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A Low Cost IoT-Based Hybrid Multiscale CNN-LSTM Approach for Bearing Fault Diagnosis Using Low Sampling Rate Vibration Data

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Abstract

Electric motors are vital in energy systems for converting energy efficiently. Their reliability ensures consistent performance, making them indispensable in renewable energy applications and industrial processes. Bearings are crucial for motor operation, yet they are vulnerable to faults that can impair performance and reduce lifespan. Conventional fault detection methods require high sampling rate vibration data and expensive sensors. This paper presents a cost-effective solution by introducing a hybrid model combining Multiscale Convolutional Neural Networks (MSCNN) with Long Short-Term Memory (LSTM) networks for bearing fault diagnosis using low sampling rate data. We developed dedicated IoT-based hardware and a web server for real-time monitoring. Our approach leverages MSCNN for spatial feature extraction and LSTM for temporal pattern recognition, achieving high diagnostic accuracy with lower resolution data. Experimental results show that our MSCNN-LSTM model provides diagnostic accuracy comparable to or surpassing that of high sampling rate methods, offering a robust and economical solution for bearing fault detection.

Keywords: Multiscale Fault Diagnosis; Convolutional Neural Network; Long Short-Term Memory; Bearing Fault, Internet of Things.

1. Introduction

Electric machines are extensively used in a variety of domestic and industrial applications. These devices are integral to the construction of various pumps, compressors, blowers, fans, industrial machinery, cranes, and electric vehicles [1]. Among these, induction motors are one of the most prevalent and crucial machines across different industries. As a key technology in industrial advancements, induction motors are utilized in nearly every sector, accounting for over 80% of the motors in industrial environments [2]. Induction motors rely on bearings to support the rotor and allow it to spin freely within the stator. These components are essential for reducing friction between moving parts and maintaining the precise alignment of the motor shaft [3]. Bearings play a crucial role in the operation and longevity of motors and must withstand various stresses and adverse environmental conditions such as dust, moisture, and temperature fluctuations [4]. Therefore, the maintenance of bearings is a critical factor in the design and operation of motors. Bearing failures can lead to significant downtime and maintenance costs [5]. Advanced monitoring techniques and predictive maintenance strategies are employed to detect early signs of bearing degradation, thus preventing unexpected breakdowns and extending the motor's service life [6]. Bearing fault detection is carried out by monitoring various signals such as vibration signals [7, 8], current signals [9], acoustic emission [10], thermal imaging [11], and flux monitoring [12]. Among these, vibration is the most predominant and effective method [13].

As a bearing operates, it generates characteristic vibration patterns [14]. Any deviation from these normal patterns can indicate the presence of faults such as imbalance, misalignment, lubrication deficiencies, or wear and tear on the bearing surfaces. Techniques such as Fast Fourier Transform (FFT) [15,16] and wavelet transform (WT) [17] are commonly used to convert the time-domain signals into the frequency domain, where patterns related to specific faults become more apparent. Recent research shows that deep learning methods such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), can directly learn from raw vibration data without the need for explicit feature extraction using techniques like FFT or WT. [18]. This end-to-end learning approach enables the model to automatically extract relevant features from the data, potentially capturing complex patterns and relationships that may be overlooked by manually engineered features. Due to their powerful processing capabilities and strong feature extraction, researchers have proposed various models based on CNNs [19, 20], Auto-Encoders [21], Deep Belief Networks (DBN) [22], Generative Adversarial Networks (GAN) [23], Long Short-Term Memory (LSTM) [24], and Gated Recurrent Neural Networks (GRNN) [25] for effective and accurate bearing fault detection.

Liu et al. introduced a CNN-based method for rolling bearing fault recognition that integrates data mining techniques for assessing fault severity. This approach mines resonance vibration impulses using a matrix profile to enhance fault recognition accuracy [19]. In [20], a real-time bearing fault diagnosis system employing a compact adaptive one-dimensional convolutional neural network (1D CNN) classifier was proposed. This method demonstrates competitive classification performance on vibration datasets. The study confirms the effectiveness of the 1D CNN-based approach. Mao et al. suggested a deep auto-encoder approach for bearing fault diagnosis, which combines discriminant and structural information to improve feature representation and diagnostic accuracy [21]. Shao et al. proposed a continuous deep belief network with local linear embedding for rolling bearing fault detection, resulting in enhanced stability and accuracy compared to traditional methods [22]. Bai et al. developed a GAN-based method for bearing fault diagnosis using an intertemporal return plot and the Wasserstein Generative Adversarial Network (WGAN) for data augmentation. The WGAN architecture includes a generator and discriminator, with gradient clipping and penalty terms to control the gradient [23]. A method combining periodic sparse attention and LSTM for rolling bearing fault diagnosis is presented in [24], claiming enhanced feature extraction and reduced random interference influence, although it requires a large number of samples during model training. In [25], a combination of LSTM and gated recurrent unit for bearing fault diagnosis is proposed, achieving high accuracy and reliability. However, this model has a longer training time compared to other models, indicating a need for improvement in this aspect.

In previous studies, high sampling rate vibration data has been commonly used to capture more precise vibration patterns, which can enhance fault detection accuracy. However, high sampling rates typically require more advanced and expensive sensors and hardware resources, leading to increased costs related to data sampling, storage, transmission, and processing. These demands are often not feasible for real-time or resource-constrained IoT environments, where handling high-frequency data can pose significant challenges for real-time transmission due to the need for higher bandwidth and lower latency. Additionally, high sampling rates may introduce redundant data that does not contribute to better diagnostic outcomes, further increasing computational overhead. Conversely, employing a low sampling rate offers a more cost-effective and efficient approach, particularly for low-power devices typical of IoT setups. While this may result in the loss of some highfrequency fault characteristics, our proposed hybrid Multiscale CNN-LSTM model compensates for this by leveraging multiscale feature extraction and temporal pattern recognition, which enables it to capture essential fault patterns even at lower sampling rates. Our approach carefully manages the trade-off between sampling rate and diagnostic performance, ensuring a balance between cost, computational efficiency, and fault detection capability. This demonstrates that effective fault diagnosis can be achieved without relying on high sampling rates, thus expanding the applicability of such systems in resource-constrained environments. Manufacturing industries are

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increasingly leveraging IoT (Internet of Things) to enhance the accuracy, efficiency, and responsiveness of their condition monitoring and control systems [26]. IoT enables continuous monitoring of machinery by integrating sensors, data processing units, and communication modules that can provide real-time insights into machine health. However, for an IoT-based condition monitoring platform to be feasible in industrial settings, the monitoring devices need to be both effective and affordable. The use of cost-effective sensors and low-cost data transmission methods ensures a scalable and economically viable solution for large-scale deployment.

Combining IoT with AI in Industry 4.0 significantly reduces costs associated with industrial monitoring. Traditionally, deploying AI models like CNNs required expensive local devices to handle the computational load. IoT changes this by allowing data from low-cost edge devices to be processed on a centralized server or cloud, eliminating the need for powerful hardware at each client site. This centralized approach enhances scalability, as a single server can serve multiple clients, reducing the incremental cost of adding more devices. Maintenance is also simplified and less expensive because updates and repairs are managed centrally rather than on numerous local devices. Additionally, energy consumption is reduced since edge devices only handle data collection and transmission, not heavy processing tasks.

This paper introduces an IoT-based platform specifically designed for bearing fault detection that utilizes inexpensive vibration sensors along with low sampling rate vibration data. This approach significantly reduces the overall system cost while maintaining high diagnostic accuracy. The IoT framework enhances the fault diagnosis process by enabling real-time data acquisition, processing, and remote monitoring, which are critical for predictive maintenance in industrial environments. By leveraging IoT technology, the platform can continuously monitor the health of machinery, detect faults early, and alert maintenance personnel in a timely manner, thereby minimizing downtime and preventing potential machinery failures. This paper is structured as follows: Section 2 covers the principles of CNN, MSCNN, and LSTM. Section 3 introduces the proposed MSCNN-LSTM model. Section 4 details the comprehensive experimental procedure, presents an in-depth analysis of the results, and compares the proposed methods with those from previous studies. Finally, Section 5 presents the conclusions drawn from this study.

2. Theoretical Background

In this paper, a method for bearing fault diagnosis using vibration signals measured at a low sampling rate is presented. In this method, feature extraction from raw vibration data is first performed at three different scales using a multi-scale convolutional neural network (MSCNN). An LSTM network layer is then used to better identify the time series patterns. The foundations of these networks are introduced as follows:

2-1. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of deep learning models designed to process data with a grid-like topology, such as images and time series data [27]. They are particularly effective for feature extraction due to their ability to capture spatial hierarchies in data through convolution operations [28]. The overall structure of CNN is demonstrated in Fig. 1. A typical CNN architecture consists of multiple layers, including:

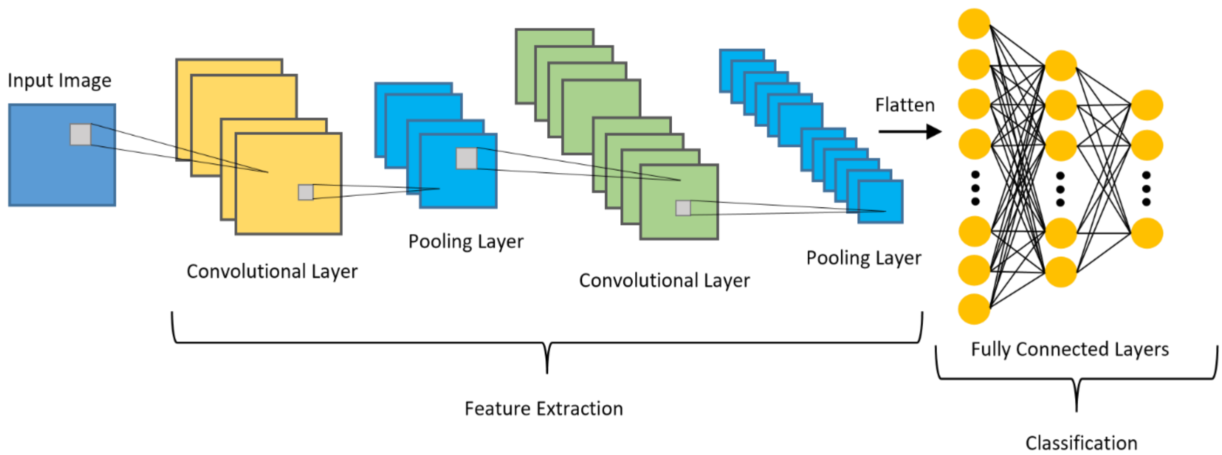

Fig 1. The overall architectue of a CNN

2-1-1. Convolutional Layers

These layers apply a set of filters (kernels) to the input data, performing convolution operations to produce feature maps. Each filter slides over the input data and performs element-wise multiplications, followed by a summation. This process helps in detecting various features such as edges, textures, and shapes. The feature map in the convolution layer is defined as:

$$y_j^l = f\left(\sum_{i=1}^{M_j}(y_i^{l-1} \otimes W_{ij}^l + b_j^l)\right) \tag{1}$$

In this context, y_j^l represents the output of the lth layer, $f(\cdot)$ is the activation function, W_{ij}^l denotes the kernel weight that links the jth feature map in the lth layer to the jth feature map in the $l-1$th layer, and b_j^l is the corresponding bias matrix. The convolution operation is represented by the symbol $\otimes$ [29].

2-2-2. Pooling Layers

After convolutional layers, pooling layers are typically used to reduce the spatial dimensions of the feature maps. This operation helps in down-sampling the data, reducing computational scomplexity, extracting prominent features while discarding less significant ones, and making the network more robust to spatial variation. Various techniques and functions are employed in these layers, such as max-pooling, average-pooling, min-pooling, and stochastic-pooling. In this study, max-pooling has been utilized, which effectively preserves data compared to other methods. Empirical evidence suggests that max-pooling generally enhances network performance [27]. A maxpooling layer is defined as (2).

$$y_{ij}^l = \max\,(y_{i_l j_l}^l : i \le i_l \le i + l_p \cdot j \le j_l \le j + W_p) \tag{2}$$

Here, y_{ij}^l denotes the output at position (i, j) of the lth layer of the neural network, The input feature map values at layer l that will be subjected to the maxpooling operation are represented by $y_{i_l j_l}^l$. The dimensions of the pooling window are indicated by l_p for length and W_p for width, respectively [29].

2-2-3. Fully Connected Layers

After several convolutional and pooling layers, highlevel reasoning is performed by fully connected layers. These layers integrate features extracted in the previous layers to produce the final output, often using activation functions like ReLU (Rectified Linear Unit) and softmax. a fully connected layer is defined as (3).

$$y_j^l = W_f \cdot f\left(\sum_{i-1}^{M_j}(y_i^{l-1} \cdot W_{ij}^l + B_j^l)\right) \tag{3}$$

In this context, y_{jj}^l is the output of the jth neuron in the lth fully connected layer. The activation function applied to the sum is represented by $f(\cdot)$. The term y_j^{l-1} denotes the output from neuron i in the previous layer $(l-1)$. The weight connecting neuron i from the previous layer to neuron j in the current layer is indicated by W_{ij}^l, and the bias term for neuron j in the current layer is B_j^l.

2-2-4. Multi-Scale CNNs (MSCNNs)

Multi-Scale Convolutional Neural Networks (MSCNNs) enhance traditional CNNs by incorporating multiple scales of feature extraction. This approach leverages features of different sizes and resolutions, providing complementary information and improving the model's ability to capture intricate patterns [30]. MSCNN architectures typically involve multi-scale convolutional layers that use various filter sizes and stride lengths to capture both fine and coarse features simultaneously. After extracting features at multiple scales, these features are often concatenated or combined using additional layers to form a unified representation, enhancing classification or regression performance. In bearing fault diagnosis, MSCNNs effectively capture detailed fault characteristics at different frequency components and scales in vibration signals, leading to more accurate fault detection and diagnosis.

2-2-5. Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) designed to model sequential data by maintaining a form of memory [31]. LSTMs address the vanishing gradient problem commonly encountered in traditional RNNs, allowing them to capture long-term dependencies in data [32]. The key components of LSTM architecture include the cell state, which acts as a memory that carries information across time steps. This state allows the network to preserve long-term dependencies by maintaining and updating the cell state through various gates. The internal architecture of a LSTM

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is shown in Fig. 2. LSTMs use three types of gates to regulate the flow of information. The forget gate decides what information from the cell state should be discarded. The input gate determines what new information should be added to the cell state. The output gate controls what information from the cell state should be output at each time step. Mathematically, the forget gate activation vector at time step t is computed using a sigmoid activation function, the hidden state vector from the previous time step, the input vector at the current time step, and a bias vector. The input gate activation vector at time step t is similarly calculated, with the addition of a candidate cell state vector, which is computed using a hyperbolic tangent activation function. The cell state update combines the forget gate activation vector, the previous cell state vector, the input gate activation vector, and the candidate cell state vector. The output gate activation vector at time step t is calculated in a manner similar to the forget and input gates. The hidden state vector at the current time step is obtained by combining the output gate activation vector and the updated cell state vector using a hyperbolic tangent activation function. By using these gates, LSTMs can learn to retain important information and forget irrelevant details, making them highly effective for time series analysis and sequential data processing. In bearing fault diagnosis, LSTMs are beneficial for capturing temporal dependencies in vibration signals, enabling the model to understand the evolution of fault patterns over time.

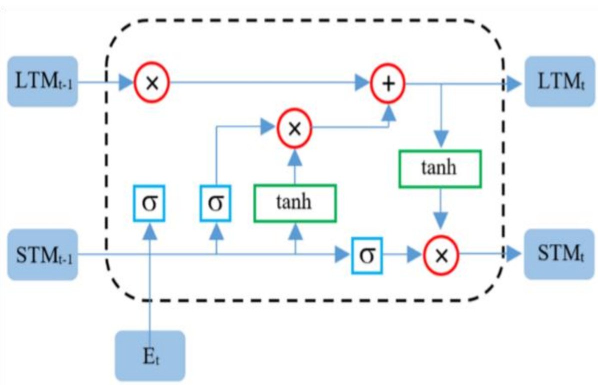

Fig. 2. Internal Architecture of a LSTM

3. The Proposed Method

3-1. Fault Diagnosis Model

In this section, we describe our hybrid MSCNNLSTM approach for bearing fault diagnosis using low sampling rate vibration data. Our proposed model leverages the strengths of CNNs for spatial feature extraction and LSTMs for capturing temporal dependencies, making it well-suited for the task of fault diagnosis in bearing systems, with high accuracy as previous studies.

Our proposed model consists of various components. The structure and parameters of the model are shown in Table 1. The input layer accepts data with a shape of 20 × 20 in 3 channels, corresponding to the reshaped vibration data windows. Each channel includes data from one accelerometer axis (X, Y and Z). We employ three parallel CNN branches with different kernel sizes to capture features at multiple scales: small-scale features with a 3x3 kernel, medium-scale features with a 5x5 kernel, and large-scale features with a 7x7 kernel. Each of these convolutional layers is followed by a max pooling layer.

The output features from the three CNN branches are concatenated along the channel dimension and reshaped to prepare them for input to the LSTM layer. A single LSTM layer with 256 units processes the reshaped features to capture temporal dependencies in the data. A TimeDistributed Dense layer with 128 units and ReLU activation is applied to the LSTM output. The output from the TimeDistributed layer is then flattened, and a Dense layer with Softmax activation generates the final classification output, corresponding to the fault types. The model is compiled using the Adam optimizer with a learning rate of 0.0001. The loss function used is Categorical Crossentropy, and accuracy is the evaluation metric. The model is trained with a batch size of 32 for 10 epochs. The training and validation performance are monitored to ensure the model's effectiveness. Our hybrid multiscale CNN-LSTM model combines the spatial feature extraction capabilities of CNNs with the temporal modeling strengths of LSTMs. This architecture enables effective fault diagnosis in bearing systems using low sampling rate vibration data, providing a robust solution for predictive maintenance in industrial applications. Normalization techniques like Min-Max scaling are commonly used in machine learning to ensure data consistency and improve model performance. However, many studies in bearing fault detection do not apply normalization, as it does not always enhance model outcomes. In our initial approach, we did not use normalization because the vibration signals already had a consistent range. To explore its potential impact, we later applied Min-Max normalization, scaling the data between 0 and 1, but this did not result in an increase in model accuracy. This suggests that our hybrid Multiscale CNN-LSTM model is already highly effective without normalization and performs exceptionally well with the raw data, as it can naturally handle the original data distribution.

This highlights the importance of empirically testing different preprocessing strategies to determine the most effective approach for a given dataset and model architecture. It also demonstrates that normalization is not always necessary, as our model achieves excellent performance without it.

Table 1. Architecture and parameters of proposed model

Layer (type)	Output Shape	No. of Kernels	No. of trainable parameters
Input_1	20 × 20		0
Conv2D	20 × 20	32	896
Max-Pooling2D	10 × 10	32	0
Conv2D_1	20 × 20	128	9728
Max_Pooling2D_1	10 × 10	128	0
Conv2D_2	20 × 20	256	37888
Max_Pooling2D_2	10 × 10	256	0
LSTM	16		2925568
Time-Distributed	16		32896
Dense_1	7		14343

3-2. IoT Approach

In our approach, the integration of IoT techniques significantly enhances the fault diagnosis process by enabling real-time monitoring and remote diagnostics of machinery health. Traditional fault diagnosis systems often require manual data collection and offline analysis, which can lead to delayed detection of faults and increased downtime. By leveraging IoT, our system continuously collects vibration data from sensors attached to machinery and transmits it to a central processing unit in the cloud, for immediate analysis using our hybrid Multiscale CNN-LSTM model. This real-time data flow allows for early detection of potential bearing faults and continuous condition monitoring, which can reduce maintenance costs and prevent unexpected equipment failures. Moreover, IoT facilitates scalability and flexibility in the deployment of the diagnostic system across different types of industrial equipment and environments. The use of IoT also enables seamless integration with other Industry 4.0 technologies, such as predictive maintenance and digital twins, further enhancing the decision-making process through data fusion and cross-domain analysis. Additionally, the low sampling rate approach employed in this study reduces data transmission costs and ensures efficient use of network resources, making the system more suitable for deployment in bandwidth-limited or remote locations. These benefits demonstrate how IoT enhances not only the efficiency but also the applicability and effectiveness of fault diagnosis in diverse industrial settings.

Proper sampling of signals and key equipment parameters is one of the main factors affecting the process of condition monitoring and intelligent fault diagnosis. This task requires the use of appropriate hardware for measuring, processing, and efficiently exchanging data. Therefore, in this project, an electronic board based on printed circuit boards (PCBs) was designed with the capability to measure vibration and motor current and to exchange real-time data over the internet through an IoT web server developed for data processing, as described in Section IV. Altium Designer software was used for designing the PCB. The PCB is a two-layer board with dimensions of 70 mm by 55 mm. For measuring vibration signals, considering the study's goals of reducing fault diagnosis costs and using low sampling rate data, a MEMS sensor named ADXL345 was utilized. The ADXL345 is a 3-axis accelerometer with selectable measurement ranges of ±2g, ±4g, ±8g, and ±16g, with a maximum resolution of 13 bits. It measures both dynamic acceleration resulting from vibration or shock and static acceleration such as gravity. The maximum sampling rate of this sensor is 3200 Hz. The ADXL345 accelerometer supports both SPI and I2C interfaces for data exchange with microcontrollers; in this study, the SPI interface is used for communication with the processing unit [33].

To facilitate the hardware's connection to the server for exchanging measured data, an ESP8266-12F chip was used. This device complies with IEEE 802.11 b/g/n (Wi-Fi) standards and includes an internal antenna that provides a relatively non-uniform radiation pattern with a ring-shaped geometry rotating around the module's axis and perpendicular to the antenna's longitudinal direction. The 32-bit processor in the ESP8266-12F provides the necessary computational power to implement various IoT features such as a real-time operating system and TCP/IP protocol.

4. Experiments

To validate the proposed model's flexibility and effectiveness in bearing fault diagnosis with low sampling rate vibration data, we introduced faults of varying intensities on bearing surfaces and collected vibration data using custom-designed hardware specifically developed for this project.

4-1. Experimental Setup

In this project, to simulate bearing faults in induction motors and create a dedicated dataset of faulty and healthy motor states for training the model, we used a 250 Watt three-phase induction motors. The machine used in this study is an Electrogen 3-phase induction motor, model IMB3. The motor has 4 poles with power rating of 250 W. Nominal voltage, current, speed, efficiency and power factor are 400 V, 0.8 A, 1365 rpm, 61.5% and 0.73 respectively. The inertia of the motor (J) is around 0.01 kg·m², with a rated torque of about 1.8 Nm. The bearing used in conjunction with the motor is an RS6202, a single-row deep groove ball bearing. This bearing has a bore diameter of 15 mm, an outer diameter of 35 mm, and a width of 11 mm, with rubber seals on both sides (RS type). It has a dynamic load rating (Cr) of approximately 7.7 kN and a static load rating (Cor) of approximately 3.2 kN. The limiting speed of the RS6202 bearing can reach up to 19,000 RPM, depending on lubrication and load conditions.

An LS IG5A drive was used to operate the motors at a fixed operating frequency of 50 Hz during data sampling. The bearings used in this project are of the RS 6202 model, a standard bearing type commonly used in various industrial applications. During data collection, the motor was run with no load. The PCB board was mounted at the center of the motor's frame, and the faulty bearings were located at the drive end. The experimental setup is shown in Fig. 3.

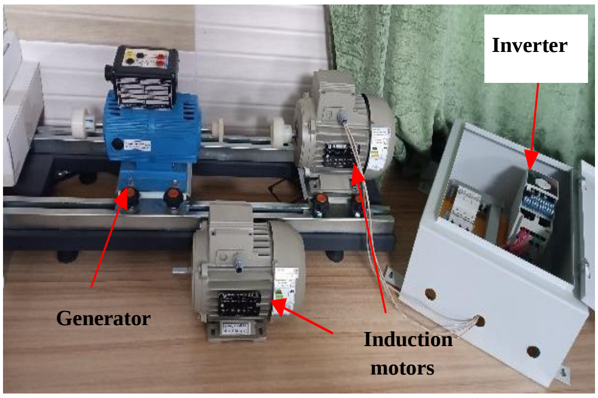

Fig. 3. Experimental setup

4-1-1. Fault Introduction Methods

The experimental setup involved both controlled machining and real-world induced faults to comprehensively capture different fault scenarios that can occur in industrial environments. Faults were introduced in the bearings through two primary methods:

Machined Faults: Some faults were artificially created using precision machining techniques to simulate common bearing defects such as inner race faults, outer race faults, and ball defects. These machined faults allow for a controlled environment where the exact type and severity of the fault can be defined. For instance, a defect on the outer race was created by drilling a small hole of 2mm diameter. 2mm, 3mm, 4mm, and 5mm were chosen to represent a range from minor to severe damage, with each level providing a unique challenge for the fault detection model. These faults were introduced using an electrical discharge machine (EDM) to create standardized grooves. These controlled defects help in systematically studying the model's ability to detect specific types of faults. An example of two faults created in the bearing is shown in Fig. 4, demonstrating the machined induced defects.

Fig. 4. Outer race bearing defect with a severity of: (a) 2mm diameter (b) 5mm diameter

Real-World Induced Faults: In addition to machined faults, some faults were induced under real working conditions to simulate actual wear and tear that bearings undergo in an industrial setting. These faults were created by running the motors under varying load conditions, with exposure to contaminants (like dust and moisture) and inadequate lubrication over extended periods. For ball faults, no specific severity levels were defined. This approach was chosen to reflect typical real-world scenarios where the exact severity of ball faults may not always be precisely known. This method allows us to capture more complex fault patterns that are often seen in real-life scenarios, such as fatigue spalling, pitting, and wear, providing a more diverse dataset.

This approach ensures that the model is exposed to a wide variety of fault types, improving its generalizability and robustness in detecting faults under different conditions.

4-1-2. Measurement Device

To collect vibration data, a PCB-based electronic board was designed with the capability to measure both vibration signals an d stator current, and to exchange data over both the internet and Wi-Fi, as shown in Fig. 5. An ADXL345 sensor was used for measuring the vibration signals. The ADXL345 is a compact, lightweight, and extremely low-power 3-axis accelerometer capable of high-resolution (13-bit) measurements up to ±16 g. Its digital output data is presented in a 16-bit two's complement format and can be accessed via either an SPI (3- or 4-wire) or I2C digital interface.

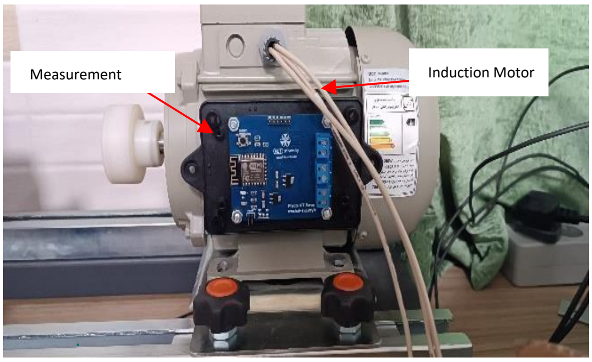

Fig. 5. The measurement setup

This comprehensive experimental setup, combining both controlled and real-world fault introduction methods, along with robust data acquisition tools, allows for the development and validation of an effective bearing fault diagnosis model that is applicable in real industrial environments.

4-2. Dataset

The vibration data used for training and evaluation are stored in a CSV file. The sampling frequency is 3.2kHz, and the data have been collected in 3 axes. In this dataset, a total of 1,128,687 instances are collected across 7 classes, including 6 classes for faulty bearings and 1 class for healthy bearings. The details of the dataset are provided in Table 2. Some samples of raw vibration data for faulty bearings and healthy bearings are shown in Fig. 6.

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Table 3 provides a list of popular bearing datasets commonly used in studies, along with a comparison to the dataset collected for this project.

Table 2. Details of dataset

Fault type	Fault severity	No. samples	Label	Motor operating frequency	Sampling rate
Outer Race	2mm	146941	F1	50HZ	3.2KHz
Outer Race	3mm	73471	F2	50HZ	3.2KHz
Outer Race	4mm	181261	F3	50HZ	3.2KHz
Outer Race	5mm	181431	F4	50HZ	3.2KHz
Ball	-	180765	F5	50HZ	3.2KHz
Ball	-	184221	F6	50HZ	3.2KHz
Healthy	-	180597	N	50HZ	3.2KHz

Table 3. Comparison of popular bearing datasets

Dataset	No. of axis	Fault mode	Sampling rate
Paderborn University	1	Artificial & accelerated aging	64kHz
Case Western Reserve University (CWRU)	1	Artificial	12 & 48kHz
PRONOSTIA Dataset	1	Natural	25.6kHz
Intelligent Maintenance Systems	1	Natural	20kHz
Our Dataset	3	Artificial & Natural	3.2kHz

4-3. Data Processing and Results

The data preparation process involves several steps to transform the raw vibration data into a format suitable for training a machine learning model. Initially, the vibration data, stored in a CSV file, is loaded into a DataFrame. This data includes different fault types identified by specific labels, which serve as the target variable for classification. The first significant step in preprocessing is segmenting the vibration data into overlapping windows. Each window has a fixed length of 400 data points, with a stride of 200 data points. This method generates multiple samples from the original time series data, increasing the dataset's size and diversity. Overlapping windows capture more variations and transitions in the data, which can enhance the model's ability to detect and classify faults accurately. Within each window, the feature data- excluding the fault type label—is reshaped into a 3D array with the dimensions (20, 20, 3).

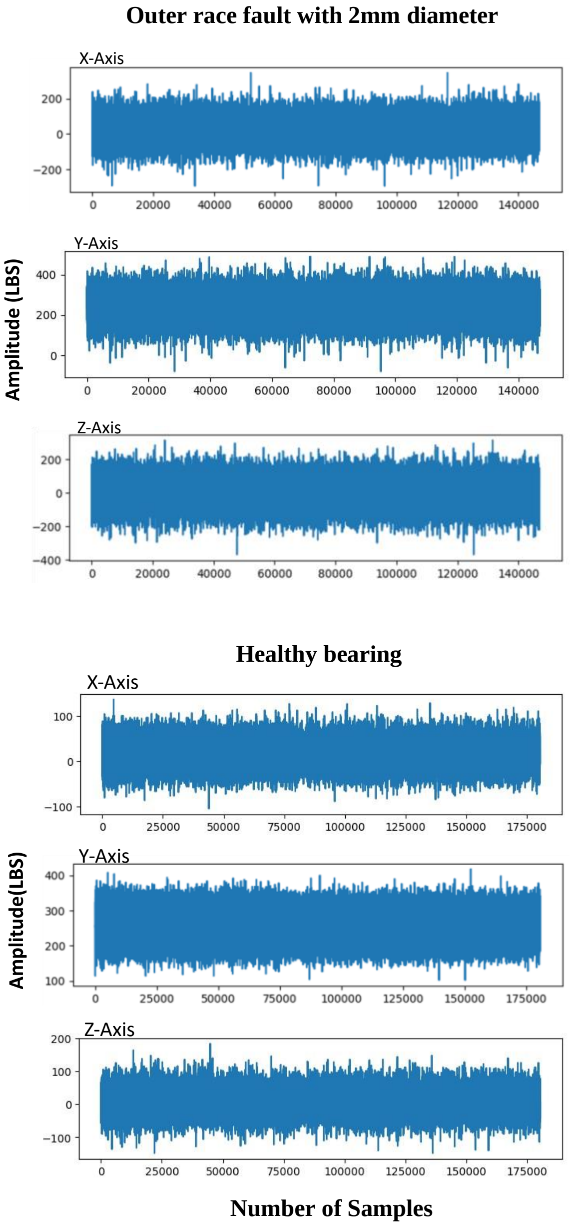

Fig. 6. Samples of collected raw vibration

This reshaping is crucial as it formats the data into a structure compatible with convolutional neural networks (CNNs). The dimensions (20, 20, 3) suggest that each window is treated as a small image with three channels, likely representing different sensors or components of the vibration data. This transformation enables the CNN to extract spatial features effectively, leveraging its strength in image processing to analyze time-series data. The next step involves processing the fault type labels. These categorical labels are initially encoded into numerical values using a LabelEncoder, converting the fault type categories into a format that machine learning algorithms can process. Subsequently, the numerical labels are transformed into one-hot encoded vectors using TensorFlow's to_categorical function. One-hot encoding represents each label as a binary vector, with only one element set to 1 (indicating the presence of the fault type) and all other elements set to 0. This format is particularly suitable for classification tasks, as it allows the model to output probabilities for each fault type and easily identify the predicted class.

Finally, the dataset is split into training, validation, and testing sets using an 7:1.5:1.5 split, meaning that 70% of the data is used for training the model, while the remaining 30% is reserved for tuning hyperparameters and evaluating the model's performance, with 15% for validation and 15% for testing. This split ensures that the model is trained on a substantial portion of the data while retaining enough data to validate its generalization capabilities.

Additionally, the data is shuffled before splitting to ensure that both the training and testing sets are representative of the overall dataset, reducing the risk of bias and overfitting. By following these steps, the raw vibration data is effectively preprocessed and transformed into a format suitable for training a robust machine learning model for fault detection and classification. Fig. 7 presents the results obtained from training the model over 10 epochs. Also, the confusion matrix is shown in Fig. 8.

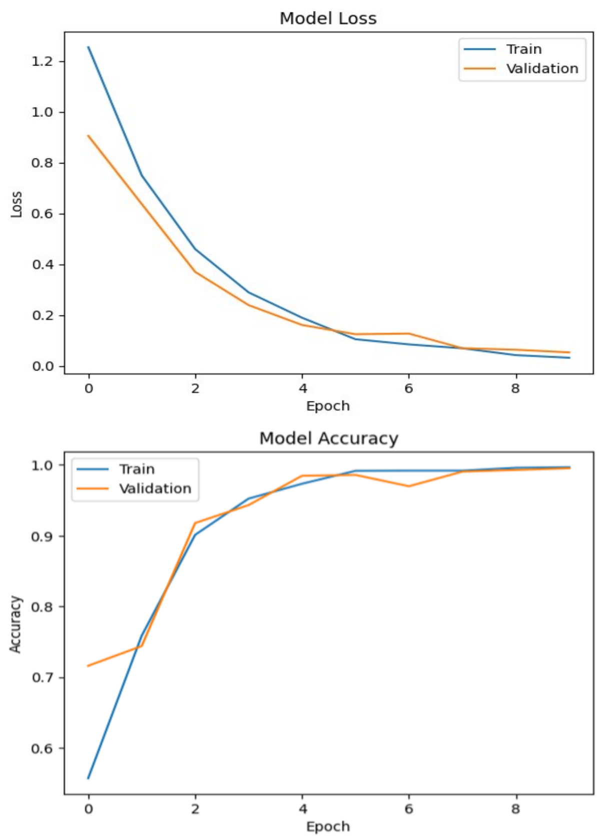

Fig. 7. Model accuracy and loss curves during 10 epochs

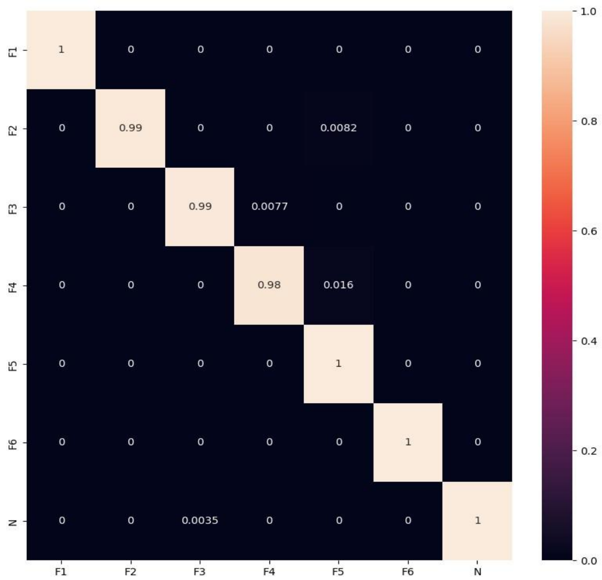

Fig. 8. The model's confusion matrix

In this study, our results indicate that we achieved 99.47% accuracy using low sampling rate data with a robust architecture of deep learning models.

In addition to accuracy, which measures the overall correctness of the model's predictions, we also evaluated our model using other important performance metrics: precision, recall, and F1-score. These metrics provide a more comprehensive understanding of the model's performance, particularly in imbalanced or multiclass classification scenarios.

For our model, as shown in Table 4, the precision scores for all classes are extremely high, ranging from 0.99 to 1.00, indicating that the model makes very few false positive errors across all fault types and conditions.

According to Table 4, our model's recall scores are also high, ranging from 0.97 to 1.00. A recall of 0.97 for class '1' suggests a slight underestimation in detecting some instances of this particular class, but overall, the model performs excellently in identifying the majority of fault types.

The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. With F1-scores between 0.99 and 1.00 for all classes, our model demonstrates strong performance in both precision and recall, effectively managing the trade-off between false positives and false negatives. This balance is critical for practical applications in fault diagnosis where both missed detections and false alarms have significant consequences.

Additionally, the macro average of precision, recall, and F1-score is 0.99, indicating that the model's performance is consistently high across all classes. The weighted average also stands at 0.99, further confirming that our model maintains robust performance even when accounting for class distribution.

These results, as detailed in Table 20, show that our proposed hybrid Multiscale CNN-LSTM model is not only highly accurate (99.47%) but also reliable and effective across multiple performance metrics, making it suitable for real-world applications in bearing fault diagnosis.

Table 4. Classification Report:

	Precision	Recall	F1-Score	Support
Accuracy			0.99	1690
Macro Avg	0.99	0.99	0.99	1690
Weighted Avg	0.99	0.99	0.99	1690

To evaluate the effectiveness of the proposed hybrid Multiscale CNN-LSTM model for bearing fault diagnosis using low sampling rate vibration data, a comparative analysis with several well-known models was conducted: a 2D Convolutional Neural Network (2D CNN), a 1D Convolutional Neural Network (1D CNN), and a Support Vector Machine (SVM). These models are frequently used in fault diagnosis tasks and serve as strong benchmarks for comparison.

The results from these experiments clearly demonstrate that our proposed hybrid Multiscale CNN-LSTM model outperforms the other models on the same dataset. The hybrid model achieved an accuracy of 99.47, compared to 79.3% for the 2D CNN, 83.2% for the 1D CNN, and 75.5% for the SVM model. The superior performance of our hybrid model can be attributed to its ability to effectively combine both convolutional layers for multiscale feature extraction and LSTM layers for capturing long-term dependencies in the vibration signals. This dual capability allows the model to maintain high diagnostic accuracy even with low sampling rate data, where capturing subtle temporal patterns is crucial for accurate fault detection.

When comparing our findings to other bearing fault diagnosis studies, it is observed that they achieved similar or lower accuracy with higher sampling rate data, which requires advanced sensors and increases the costs of detection.

To elucidate the efficacy of the hybrid model proposed in this paper, Fig. 9 presents a comparison between the results obtained in this study and those reported in recent literature employing various deep learning techniques for bearing fault diagnosis. These techniques include 1D-CNN [34], 2D-CNN [35], DGNN [36], Mel-

CNN [37], GNN [38], ResNet-152 based model [39], RNN [40], A custom CNN architecture [41], PNN-SFAM [42], CNN-HMM [43], DAFD [44].

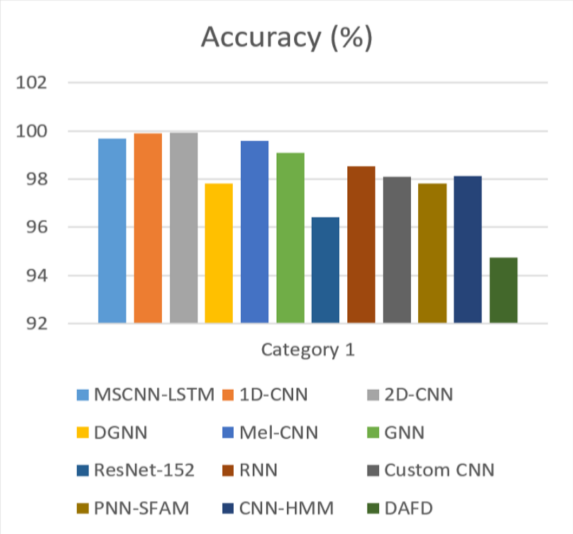

Fig. 9. Comparison of proposed methods with previous studies

5. Conclusion

In this study, we developed and validated a hybrid Multiscale CNN-LSTM model for bearing fault diagnosis using vibration data sampled at a low frequency of 3.2 kHz. Our proposed approach effectively integrates multi-scale convolutional neural networks (MSCNNs) and Long Short-Term Memory (LSTM) networks to leverage both spatial feature extraction and temporal pattern recognition, ensuring high diagnostic accuracy. The model achieved a remarkable accuracy of 99.47%, demonstrating its high effectiveness in diagnosing bearing faults using low sampling rate data. This performance is comparable to or even exceeds results obtained from studies utilizing high sampling rates and advanced sensors, thereby reducing overall system costs. Beyond accuracy, the model showed impressive precision, recall, and F1-scores across all fault types, with scores ranging from 0.99 to 1.00. This indicates that the model is proficient at minimizing both false positives and false negatives, which is crucial for practical fault diagnosis applications. The study highlights the successful transformation of raw vibration data into a structured format suitable for

CNNs and LSTMs, including segmentation, reshaping, and encoding. This preprocessing methodology ensures that the model is trained on diverse and representative samples, enhancing its generalization capabilities. When compared to various advanced deep learning techniques, our hybrid model demonstrated superior performance with lower sampling rates. This underscores the efficacy of combining MSCNNs and LSTMs for fault diagnosis while mitigating the need for expensive highsampling-rate data.

To advance this research further, the following areas warrant exploration:

Generalization to Other Machinery: Extending the model to other types of machinery and different fault scenarios will be crucial for validating its robustness and adaptability in diverse industrial settings. Integration with IoT and Industry 4.0: Future work could focus on enhancing the IoT integration to facilitate more seamless data acquisition and real-time analysis. Incorporating technologies such as digital twins and advanced predictive maintenance algorithms could provide more comprehensive insights and decision-making support.

Data Augmentation and Normalization: Although the current study showed that normalization did not significantly impact model performance, experimenting with different data augmentation techniques and normalization methods could further optimize the model's capabilities and applicability. Hardware and Software Optimization: Continued development of the hardware components, such as sensors and communication modules, as well as refining the software algorithms, can improve the system's overall efficiency and cost-effectiveness.

In conclusion, the research demonstrates that our hybrid Multiscale CNN-LSTM model offers a highly accurate and cost-effective solution for bearing fault diagnosis, leveraging low sampling rate data. The findings not only validate the effectiveness of our approach but also pave the way for further advancements in predictive maintenance and fault detection technologies.

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