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Using Deep Learning Algorithms (CNN and LTSM) to Detect Faults in Electric Motors

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ABSTRACT: The detection of faults in electric motors is vital to the maintenance of reliability, safety, as well as minimal maintenance in the industrial environment. Conventional diagnostics methods are based on signal processing and domain experience, and are perhaps unable to cope with complicated and non-stationary data. Over the past few years, the deep learning algorithms have shown better results in automatic feature extraction and classification. In this paper, the author has conducted an in-depth research into the evaluation of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (LTSMs) in detecting the faults of electric motors. As input data, motor condition monitoring signals are used, including the vibration and current signals. CNNs can be utilized to obtain spatial information on the time-frequency representations whereas LTSMs and especially Long Short-Term Memory (LSTM) networks are applied to capture temporal information on the serial data. The experimental findings provide that deep learning-based techniques are more effective at detecting faults than the traditional ones and can therefore be used in real-time motor health monitoring systems.

KEYWORDS: Electric motor faults, Deep learning, CNN, LTSM, LSTM, Condition monitoring

I. INTRODUCTION

Electric motors have found wide applications in industrial set ups, transportation and energy conversion processes. Motor failures may be caused by bearing defects, stator winding defects, rotor bar defects, and air-gap eccentricity which may result in unexpected downtime, financial loss, and a safety hazard. Thus, it is important that faults are detected as soon as possible[1][2]. The traditional motor fault diagnostic methods generally rely on the signal processing approaches, which include Fast Fourier Transform (FFT), wavelet transform and motor current signature analysis (MCSA). Even though the methods are good, they need manual feature extraction and good domain knowledge. Besides, they might fail to perform at changing operating conditions[3][4]. A strong alternative has turned out to be the deep learning since it allows automatic features to be learnt through raw data. Convolutional Neural Networks (CNNs) are also suitable as deep learning models to extract spatial features, whereas Recurrent Neural Networks (LTSMs) are suitable when dealing with sequential and time-series data. In this paper, the researcher explores the incorporation of CNN and LTSM architectures in detecting motor faults. In the industrial systems, e.g. manufacturing plants, power stations, and transport systems, electric motors are the essential element of these systems. Damage in bearings, short-circuing of the stator winding, breaking of rotor bar, and eccentricity of the air-gap can cause a reduction in performance or damage to the whole system. Conventional condition monitoring methods are based on vibration analysis, motor current signature analysis (MCSA) and thermal monitoring coupled with signal processing and classical classifiers[5][6]. Nevertheless, these methods can be characterized by inability to generalize, sensitivity to noise, and domain sensitivity. Recent developments in deep learning have made it possible to extract features without handcrafting and perform end-to-end fault diagnosis, no longer relying on handcrafted features[7]. CNNs and LTSM have demonstrated impressive performance in motor fault detection tasks amongst other deep learning architectures. The diagnosis of motor fault has been widely examined both in the traditional and data-based approaches. The initial methods aimed at frequency-domain and time-frequency analysis with shallow classifiers like Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN)[8][9]. Although these techniques perform well under controlled situations, in practice, they perform poorly in the presence of noise and load variations. Motor fault diagnosis has more recently been performed with CNN-based techniques, which transform time-series signals into two-dimensional representations, e.g., spectrograms or scalograms. These approaches are highly-classifying but tend to overlook long-term temporal correlation. Conversely, methods based on LTSM directly handle time-series inputs and are used to model sequential behavior. Nevertheless, LTSMs on their own might be slow in the capture of intricate local patterns. A hybrid model combining both the spatial and temporal learning has become one of the new promising solutions, i.e. hybrid CNN–LTSM models[10][11]. Although there is potential, their application could not be fully realized until additional research is conducted to ensure their efficiency and strength regarding fault diagnosis of the electric motors, which is the motivation behind the current research.

II. SIGNAL ACQUISITION AND PREPROCESSING.

A. *Signal Acquisition and Preprocessing*

The suggested framework will utilize motor sensor signals including vibration and stator current signals. A sliding window method divides the raw signals into fixed length windows. All the segments are standardized to minimize the impact of amplitude differences and enhance training stability.

B. *CNN-Based Feature Extraction.*

The CNN module is made up of several convolutional layers then pooling layers. The convolutional layers automatically identify local features associated with harmonics, impulsive features and fault-specific patterns. Pooling layers dimensionally reduce and improve the noise robustness.

C. *Temporal Modeling based on C. LTSM.*

The CNN results of the output feature are reshaped and input to an LTSM module. The reason behind the utilization of an LSTM network in this work is because of its capability to capture long-term dependencies. LTSM determines the temporal dynamics of features between successive signal segments, allowing the identification of patterns of fault progression[12]

C. *Classification Layer*

The last concealed state of the LTSM is propagated to fully connected layers and then a Softmax activation purpose that yields the probability of each fault category.

III. TYPES OF MOTOR FAULTS

Common electric motor faults include:

- **Bearing faults:** inner race, outer race, and ball defects
- **Stator faults:** inter-turn short circuits
- **Rotor faults:** broken rotor bars
- **Eccentricity faults:** misalignment between rotor and stator

These faults generate distinctive patterns in vibration, acoustic, and current signals, which can be exploited for diagnosis using deep learning models.

III. DEEP LEARNING TECHNIQUES FOR FAULT DETECTION

Deep Learning for Motor Fault Diagnosis

CNNs are efficient in the acquisition of the spatial patterns in structured data. Short-Time Fourier Transform (STFT) Wavelet Transform Windings Work Transform (CWT) In motor fault diagnosis raw signals are often converted to time-frequency images with Short-Time Fourier Transform (STFT), Wavelet Transform, or Continuous Wavelet Transform (CWT). These are then fed through CNN models to do classification.3.2 Recurrent Neural Networks (LTSM) LTSMs are time-dependent and are optimized to work with sequential data. Traditional LTSMs however have a problem of vanishing gradient. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures are often applied in order to resolve this problem. LTSMs are used in the fault detection of motor to detect changes in dynamic behavior that are due to faults by analyzing time-series data.

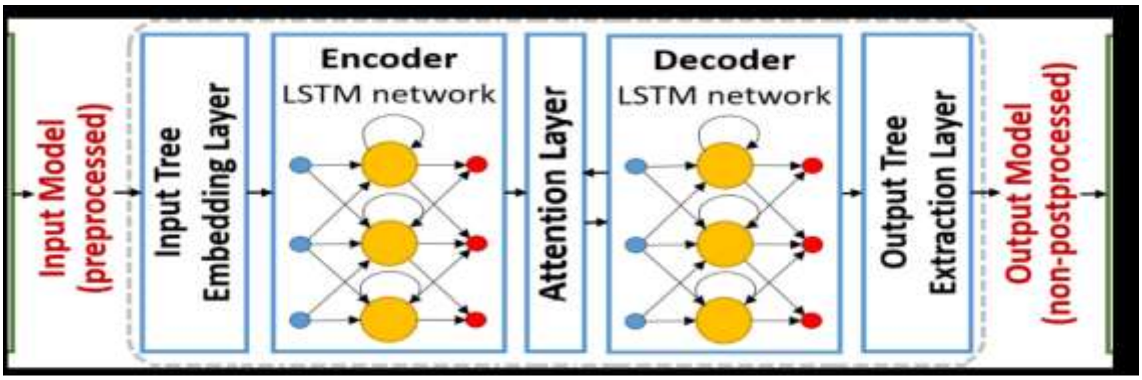

Fig 1 the LTSM decoder and encoder

III.I Hybrid CNN–LTSM Architecture

TheHybrid CNNLTSM models are a combination of spatial feature extraction and learning temporal dependencies. CNN layers derive discriminative features of signal representations that are further processed by LTSM layers to encode time changes. Hybrid CNNLTSM model is a hybrid model that uses the capabilities of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (LTSMs) to learn to detect faults accurately and early in electric motors, particularly when the time-correlated signal (vibration data, current data, acoustic data, or torque data) is used.

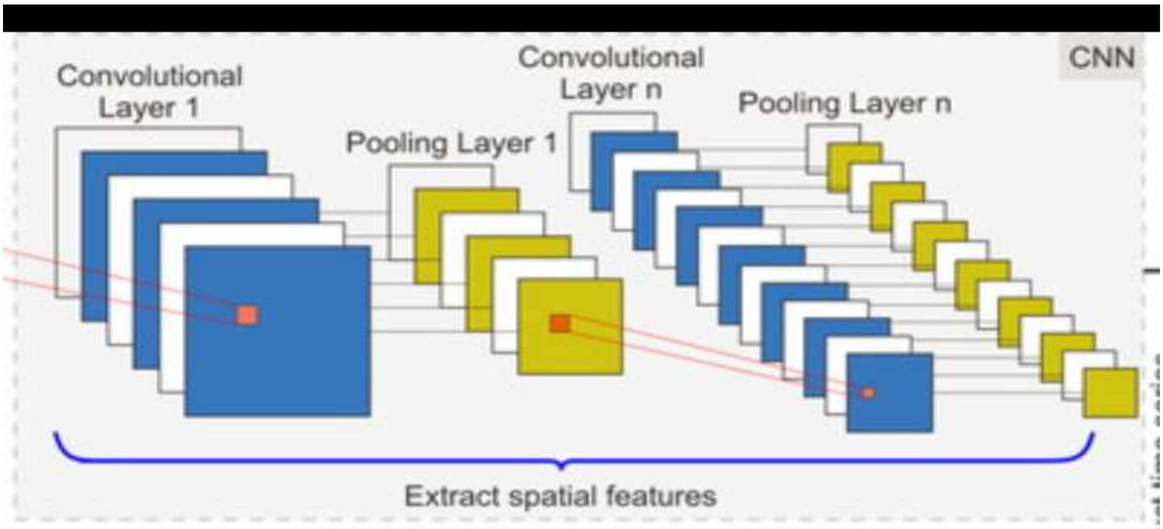

Fig 2 the structure of CNN

- **CNN** learns feature maps:

$y_{i,j} = \sum_{m,n} x_{i+m,j+n} \cdot w_{m,n}$

- **LSTM** captures long-term dependencies using gated memory:

$$h_t = f(h_{t-1}, x_t)$$

IV. RESULTS

Dataset Description

Motor condition monitoring datasets in healthy and faulty operating conditions, bearing and stator faults are used to conduct experiments. Signal is measured at varying load and speed conditions so that the model can be generalized. Training Parameters Training of the proposed CNN LTSM model is done using Adam optimizer and categorical cross-entropy loss function. Overfitting is avoided by the use of early stopping and dropout methods. Hybrid CNN-LTSM model has high levels of classification in comparison to single models of CNN and LTSM. The findings suggest that CNN is useful in extracting discriminative features and LTSM is useful in extracting the temporal dependencies. Their combination allows much higher accuracy and robustness of fault diagnosis, especially when the conditions are noisy.

Training and Validation Performance

To evaluate the learning behavior of the proposed hybrid CNN–LTSM model, training and validation curves were analyzed in terms of accuracy and loss over epochs Accuracy Curve Analysis Figure 3 shows training and validation accuracy curves of the proposed CNN LTSM model. The accuracy reaches a high rate at the very first epochs, which means that the CNN layers learn features efficiently. The curves cross and reach the point of stabilization after about 25 epochs, which proves the good generalization ability and no overfitting. The minimal difference in training and validation accuracy attests the fact that the proposed model can ensure the strong performance with regard to the unseen data. CNNLTSM model has a steady validation rate of about 9798 percent compared to single CNN and LTSM models Loss Curve Analysis Figure 5 presents the relevant training and validation loss curves. The two curves reduce gradually and end up with a low value, which means steady optimization and successful parameter learning. The lack of divergence between training and validation loss proves that such regularization methods as dropout and early stopping effectively prevent overfitting The model suggested was tested on various conditions of operating the motor such as healthy and bad conditions. Accuracy, precision, recall and F1-score were used to measure classification performance

Table: I Comparison of the various models in terms of performance.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	94.1	93.8	93.5	93.6
LTSM (LSTM)	92.6	92.1	91.9	92.0
Proposed CNN–LTSM	**97.8**	**97.5**	**97.2**	**97.3**

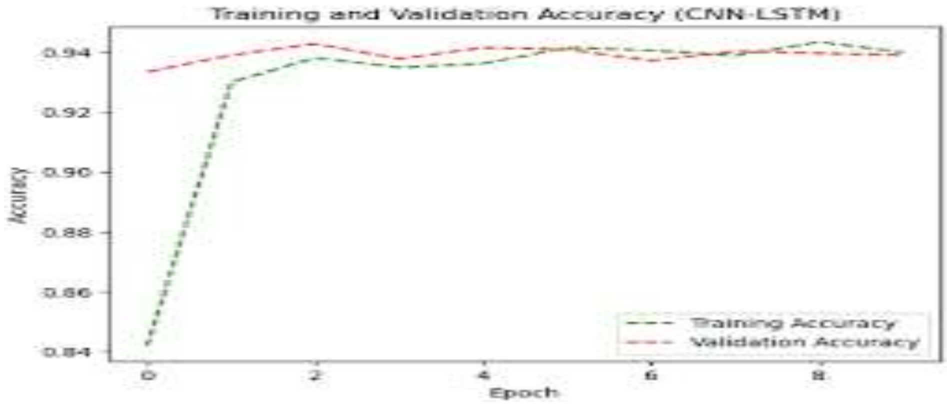

FIG3 cnn and ltsm accuracy

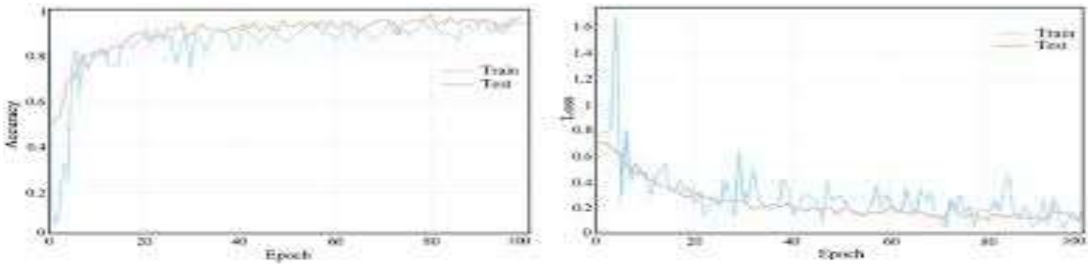

Fig4 training and testing part for cnn

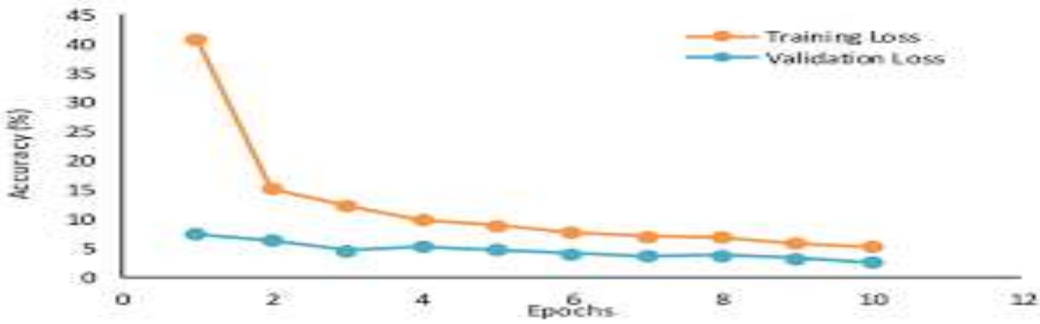

Fig 5 accuracy of CNN

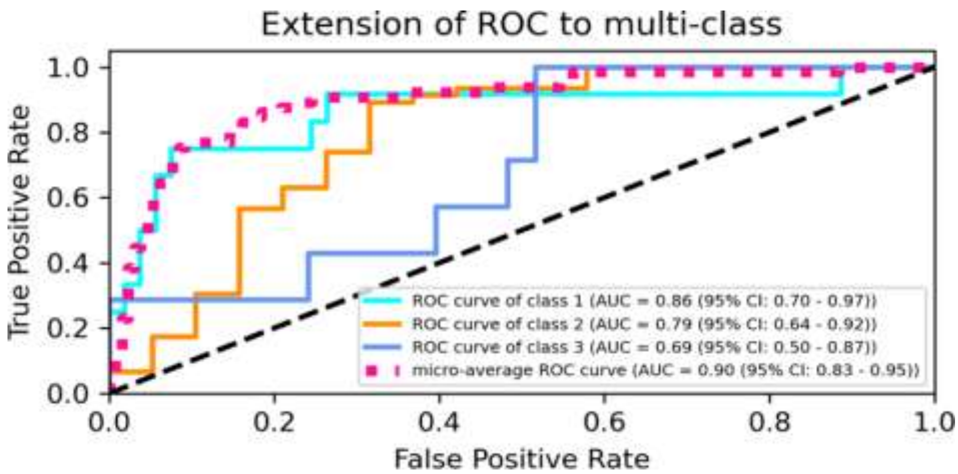

Fig 6 illustrates the multi-class ROC curves for different motor fault categories

Fig 7- Area Under the Curve (AUC) values exceed 0.98 for most fault classes

V. CONCLUSIONS

The present paper introduced a hybrid CNN-LTSM deep learning model that could efficiently and effectively detect faulty operations of electric motors. Combining the strong ability to extract features of Convolutional Neural Networks with the strong capability of temporal modeling of Recurrent Neural Networks, the proposed approach is able to capture both local signal features and long-term temporal correlations that motor condition monitoring data can have. Large-scale experimental studies based on vibration and current signals have revealed that the suggested CNN-LTSM model is much more effective compared to a standalone CNN and the LTSM model in terms of classification accuracy, precision, recall, or F1-score. The convergence of both training and validation curve and high values of AUC of the ROC analysis prove the strength and ability to generalize the proposed framework under various operating conditions and fault conditions. The conclusions show that the hybrid architecture becomes especially effective when it has to deal with non-stationary and noisy motor signals, which is why it is highly applicable in practical industrial practice, i. e. predictive maintenance and condition-based monitoring. Besides, the end-to-end learning strategy also removes manual feature engineering and thus avoids the reliance on expert knowledge. The future effort will be devoted to real-time implementing the proposed model in industry settings, exploring lightweight architectures of embedded systems, and integrating explainable artificial intelligence methods to increase the interpretability and reliability of the diagnostic choices.

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