yielding 448 data points.

Fig. 6 (b) presents the collected vibration data of the grinding machine in the *x*, *y*, and *z* directions (i.e., vibration accelerates of the grinding machine in the *x*, *y*, and *z* axes). It was noted that the vibration data of the grinding machine exhibited the smallest magnitude in the *z* direction compared to the other directions. This measurement data is reasonable, as the vibration of the grinding machine in the *z* direction is constrained by the floor.

(a) Grinding experiments under normal working conditions



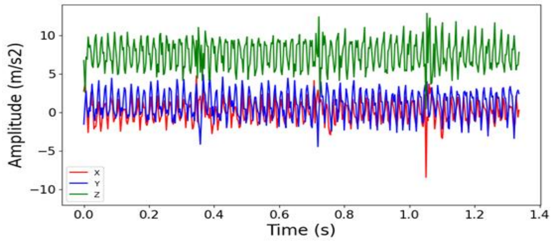
(b) Vibration data of the grinding machine measured under normal working conditions

Fig. 6. Experiment setup for collecting vibration data from the grinding machine under normal working conditions

Fig. 7 (a) illustrates the experimental setup for measuring vibration data of the grinding machine under abnormal working conditions by artificially inducing impact forces. The impact forces were applied to the grinding machine in the *x*, *y*, and *z* directions while it was operating to generate artificial abnormal vibration data. In total, 450 vibration data samples were collected, corresponding to various magnitudes and directions of impact forces. Each abnormal vibration data sample was recorded over 1.5 seconds, yielding 448 data points.

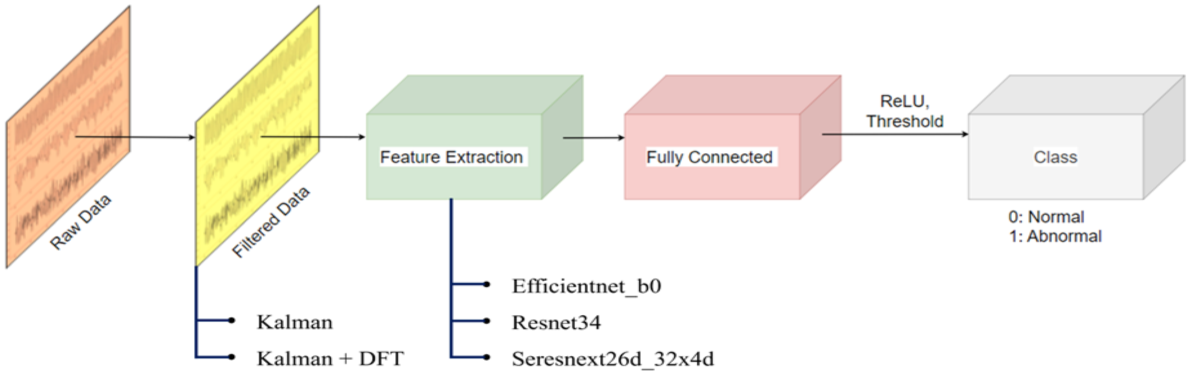
Fig. 7 (b) displays the measured vibration data of the grinding machine in the *x*, *y*, and *z* directions under abnormal conditions (i.e., vibration accelerates of the grinding machine in these directions when the impact force is suddenly applied). It is noted that when the impact force is exerted on the grinding machine, the vibration accelerates, and the magnitudes increase abruptly.

(a) Grinding experiments under abnormal working conditions

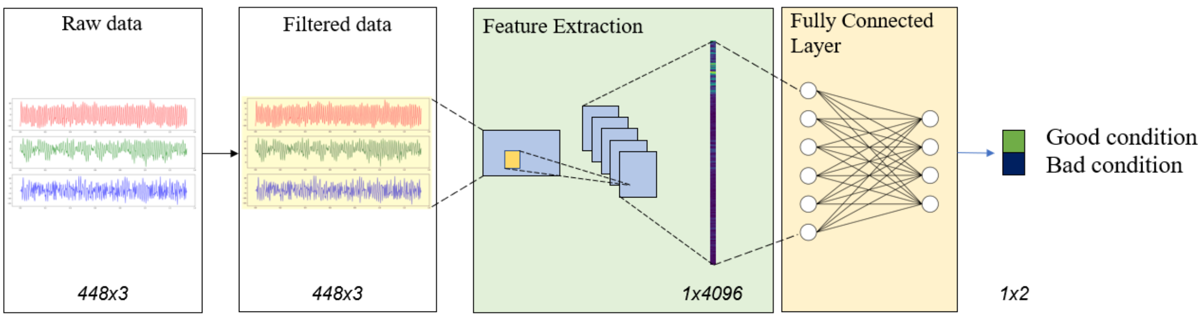


(b) Vibration data of the grinding machine measured under abnormal working conditions

Fig. 7. Experiment setup for collecting vibration data from the grinding machine under abnormal working conditions



(a) Flowchart for predicting the working condition of an electric motor based on vibration data using a deep learning algorithm



(b) Data architecture in deep learning algorithm

Fig. 8. Flowchart for predicting the working condition of an electric motor and the data architecture utilizing a deep learning algorithm

4. Prediction of Anomalies in Electric Motors Using Artificial Intelligence

Fig. 8 (a) illustrates the flowchart of the electric motor's working condition prediction process based on vibration data using a DL algorithm. Firstly, raw vibration data was filtered to denoise it. In this work, Kalman filter was utilized to remove noise. Two types of filtered data were utilized as datasets for training the model in the DL algorithm. The first type is filtered vibration data (i.e., vibration data in the time domain), while the second is the discrete Fourier transform (DFT) of the filtered vibration data, which converts the vibration data from the time domain to the frequency domain. The details of the DFT of the vibration data were previously presented [5]. The filtered vibration data of the motor served as the dataset for model training in the DL algorithm. The dataset was divided into two separate subsets: the training set, which comprises 80% of the total data, and the remaining 20%, which is the test set. The filtered data undergoes feature extraction and classification processes using the DL algorithm to predict abnormal vibration signals of the electric motor. In the experiment, three different models for feature extraction were used to assess the accuracy of each model. These models are EfficientNet_b0, Resnet34, and Seresnext26d_32x4d.

Fig. 8 (b) illustrates the data architecture for predicting the working condition of an electric motor based on vibration data using a deep learning (DL) algorithm. The raw vibration data, sized at 448×3 and collected from the developed device, was filtered to eliminate unwanted noise. It is important to note that the filtering process may alter the mean value and variance of the data, but the data size remains unchanged. The filtered vibration data (i.e., still sized at 448×3) underwent a convolutional neural network (CNN) layer for feature extraction. The output from the feature extraction layer is a vector sized at 1×4096, which contains several valid characteristics of the vibration data for classification. This vector was then passed through a fully connected layer that includes hidden layers. The hidden layers were interconnected via weight and bias parameters for signal classification. In this study, the cross-entropy loss function was employed to calculate the error between the prediction results and the original input signal (i.e., the labeled input signal). During the model training process, the weights and biases were continuously updated through the calculation of the loss function and backpropagation. By utilizing a rectified linear unit (ReLU) activation function, the output value of the ReLU function of the model ranges between $[0, +\infty)$, and the classification of the signal is determined using a threshold. Through experiments, a threshold ReLU value of 0.5 was found to be optimal for signal classification. Signals resulting in a ReLU value smaller than 0.5 correspond to normal or good conditions, while those exceeding this threshold indicate abnormal or bad conditions.

5. Results and Discussions

Fig. 9 illustrates the variation of the cross-entropy loss function against the training step for predicting the working condition of the grinding machine based on vibration data using a DL algorithm. Curves a, b, and c represent the loss function variation for input vibration data in the time domain, utilizing the Efficientnet_b0, Resnet34, and Seresnext26d_32x4d feature extraction models, respectively. Similarly, curves d, e, and f depict the loss function variation for input vibration data in the frequency domain, also using the Efficientnet_b0, Resnet34, and Seresnext26d_32x4d feature extraction models. It is observed that the loss function decreases as the training step increases for all types of input data and feature extraction models. Notably, the loss function decreases rapidly when the training step is below 300, slows down between 300 and 600, and reaches saturation when the training step exceeds 600.

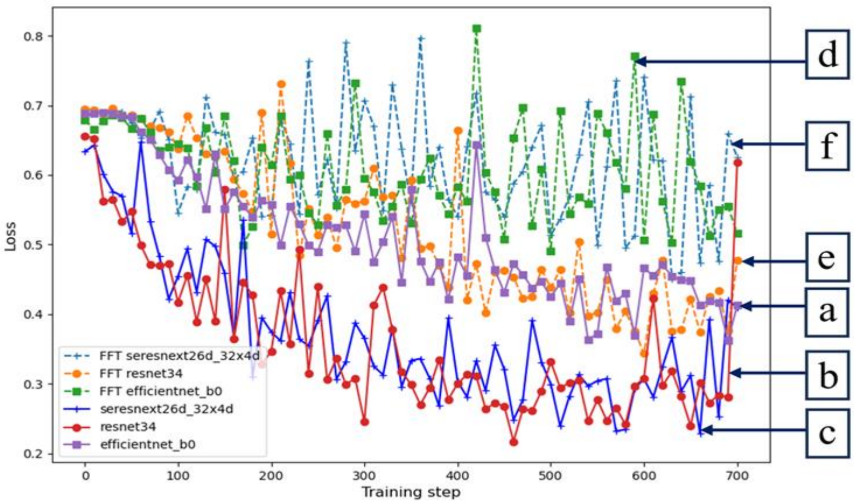


Fig. 9. Variation of the loss function during the training of a model in deep learning algorithms

It is observed in Fig. 9 that, with the same feature extraction model, utilizing vibration data in the time domain yields a lower loss function value compared to using vibration data in the frequency domain. This indicates that predicting the working condition of the grinding machine with time-domain vibration data is more effective than with frequency-domain data. The reason for this is that the stimulating impact forces acting on the grinding machine are random in direction, timing, and magnitude. Applying the DFT to convert the vibration data from the time domain to the frequency domain may diminish or obscure the characteristics of the impact process. Consequently, the loss function is higher for predicting the working condition of the grinding machine when using vibration data in the frequency domain. Additionally, it is noted that the Seresnext26d_32x4d and Resnet34 feature extraction models achieve superior training results when employing time-domain vibration data compared to other models.

The results of employing various training models to assess the test set (which constitutes 20% of the total dataset) are summarized in Table 1. The experiments were conducted using a GPU P100. The F1-score is utilized to evaluate the quality of predictions regarding abnormal working conditions of the electric motor in the grinding machine. The F1-score [8, 9] is defined as shown as below:

$$F1 = 2\frac{Precision.Recall}{Precision+Recall} \tag{1}$$

where

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

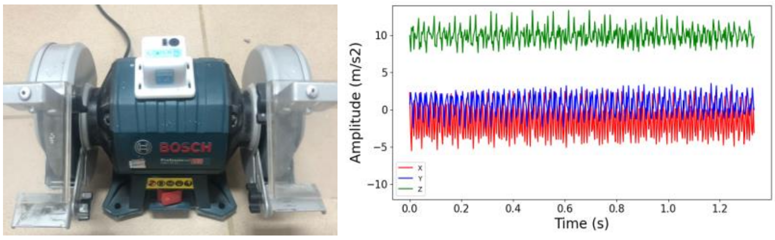
It is found from Table 1 that the F1-scores of all prediction models exceed 0.9, with calculation times ranging from 0.01 to 0.02 seconds. This indicates that the prediction of the electric motor's working condition in the grinding machine is highly accurate and suitable for real-time monitoring of abnormal working conditions. It is noted that, using the same feature extraction model, the vibration data in the time domain yields a superior F1-score. This suggests that predicting the electric motor's working condition with time-domain vibration data is more effective than using frequency-domain data. Among the feature extraction models, the Resnet34 model demonstrates the best prediction capability for the grinding machine's working condition, achieving an F1-score of 1 and an average running time of 0.0126 seconds (when utilizing GPU P100), which is significantly shorter than the device's sampling time of approximately 1.5 seconds. Thus, it confirms that the device can effectively perform real-time predictions of the electric motor's working condition using vibration data.

Fig. 10 illustrates the prediction results of the grinding machine's working condition across various grinding experiments utilizing the DL algorithm on a GPU P100. In this experiment, the Resnet34 model was employed for feature extraction of vibration data in the time domain. Fig. 10 (a) presents the vibration acceleration data when the grinding machine operates without cutting. The prediction result closely aligns with the actual labeling, indicating that the grinding machine is functioning under normal conditions.

Similarly, Fig. 10 (b) displays vibration acceleration data during the grinding of an aluminum rod. The ReLU function value of the model is 0.3221, which is below the threshold (i.e., 0.5). Consequently, the prediction result is 0, suggesting that the grinding machine is operating normally. In contrast, when the grinding machine operates under impact force in the *x* direction (as shown in Fig. 10 (c)) or in the *z* direction (as depicted in Fig. 10 (d)), some sudden variations in the vibration acceleration data are observed in the Fig.10 (c) and Fig. 10 (d). The values of the ReLU function of the model are 2.1341 and 14.929 when the grinding machine is operating under impact force in the *x* and *z* directions, respectively. These values exceed the threshold, indicating that the grinding machine is operating under abnormal conditions. The prediction results demonstrate that the deep learning model used in this study is highly accurate for predicting the working condition of the grinding machine

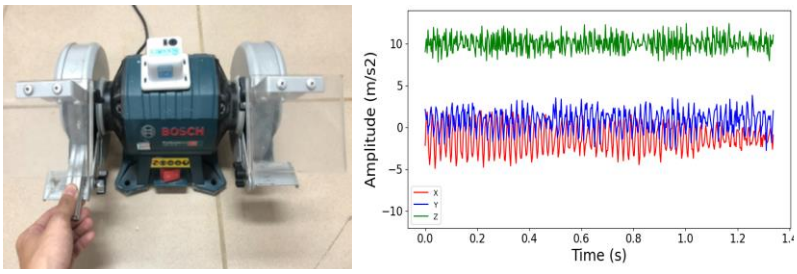
Table 1: Results of using different training models to evaluate the test set (using GPU P100)

Dataset	Model	Parameters	F1 score	Running time (s)
Kalman Filter Data (in the time domain)	*Efficientnet_b0*	5.3M	0.9292	0.0097
	Resnet34	21.3M	1.0000	0.0126
	Seresnext26d_32x4d	16.8M	0.9955	0.0136
Kalman Filter and DFT Data (in the frequency domain)	*Efficientnet_b0*	5.3M	0.9114	0.0155
	Resnet34	21.3M	0.9655	0.0167
	Seresnext26d_32x4d	16.8M	0.9614	0.0177



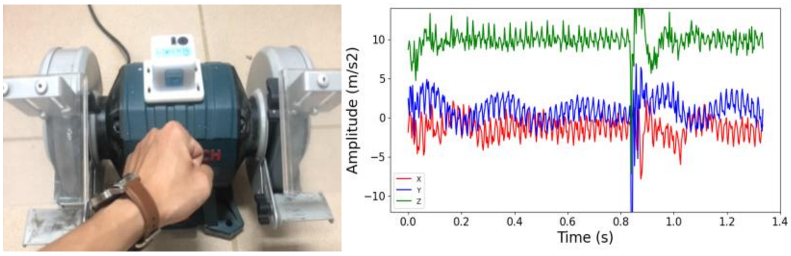
Actual Labeling	*ReLU* Value	Prediction Result
0	0.000	0

(a) Free cutting running experiment



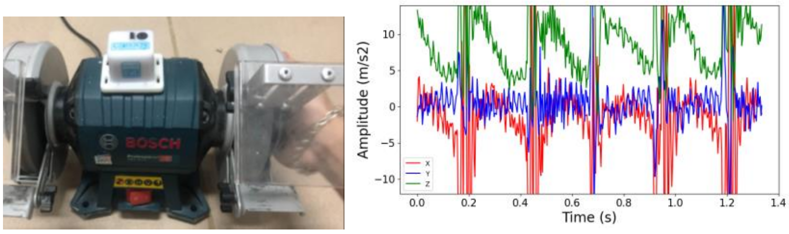
Actual Labeling	*ReLU* Value	Prediction Result
0	0.3221	0

(b) Grinding of aluminum rod experiment



Actual Labeling	*ReLU* Value	Prediction Result
1	2.1341	1

(c) Operating under impact force in *x* direction



Actual Labeling	*ReLU* Value	Prediction Result
1	14.929	1

(d) Operating under impact force in *z* direction

Fig. 10. Prediction results of working conditions for the grinding machine using a deep learning algorithm

6. Conclusion

In this paper, the authors developed a compact, non-invasive smart device for real-time monitoring of electric motor working conditions based on IoT technology and deep learning algorithms. The device predicts anomalies in electric motors by analyzing their vibration data using deep learning algorithms. Additionally, a mobile application was created to track the real-time working conditions of the electric motors. Whenever an anomaly is detected, a notification message is immediately sent to the user via the application as a warning. Experiments were conducted on an electric motor of a grinding machine operating under various grinding conditions to evaluate the device's prediction accuracy. Vibration data from the grinding machine in both the time and frequency domains was used as two types of datasets for the deep learning algorithms. Furthermore, various feature extraction models were employed to assess the prediction accuracy of the grinding machine's anomalies. The experimental results indicate that predicting the working condition of the grinding machine using time-domain vibration data is more accurate than using frequency-domain data. It was also found that the Seresnext26d_32x4d and Resnet34 feature extraction models yield better training accuracy when utilizing time-domain vibration data compared to other models. The Resnet34 feature extraction model achieves the highest prediction accuracy, with an F1-score of 1, when predicting the working condition of the grinding machine. The developed device successfully predicted various working conditions of the grinding machine. It is demonstrated that the device is capable of real-time monitoring of electric motors. The success of this research lays the foundation of several future applications, including real-time monitoring of numerous machines utilizing electric motors. Additionally, it facilitates predictive maintenance of electric motors inside many machines, enabling technicians to detect potential issues before they escalate into costly failures. Consequently, it heralds a new era of intelligent manufacturing, where precision and reliability enhance productivity and growth. Future research will concentrate on testing the measuring device across various engine types and measurements in real production environment conditions to assess the device's features and accuracy.

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