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Diagnosis of bearing faults under variable speed conditions using deep learning

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Abstract

Bearings are fundamental and delicate elements directly influencing performance, efficiency, stability, and operational lifespan. However, harsh and fluctuating operating conditions not only jeopardize the safe working environment but also lead to abrupt and unforeseen component faults, resulting in economic losses. Diagnosing faults in bearings operating under variable speed conditions necessitates a shift from traditional methods towards more intricate signal processing techniques and artificial intelligence models with more challenging interpretations. Nevertheless, this research article aims to significantly reduce computational burden and complexity by employing simpler and more straightforward models both in the process of feature extraction and classification, utilizing deep learning methodologies. The research article encompasses the transformation of raw vibration data obtained from bearings operating under variable speed conditions into visual representations and their subsequent classification using the Long Short-Term Memory (LSTM), one of the deep learning models. The developed LSTM-based fault classification model, trained with very limited data, achieves 100% accuracy in classifying four different states of the bearing.

Keywords: *Bearing, Fault Diagnosis, Deep Learning, LSTM, Signal To Image Mapping*

Değişken hız koşullarında rulman arızalarının derin öğrenme kullanılarak teşhisi

Özet

Rulmanlar, performansı, verimliliği, stabiliteyi ve operasyonel ömrü doğrudan etkileyen temel ve hassas bileşenlerdir. Ancak, zorlu ve değişken çalışma koşulları, yalnızca güvenli çalışma ortamını tehlikeye atmakla kalmaz, aynı zamanda ani ve öngörülemeyen bileşen arızalarına yol açarak ekonomik kayıplara neden olmaktadır. Değişken hız koşulları altında çalışan rulmanlarda arıza teşhisi, geleneksel yöntemlerden daha karmaşık sinyal işleme tekniklerini ve yorumlanması daha zor yapay zekâ modellerini gerektirir. Buna rağmen, bu araştırma makalesi, hem özellik çıkarma hem de sınıflandırma sürecinde daha basit ve anlaşılır modeller kullanarak hesaplama yükünü ve model karmaşıklığını önemli ölçüde azaltmayı amaçlamaktadır. Araştırma makalesi, değişken hız koşulları altında çalışan rulmanlardan elde edilen ham titreşim verilerinin görsel temsillere dönüştürülmesini ve ardından derin öğrenme modellerinden biri olan LSTM ile sınıflandırılmasını kapsamaktadır. Geliştirilen LSTM tabanlı arıza sınıflandırma modeli, oldukça sınırlı verilerle eğitildiğinde, rulmanın dört farklı durumunu %100 doğrulukla sınıflandırmayı başarmaktadır.

Anahtar Kelimeler: *Rulman, Arıza Teşhisi, Derin Öğrenme, LSTM, Sinyal Görüntü Haritalama*

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1 Introduction

Signal analysis constitutes a comprehensive array of mathematical methods employed for interpreting analog and digital signals, prevalent across a multitude of technological sectors ranging from healthcare to industry, defense, and energy systems. Through these methodologies, signals are scrutinized to discern their temporal and spatial variations. The outcomes gleaned from such analyses play pivotal roles in the detection of diverse ailments, the design of electronic limb prosthetics, the establishment of radar systems, or the diagnosis of mechanical equipment faults.

Signal analysis finds widespread application in diagnosing a range of faults occurring in rotating machinery and scheduling maintenance activities. In modern industries, the analysis of signals acquired from real-time sensors (including sound, heat, vibration, image, magnetic field, etc.) facilitates the prediction of potential component failures, maintenance intervals, and the remaining operational lifespan of machines. Among the techniques employed in this form of predictive maintenance analysis, vibration analysis stands out as the most commonly utilized method.

Vibration analysis is a process aimed at investigating the temporal and spatial changes of vibration transmitted from any component, machine, or structure. Its objective is to assess the overall health condition and detect any abnormal incidents. Vibration analysis is widely employed for diagnosing bearing faults [1–10]. Such faults can manifest in diverse forms, including cracks, fractures, clearances, or ball spalling in different parts like the outer race, inner race, balls, or cage. These defective components, upon interacting with other metal surfaces, influence and modify the vibration and sound signals transmitted by the machine [10].

When examining artificial intelligence models developed for bearing faults, the procedural steps involve applying diverse signal processing techniques to vibration data to extract features, interpreting these features using artificial intelligence models, and assessing the model's performance. Meaningful information uncovering fault characteristics from vibration signals is obtained through transformations in the Time Domain (TD), Frequency Domain (FD), or Time-Frequency Domain (TFD) during the feature extraction process. Statistical properties of the signal such as variance, standard deviation, mean, skewness and kurtosis are extracted in the TD. In the FD, various transformation methods such as Fast Fourier Transform (FFT), Cepstral Analysis or Envelope Analysis are generally used. In the TFD, various transformation techniques such as Wavelet Transform (WT), Short Time Fourier Transform (STFT), Variational Mode Decomposition (VMD), Empirical Mode Decomposition (EMD), Hilbert Huang Transform (HHT) or Welch Method are used [11]. In some studies, a single feature is employed, whereas in others, diverse combinations of these features are utilized. It is seen that various Machine Learning (ML) models such as Decision Trees, Support Vector Machines (SVM) and Deep Learning (DL) models such as LSTM, Convolutional Neural Network (CNN), and Auto Encoder (AE) are used in the process of interpreting the extracted features [11,12]. Nevertheless, upon scrutiny of the analyzed studies, it becomes apparent that deep learning (DL) models are employed with greater frequency [12]. The primary rationale behind the preference for DL algorithms over other ML algorithms lies in their capacity to autonomously extract features from raw data and adeptly interpret both image and sequential data.

Upon scrutinizing fault diagnosis methods for variable speed conditions, it becomes evident that more intricate artificial intelligence architectures are utilized. This is attributed to the fact that the variable speed generates both Amplitude Modulation (AM) and Frequency Modulation (FM) in addition to the vibration data [1]. Additionally, domain shifts occur across various domains, such as training, validation, and testing, resulting in differences in sample distributions [2]. Nevertheless, accessing fault data in actual industrial applications poses a significant challenge. Consequently, researchers investigating fault diagnosis under variable speeds have directed their focus towards fault diagnosis models developed with limited datasets [2]. Therefore, prior to fault diagnosis, addressing these challenges is essential.

This study investigates artificial intelligence-based research that analyzes vibration data collected under variable speed conditions. The research examined utilized the OTTAWA dataset [13,14], which comprises vibration data from the bearing under variable speed conditions. This data set encompasses vibration data corresponding to healthy, ball faults, outer race faults, inner race faults, and compound faults of bearings operating under variable speed conditions (decreasing, increasing, first increasing then decreasing, first decreasing then increasing,) [14].

In [1], a deep learning model comprising Speed Normalization (SN) and AE branches was proposed. The SN structure, constructed using CNN architecture, separates speed information from the vibration signal, thereby eliminating the AM present in the vibration signal. Subsequently, the AE unsupervised learning model segregates the data into healthy and faulty categories. The proposed deep learning model was trained solely on healthy data, while during the testing phase, it was evaluated using both healthy and faulty data. AUC value was selected as the performance metric in the study conducted on three different datasets, achieving a performance of 99.8% on the OTTAWA test data.

In [2], taking into account both the overfitting problem induced by inadequate data and the domain shift resulting from variable speed, an advanced method termed Hybrid Augmented Network with Balance Domain Window (BW-HAN) is proposed to address these challenges. In the proposed model, multiple integration of BW-HAN blocks is used, including a convolutional subsampling patch embedding section and a window multi-head self-attention mechanism section. The first section catches the low-level local features of the samples, while the second section extracts the high-dimensional global features of the samples. In order to overcome the domain shift, a partitioning method for balancing the distribution of the data space by means of data reconstruction was developed in this study. In the study, where the data length was chosen as 4096, a total of 1000 samples were utilized, comprising 600 samples for the healthy condition, 200 for inner race faults, and 200 for outer race faults. Of these samples, 4% are reserved for training and the remaining 96% for testing. In the study involving the classification of three classes, an achievement of 99.43% accuracy was attained.

In [3], the mathematical equation of the Fault Response Waveform (FRW) is constructed by including the fault frequency. This mathematical equation is used as the mother wavelet when the WT is applied to the raw vibration data. In this study, a new method was developed by analyzing the similarity between the computations used in the WT method and the computations obtained by convolving the raw data with the kernel in the 1D CNN model. Based on this similarity, the FRW was used to assign values for the kernel in the CNN model. Based on this idea, Fault Response Convolutional Layer (FRCL) was developed to extract features that are not affected by operating conditions. In addition, Improved Soft Threshold Function (ISTF) and The Multi-Scale Attention Module (MSAM) modules were developed to improve diagnostic performance. In this study, where healthy, outer race fault and inner race fault were classified, the proposed CNN model was trained using data from increasing speed conditions and tested with data from decreasing speed conditions and vice versa. In the study where the data length was selected as 2048, 97 samples were used for each class in both training and test phases and the highest success was obtained as 98.45% in the accuracy value in the test data.

In [4], in the feature extraction phase, Automated Relative Energy-based Empirical Mode Decomposition (AREEMD) was first used. With AREEMD, the signal was first decomposed into IMFs components. Then all IMFs with low amplitude compared to the original signal were eliminated. All selected IMFs were collected in the next step. Low amplitude and high frequency components were thus filtered out from the original signal. Subsequently cepstral analysis was applied to the obtained signal. In this analysis method, cepstrum was obtained by taking Inverse FFT (IFFT) of the logarithm of the FFT of the signal. In the next step, Autoregressive Features were extracted with the 5th Order Yule-Walker Model. In this study, weighted-KNN (wKNN) was proposed in the classification stage. In addition to cepstral autoregressive features, time autoregressive, shape and statistical features, hjorth features were used comparatively. In the classification stage, five different classifiers were used in addition to wKNN. In the application developed on three different data sets and the combination of these data sets, healthy, outer race faults, inner race faults were classified for OTTAWA data set. The model proposed in this study achieved 100% success in accuracy value.

In [5], first, a Noise Eliminated Ensemble Empirical Mode Decomposition (NEEEMD) method was used to suppress noise in the vibration data. This method decomposes the vibration data into IMFs and then obtains the wavelet packet energy entropy, small packet energy coefficients and Gini coefficients for each IMF as a TFD feature. In addition, dimensional statistical properties (mean, standard deviation, kurtosis, skewness, etc.) and dimensionless statistical properties of the vibration data for the TD were used. At the same time, in the TFD, features of the FFT of the signal (concentration and dispersion of the spectrum, positional changes of the main frequency band, etc.) were used. Robust Unsupervised Feature Selection with Local Preservation (RUSLP) was used in an attempt to choose effective features from the extracted multidimensional feature space. In the classification stage, Binary Tree Least Squares Twin Support Vector Machine (BTLSTSVM) was used. In the article, studies were carried out on three different data sets. In the study where only increasing speed data for healthy, outer race faults and inner race faults were used for OTTAWA dataset, the data length was selected as 2000. For the seven features selected with RUSLP, BTLSTSVM achieved 100% on the precision performance metric.

In [6], the effectiveness of different ML and DL techniques was examined using MATLAB's Classification Learner application, employing nine commonly utilized statistical features pertaining to vibration data. In this study, the effectiveness of Principal Component Analysis (PCA) and Curvilinear Component Analysis (CCA) methods in dimensionally reducing the feature space was investigated. In the study, it was stated that PCA results showed that there were five intrinsic dimensionalities for the data, but it was insufficient for class differentiation. In the CCA method used to analyses data geometry and topology, the first five components showed a better discrimination between class clusters. In the study where healthy condition, ball faults, outer race faults and inner race faults were classified, about 30 ML techniques and CNN model were used comparatively. In the study based on the CCA technique, the data was distributed as 30% validation and testing set and 70% training set. According to the results, the classification models using raw data achieved higher performance than the CCA method. In the study analysed, it is stated that this is due to the fact that the reduction in complexity of the original data that occurs when CCA is applied is accompanied by a reduction in the discriminative feature space. Contrary to this, raw data encapsulates all the original features, which are inherently more intricate and potentially more discernible. According to the classification results tested with raw data, Artificial Neural Network (ANN) achieved the highest success with 97.7% accuracy.

In [7], a Convolution Enabled Transformer (Con-eT) was developed as a deep encoder. This model combines the advantages of the vanilla transformer and the convolution process in CNN. Within the research, local features were extracted utilizing the convolutional layer, while the global features inherent in the transformer were preserved through the self-attention mechanism. The developed model was more effectively encoded depth detection features irrespective of the condition, while simultaneously reducing the number of model parameters. Later on, a Random Contrastive Regularization (RCR) method was introduced to enable the model to learn features independent of the operating conditions and enhance its generalization performance across varying conditions. In the study where healthy, outer race faults and inner race faults were classified, a data length of 4096 was selected. Only increasing speed conditions for all three classes were used during training, while decreasing, increasing after decreasing and decreasing after increasing speed conditions were used in the test phase. The recommended model, trained on 3492 examples and tested on 10476 examples, attained an accuracy of 100% on the test data.

When looking at the studies examined, it is seen that very complex artificial intelligence models are used either in the feature extraction process or in the interpretation of the extracted features. Especially the models using attention and transformer structures require additional calculations and memory allocation. The aforementioned circumstances render the interpretation of the data challenging, thereby necessitating a time-consuming model training process. This may potentially lead to difficulties, particularly in devices constrained by limited resources or in real-time applications where minimal latency is of paramount importance. In reality, the complexity observed in the models within the examined studies stems from an inability to select an appropriate data size. It is essential that the data length be chosen to encompass a complete cycle of the machine while operating at its minimum speed.

In this research article, a fault classification model is proposed for bearings operating under variable speed conditions using the OTTAWA dataset [13,14]. The study, in which the fault characteristics of the bearing are extracted from the vibration data of the bearing, consists of obtaining a two-dimensional visual representation of the data and classifying them with the LSTM model. The simplicity of both the feature extraction process and the employed LSTM model notably abbreviates the interpretation process of the vibration data. In the study focused on classifying healthy condition, ball faults, outer race faults and inner race faults of the bearing, the training phase utilized only 4% of the data for model training and validation, with the remaining 96% reserved for model testing. Notably, during testing, attaining 100% accuracy, precision, and f1-score values underscores the model's remarkable capacity for generalization.

2 Material and method

The study recommends a fault classification model for bearings operating under variable speed conditions. In this investigation, the two-dimensional representation of vibration data from the bearing is chosen as the feature, and an LSTM-based deep learning model is utilized for the classification phase. The principle diagram of the proposed model is given in Figure1.

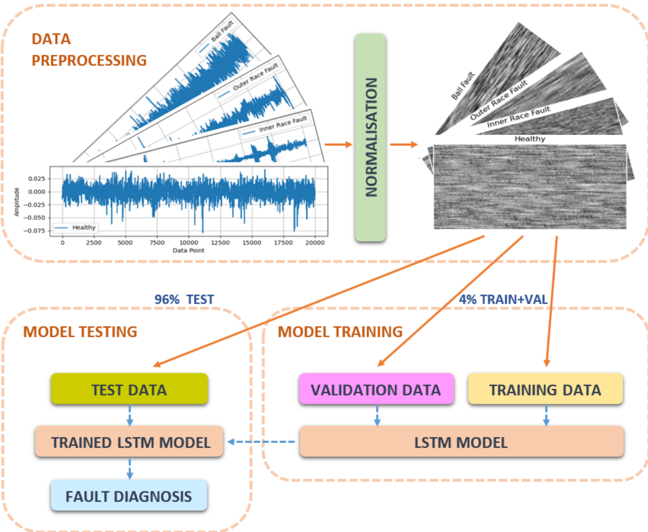

Figure 1. Principle diagram of the proposed fault classification model

The proposed model comprises three stages:

- ✓ Data preprocessing: The data length for constructing model inputs is chosen to encompass a single revolution of the machine at its lowest speed. Following the normalization process, one-dimensional vibration data is restructured into a two-dimensional format. The acquired two-dimensional data is partitioned into three subsets, allocating 4% for training and validation, and reserving 96% for testing.
- ✓ Model Training: The model is trained with training and validation data.
- ✓ Model Testing: The trained model is tested with test data.

2.1 *Acquisition of data*

During the acquisition of the OTTAWA dataset [14], experiments were conducted on a Spectra Quest machine fault simulator (MFS-PK5M) [13]. The experimental setup is given in Figure 2.

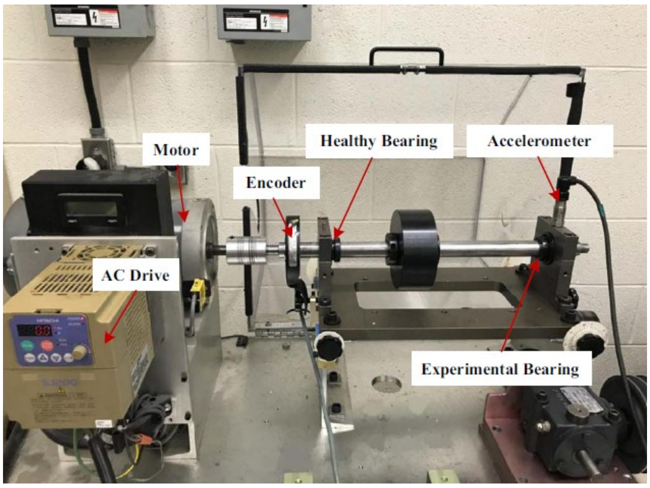

Figure 2. Experimental setup for the OTTAWA data [13]

The data comprises vibration signals emanating from bearings exhibiting diverse health conditions under varying rotational speed conditions. [14]. The health conditions of the bearing are healthy, ball fault, outer race fault, inner race fault and compound fault. The operational conditions of the bearing's rotational speed comprise speed increase, speed decrease, initial speed increase followed by decrease, and initial speed decrease followed by increase. There are 60 datasets in total and all this data is sampled at 200,000Hz and the sampling time is 10 seconds [14].

This study classifies four distinct health conditions of the bearing, namely healthy, inner race fault, outer race fault, and ball fault. The rotational speeds used for these health conditions are given in Table 1. This study employs a total of 48 distinct data, consisting of 12 rotational speeds allocated to each health condition associated with the bearing. Each data consists of 2,000,000 vibration signal. When study [13] is examined, the operating speeds vary between 29 Hz and 9.8 Hz. The minimum speed for this study is taken as approximately 10 Hz. Hence, the data length corresponding to one revolution of the bearing amounts to 20,000 (200 kHz / 10 Hz).

Figure 3 shows the vibration signals for healthy, inner race fault, outer race fault and ball fault samples.

Table 1. Rotational speeds used in the OTTAWA data

Health Condition	Rotational Speed Condition			
	Increasing	Decreasing	First Increasing Then Decreasing	First Decreasing Then Increasing
Healthy	H-A-1	H-B-1	H-C-1	H-D-1
	H-A-2	H-B-2	H-C-2	H-D-2
	H-A-3	H-B-3	H-C-3	H-D-3
Inner Race Faults	I-A-1	I-B-1	I-C-1	I-D-1
	I-A-2	I-B-2	I-C-2	I-D-2
	I-A-3	I-B-3	I-C-3	I-D-3
Outer Race Faults	O-A-1	O-B-1	O-C-1	O-D-1
	O-A-2	O-B-2	O-C-2	O-D-2
	O-A-3	O-B-3	O-C-3	O-D-3
Ball Faults	B-A-1	B-B-1	B-C-1	B-D-1
	B-A-2	B-B-2	B-C-2	B-D-2
	B-A-3	B-B-3	B-C-3	B-D-3

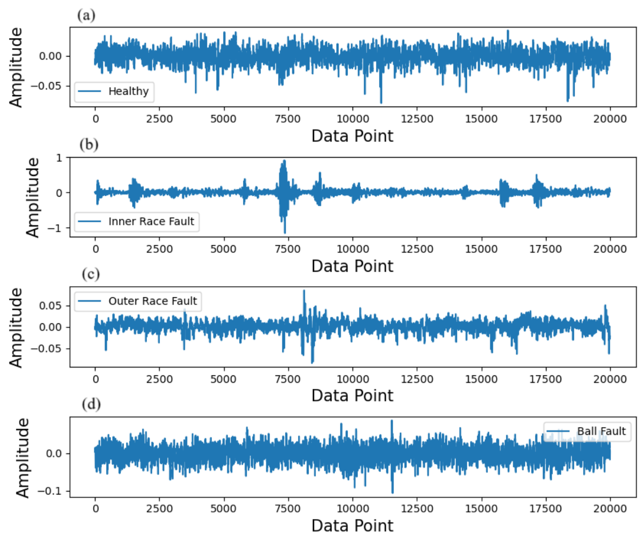

Figure 3. The vibration signals corresponding to samples of (a) healthy, (b) inner race fault, (c) outer race fault, and (d) ball fault

2.2 *Signal to image mapping*

Traditional fault diagnosis methods use various techniques such as FFT, STFT, EMD, VMD, WT, HHT, etc. to reveal the fault characteristics inherent in the raw vibration data. These methods require expert knowledge as well as highly complex and time-consuming mathematical calculations. In contrast to traditional methods, only raw data is used in the feature extraction process in this study to once again prove the ability of deep learning methods to interpret raw data. However, the utilization of a dataset with a length of 20,000 in this study will adversely affect both the efficiency and inference time of the forthcoming artificial intelligence network. In order to address this issue, researchers have enhanced the performance and interpretive process of the artificial intelligence network by transforming the data from one-dimensional space to two-dimensional space [8–10]. In this method, also known as signal to image mapping technique, one-dimensional raw vibration data are converted into grey images which are two-dimensional representations. In the studies [8–10] examined, raw data with length N^2 in one-dimensional space are transformed into two-dimensional matrices of size NxN. However, it is not possible to obtain a quadratic matrix when the data length is 20,000. Therefore, in this study, the raw data is transformed into a rectangular matrix of 100x200 dimensions rather than a quadratic matrix. During the generation of the two-dimensional representation of the vibration signal, the raw vibration data is initially normalized within the range of 0 to 1. Subsequently, each value of the one-dimensional normalized vibration signals is sequentially positioned from left to right onto the two-dimensional image, where each value corresponds to a pixel value. Figure 4 depicts randomly selected two-dimensional grayscale images representing healthy, inner race fault, outer race fault, and ball fault. When the obtained grey images are examined, it is observed that each health condition of the bearing exhibits identical patterns within itself.

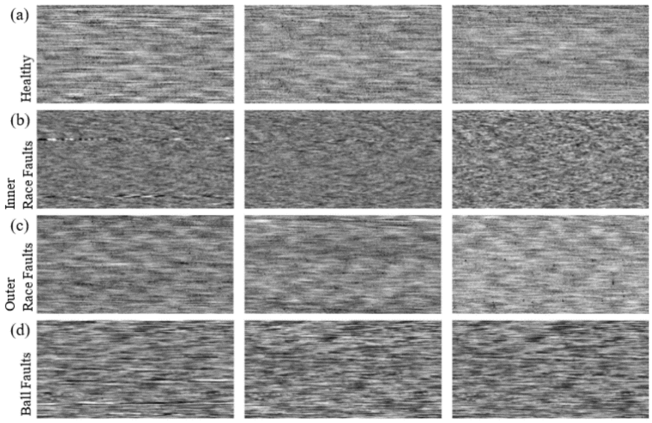

Figure 4. The two-dimensional grayscale images corresponding to samples of (a) healthy, (b) inner race fault, (c) outer race fault, and (d) ball fault

In the next stage, the grey images obtained are divided into three by random selection with 4% training and validation and 96% testing for each class. 60% of the 4% data is training data and 40% is validation data. Table 2 shows the sample distributions used for training, validation and testing.

Table 2. Sample distributions

	Training	***Validation***	***Test***
Healthy	28	20	1152
Inner Race Faults	28	20	1152
Outer Race Faults	28	20	1152
Ball Faults	28	20	1152
Total	112	80	4608

2.3 *Classification with deep learning*

The advancement of artificial intelligence technologies, propelled by the development of advanced sensor technologies, wireless communication, and information processing systems, has significantly accelerated. Deep learning, a sub-discipline of artificial intelligence, is a machine learning technique that imitates the observation, analysis, learning and decision-making processes of the human brain by using big data. LSTM, a type of deep learning model, serves as a robust tool in applications necessitating sequential analysis of data, such as text generation, text classification, handwriting recognition, and augmenting audio to silent videos. Moreover, the LSTM are extensively employed as diagnostic and predictive models in assessing machine health.

In this research article, LSTM-based deep learning model is used as a fault diagnosis model. The structure of an LSTM block with an input vector length of 3 and having 2 units [15,16] is given in Figure 5. The LSTM cell has 3 inputs (x_t, c_{t-1}, h_{t-1}) and 2 outputs (c_t, h_t). At the same time the LSTM cell has 4 dense layers (forget gate, input gates, output gate). Where:

x_t : input value at time step t

c_{t-1} : cell state value at time step t-1

h_{t-1} : hidden state value at time step t-1

c_t : cell state value at time step t

h_t : hidden state value at time step t

Here the vector lengths h_{t-1}, c_{t-1}, h_t and c_t are defined by the unit parameter of the LSTM cell, while the vector length x_t is defined by the input shape parameter of the LSTM cell [15].

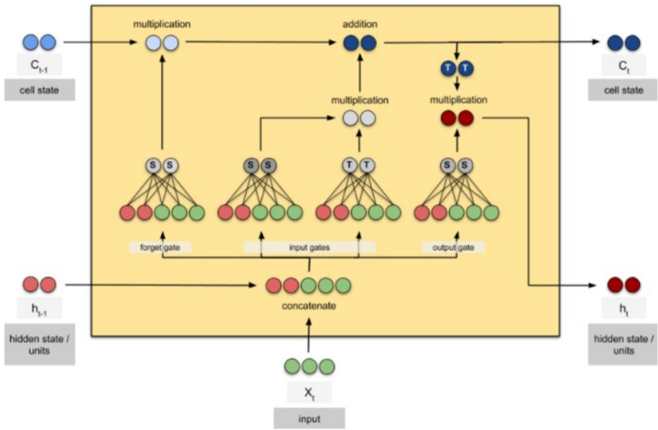

Figure 5. The structure of an LSTM block with an input vector length of 3 and having 2 units [15,16]

The output functions of four dense layers are given below [15]:

$$f_t = \sigma_s(W_f x_t + U_f h_{t-1} + b_f) \tag{1}$$

$$i_t = \sigma_s(W_i x_t + U_i h_{t-1} + b_i) \tag{2}$$

$$ii_t = \sigma_{ht}(W_{ii} x_t + U_{ii} h_{t-1} + b_{ii}) \tag{3}$$

$$o_t = \sigma_s(W_o x_t + U_o h_{t-1} + b_o) \tag{4}$$

Where:

f_t : output vector of forget gate's dense layer

i_t : output vector of input gate's first dense layer

ii_t : output vector of input gate's second dense layer

o_t : output vector of output gate's dense layer

W : weight matrix of the x_t

U : weight matrix of the h_{t-1}

b : bias vector

σ_s : sigmoid function

σ_{ht} : hyperbolic tangent function

The output functions of hidden state and cell state are given below [15]:

$$c_t = f_t \circ c_{t-1} + i_t \circ ii_t \quad (5)$$

$$h_t = o_t \circ \sigma_{ht}(c_t) \quad (6)$$

The LSTM-based fault classification model developed for bearing fault diagnosis in this study is given in Figure 6. The suggested model comprises an input layer, LSTM layer, batch normalization, fully connected layer, and classification layer. The input layer comprises two-dimensional grayscale images of size 100x200. After the input layer, a single LSTM block with an input shape of 100x200 and 8 units is used. In order to enhance the performance and generalization capacity of the network, the data derived from the LSTM layer are normalized within a specific range in the batch normalization layer. In the full connected layer, revealing which class the failure characteristic is related to, 512 neurons are used with a dropout rate of 0.3 and LeakyRelu is chosen as the activation function. In the classification layer, four neurons are used to classify the four states of the bearing (healthy, ball fault, outer race fault and inner race fault). In this layer, softmax is selected as the activation function.

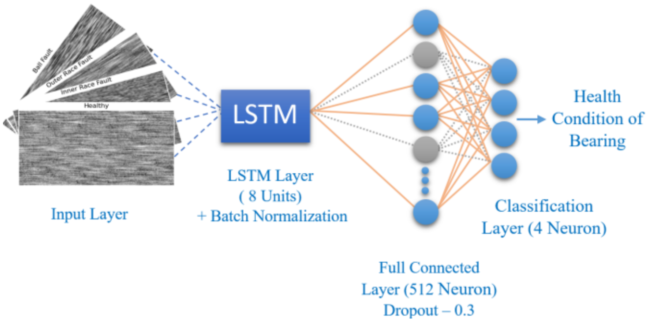

Figure 6. The proposed LSTM-based fault classification model

The proposed LSTM-based fault classification model is developed in Python 3.11 platform using tensorflow, keras and scikit-learn libraries. During the training of the model, the number of epochs is set as 5, batch size as 1, loss function as categorical cross entropy, optimization algorithm as Stochastic Gradient Descent (SGD), learning rate as 1e-4 and momentum as 0.99. The model is trained with training and validation data and tested with test data.

3 Performance evaluation

The performance of the proposed fault classification model is assessed using accuracy, precision, recall and f1-score metrics. The formulations of these metrics for multiple classifications are given in Table 3. Where i is the class number, tp_i, tn_i, fp_i, fn_i are the true positive, true negative, false positive and false negative values of class i respectively. In addition, the indices avr, μ, M denote the mean, micro and macro, respectively. In the study, calculations are made with β = 1.

The confusion matrix obtained by testing the LSTM-based fault classification model with test data is given in Figure 7. Looking at the Figure, the proposed model is able to classify all classes correctly.

The values of the performance metrics of the proposed model after testing with test data are given in Table 4. When the table is examined, it is seen that 100% success is achieved in all metrics. At the same time, the performance obtained by the loss function is 1.1585e-04. This is a remarkably successful result for a model trained with only limited data. In addition, the training of the proposed model only takes about 8 seconds. Both the very short training time and the success obtained on test data reveal the superiority of the proposed model compared to other fault diagnosis models.

Table 3. Performance metrics [17]

Metrics	***Formulation***
$Accuracy_{avr}$	$\dfrac{\sum_{i=1}^{l} \frac{tp_i + tn_i}{tp_i + tn_i + fp_i + fn_i}}{l}$
$Precision_{\mu}$	$\dfrac{\sum_{i=1}^{l} tp_i}{\sum_{i=1}^{l} tp_i + fp_i}$
$Recall_{\mu}$	$\dfrac{\sum_{i=1}^{l} tp_i}{\sum_{i=1}^{l} tp_i + fn_i}$
$Fscore_{\mu}$	$\dfrac{(\beta^2+1)Precision_{\mu}Recall_{\mu}}{\beta^2 Precision_{\mu} + Recall_{\mu}}$
$Precision_{M}$	$\dfrac{\sum_{i=1}^{l} \frac{tp_i}{tp_i + fp_i}}{l}$
$Recall_{M}$	$\dfrac{\sum_{i=1}^{l} \frac{tp_i}{tp_i + fn_i}}{l}$
$Fscore_{M}$	$\dfrac{(\beta^2+1)Precision_{M}Recall_{M}}{\beta^2 Precision_{M} + Recall_{M}}$

Figure 7. Confusion matrix obtained by testing the proposed LSTM-based fault classification model

Table 4. Performances obtained by testing the model

	Precision	*Recall*	*F-score*	*Sample*
Healthy	1.0000	1.0000	1.0000	1152
Inner Race Faults	1.0000	1.0000	1.0000	1152
Outer Race Faults	1.0000	1.0000	1.0000	1152
Ball Faults	1.0000	1.0000	1.0000	1152
Accuracy$_{avr}$			1.0000	4608
Micro$_{avr}$	1.0000	1.0000	1.0000	4608
Macro$_{avr}$	1.0000	1.0000	1.0000	4608

The training-validation loss and performance graphs obtained according to the accuracy criterion of the proposed model during training are given in Figure 8. In the graphs, the proposed model performs a very stable training process. The validation performances quickly converged to the training performances and reached a steady state. These results show that the LSTM-based fault classification model can learn the characteristics of the health condition of the bearing with high performance.

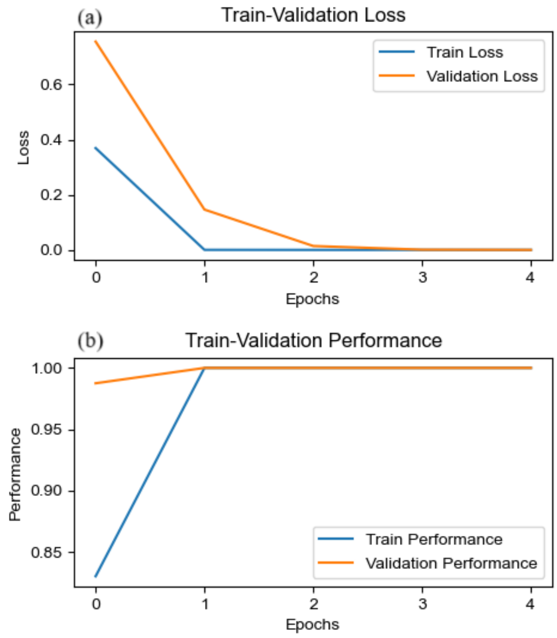

Figure 8. Training-validation results according to the accuracy metric of the proposed LSTM-based fault classification model (a) Training-validation loss (b) Training-validation performance

4 Results and discussion

In this research article, an LSTM-based deep learning model using signal to image mapping technique is proposed to diagnose bearing fault in rotating machines operating under variable speed conditions. In the model, one-dimensional vibration signals are converted into two-dimensional greyscale images with the signal to image mapping technique, and the LSTM-based model is created to extract the fault characteristics from the obtained images. In the training and testing phases of the model, OTTAWA dataset containing vibration signals obtained from bearings operating under variable speed conditions is used. The proposed model is trained with very limited data, corresponding to 4% of the data, and tested with 96% of the data. Accuracy, precision, f1-score and recall is used as performance metrics in the test phase and 100% success is achieved in all metrics. During the training of the model, the loss and performance graphs obtained according to the accuracy metric showed a very stable structure, which showed that the model is able to learn the fault characteristics and that memorization did not occur. Without the need for expert knowledge, the proposed model was able to classify the fault characteristic effectively and quickly with its feature extraction capability that does not require complex computational operations in the background.

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