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A CNN-CLSTM Approach for Condition Monitoring and Fault Diagnosis of Induction Motor on Manufacturing

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Abstract. Numerous industrial applications rely on induction motors due to their numerous advantages, especially three-phase induction motors. Their safe and reliable operation is, thus, very important. The motor is prone to problems and breakdowns, which can lead to long periods of inactivity and substantial operational and financial losses. So, early fault detection is critical for vehicle safety. Precise sequentially is required throughout the method selection, preprocessing, feature extraction, and model training processes. One non-linear signal processing method used in data preparation is Cepstrum analysis, which is the integral derivative of the logarithm of the input signal's absolute value of its DFT. With the use of ICA, a multivariate random signal can be converted into a signal with components that are statistically completely independent of each other. This process is known as feature extraction. When training a CNN-CLSTM model, feature extraction takes precedence. This new method outperforms two cutting-edge algorithms: CNN and CLSTM. Accuracy improved significantly, reaching 97.38%, according to the results.

Keywords: Induction Motors Faults · Independent component analysis (ICA) · Motor Current Signature Analysis.

1 Introduction

One may say that the induction motor is the lifeblood of the industrial sector. Electrical and mechanical fatigue are two of the many potential causes of IM failure. Any delay in detecting these errors increases the likelihood that they will develop to catastrophic failures. It follows that condition monitoring is superior to other methods for detecting defects early on. This test finds out how terrible the motor is by applying a broad variety of external defects and analyzing each one thoroughly. The induction motor was about to see widespread use in industry. Engine vibration and excessive noise were two topics that drew the attention of many engineers in the early. A number of countries published the seminal works. A basic mechanism for the generation of vibration and noise by electrical motors was uncovered. Electromagnetic vibrations in the stator core due to rotational electromagnetic forces are the key finding of these investigations. The most important finding is that the mechanical behavior of the motor's structure and the possibility of different types of spinning forces stimulating a resonance situation directly affect the levels of vibration and noise. When it comes to diagnosing issues with induction motors and keeping tabs on their state, modern industry relies heavily on vibration analysis. The dependability of vibration analysis in machine diagnostics relies on the ability to precisely evaluate vibration data, especially frequency spectra. Using examples from the author's own work in a variety of fields, this book presents a number of case studies. In order to better diagnose electromagnetic anomalies in induction motors, this study will try to explain what symptoms might be present. The author's vast experience in vibration diagnostics for electrical devices across multiple industries, along with current research and classical theory of electromagnetic vibration, are all utilized. Induction motors (IMs) have grown into an indispensable part of the industrial world due to their role in producing mechanical power, manufacturing, and transportation. Machine tools, electric vehicles, pumps, compressors, blowers, fans, conveyors, and electric instruments are among of the most common applications of IMs. About 60% of industrial electricity use and more than half of all electrical energy generated globally comes from induction motors (IMs). The adoption of IM is spreading across all industries due to its resilience, low cost, high power-to weight ratio, and adaptability. Instant messaging's dependability and accessibility are critical to the industry's seamless operation. Inevitably, IMs will experience mechanical, electrical, thermal, and environmental stressors during the operation. Natural ageing, variations in external loads, power supply fluctuations, excess heat, inadequate lubricants and poor sealing, a dusty atmosphere, and manufacturing faults are some of the many potential sources of these stresses. Consequently, the engine is prone to unexpected failures in a number of its parts. People frequently fail to notice the most critical stage of these abnormalities, which can result in devastating motor failure. The industry bears a disproportionate share of the cost associated with process shutdowns and, in the worst-case scenario, catastrophic harm to individuals. Therefore, in order to prevent catastrophic motor failure, the industry finds and analyses IM components that begin to deteriorate early on. As an IM continues to serve its purpose, condition monitoring continuously assesses its many components. Detects IM issues early on, performs condition-based maintenance with minimal downtime, and gives enough warning of imminent failures. For this sector to function, induction motors (IMs) are needed. Operating IM in a safe and continuous manner is crucial for it to achieve the high reliability standards. Monitoring IM is essential for avoiding unplanned shutdowns, making sure the system is running safely, and cutting down on maintenance and operation expenses. There are online and offline ways to monitor IM's health status. Improved motor reliability, reduced maintenance costs, less downtime, and optimal maintenance based on failure prediction are all aims of condition monitoring. Condition-based monitoring as the "mother" of condition-based maintenance. The IM may become flawed in many ways as time goes on. If the induction motor unexpectedly ceases functioning, the process that is now going will come to a halt, costing you both time and money. Because of its maturity, dependability, durability, and adaptability, the induction motor is one of the most frequent electric devices used in industrial applications. Maintaining close observation of the patient's condition is of utmost importance. The key to quickly resolving upcoming issues is to spot them early on. Preventing more costly equipment problems through rapid, unscheduled maintenance reduces downtime and financial loss. Typically, motors can experience mechanical issues such bearing failure, air gap eccentricity, or shaft bending, as well as electrical issues including stator and rotor failures. Rotor defects, such as bar and end-ring breaking, account for only about 5% of induction machine mistakes, but their detection is critical. Because stator design has evolved so much, machines can now only tolerate stator defects causing a few seconds of downtime at most. Rotors, on the other hand, tend to rely on more conventional layouts, such as the squirrel cage.

2. Literature Survey

More and more cars and industry are using induction motors (IM) since they can run on electrical energy, the best energy source. [1]Availability of these devices is dependent on the prime mover's condition. The diagnostics and prognostics it provides are thus more vital than ever in this era. The purpose of this analysis is to learn more about how IM diagnoses have developed through time, with a focus on EVs. [2]Any failure in the motor components would be catastrophic for an all-electric vehicle that relies on an integrated motor (IM) for propulsion. All industry equipment that uses an IM is subject to this as well. As their popularity skyrockets, so does the dependence on instant messaging. Both single-phase and poly-phase IMs are possible, depending on the machinery. [3]Electrical and mechanical components of an IM include the stator, rotor, bearings, winding, end rings, and so on. When working in challenging industrial and environmental environments, IM meets a wide variety of strains. It shows the several kinds of IM faults that these stresses can create. [4]Extreme weather, improperly rated power or voltage, and an imbalanced or overload load are the three most typical causes of these difficulties problems with contamination and rust, in addition to improper installation. Because the physics behind each flaw is different, the vibration, current, and acoustics that result from them are also different. It is important to monitor specific factors in order to identify these issues. [5]To keep tabs on the IM's primary parts, a plethora of physical measures and condition monitoring techniques were employed.Motors, gearboxes, wind turbines, generators, and engines are all examples of rotating machinery that are vital to modern industrial applications .These critical machines need to work consistently, accurately, and without any problems [6]. A great deal of research and analysis has focused on this critical issue in recent years, exploring several approaches to improving the CM and FDD of rotating machinery. Human data extraction of diagnosable information is required by model and signal methods, data-based methods, classic CM and FDD procedures [7], and all of these methods combined. Once the features vector was prepared, the following stage was to develop pattern recognition models. Complex feature extraction techniques and a high level of skill are required in this case [8]. Artificial intelligence (AI) techniques and methods for RM CM and FDD have been widely used as modern solutions to this challenge. When it comes to industrial processes and applications, induction motors (IMs) are indispensable. The process of continuously checking the health of an induction motor is called "condition monitoring" (CM). Reducing expenses while increasing machine availability, efficiency, and productivity are the aims here [9]. The most crucial prime movers in industrial applications, IM are an integral aspect of industrial processes due to their durability and ease of production [10]. Many different types of businesses depend on IMs, including railways, mining, woodworking equipment, cars, chemicals, and paper mills. Centrifugal pumps, blowers, home appliances, and industrial gear all make heavy use of single-phase IMs due to their efficiency and reliability. Research on induction motor issues has focused on a wide range of topics, including rotor corrosion, imbalanced stator windings, eccentricity, bearing problems, and misalignment [11]. It is common practice to perform IM maintenance at regular periods. On the other hand, operational and environmental factors may cause IM's performance to decline at regular periods. So, if you want more efficiency, you need to monitor the online IM. New methods rely heavily on predictive maintenance using CM. Its objective is to ascertain the maintenance schedule in relation to the state of the process or facility [12]. The purpose of condition-based monitoring is to enhance the efficiency and performance of IM, increase its lifespan and productivity, and decrease its internal and external damages [13]. It is now crucial to have CM and fault detection of IMs in order to eliminate unexpected breakdowns and decrease unplanned downtime. Despite induction motors' reputation as reliable rotary machinery, they can still experience unanticipated issues such as rotor bar breaks, bearing failure, stator interterm shorting, etc. [14] The sector is vulnerable to unexpected failures caused by these defects, which can lead to human deaths and a chain reaction affecting production safety and quality. Therefore, it would be prudent to think about implementing a system that could stop these types of situations from occurring in this field. [15] Current protection systems are designed to isolate the faulty component; however, they cannot be relied upon to give warnings before the actual fault occurs; hence, these systems are unable to avoid flaws. [16] Condition monitoring is one kind of preventative strategy that can notify you before the physical symptoms of a disease even appear. Thus, condition monitoring would enable the equipment to be securely turned off, preventing any potential loss of time due to unforeseen breakdowns. Technologies that have been created utilizing the fast Fourier transform (FFT) [17], wavelet transform, leaky flux sensing, and stator. An assortment of concepts, including partial discharge, voltage and current harmonics, and others, have been proposed by different scholars. Using fuzzy logic and field-programmable gate arrays (FPGA) based devices, the three line currents can be used to analyze the health of a motor [18]. On the other hand, fuzzy logic-based schemes have a few flaws, like a limited knowledge base, the time-consuming process of building fuzzy rule bases, and insufficient data regarding the correlation of error symptoms. Think of a huge power plant in Taiwan. [19] It uses an auxiliary system with a bunch of high-voltage motors to power all those huge thermal generator sets. When the auxiliary system fails, it can have a domino effect on the whole power system, lowering reliability and power quality and potentially leading to huge economic losses. [20] This highlights the critical nature of induction motor status monitoring and auxiliary system trouble diagnoses. A wide variety of damage types were identified, including interterm short-circuits, broken rotor bars, bearing inner ring failure, bearing outer ring failure, ball failure, cage failure, and eccentricity [21]. Several research have proposed ways to classify stator failures and other types of damage. Among these techniques are magnetic pendulous oscillation, motor current signatures, total harmonic voltage, and assessments of instantaneous active and reactive power. The most common issues with induction motors include broken rotor bars, stator inter-turn failure, and bearing failure. Bearing failure accounts for almost 41% of induction motor defects [22]. About 11% of failures are related to other components, whereas 13% are related to the stator and 39% are related to other parts. For a more comprehensive look, you might refer, which classifies induction motor breakdowns as either mechanical or electrical. Bearing failures (from inadequate lubrication, mechanical stresses, incorrect assembly, misalignment, etc. [23]), gearbox failures (when the rotor is not centered with regard to the stator and/or its rotation is not aligned with the stator's central axis), and eccentricity are all examples of mechanical faults that can manifest in motors that employ gearboxes. The electrical components known as the stator and rotor could both be malfunctioning. Failure of the stator might be caused by damage to the insulation of the stator windings or the speed controller of the drive. Damage to the windings, end rings, or rotor bars can indicate rotor problems. There has been extensive research into several sensing modalities for the aim of fault identification. In [24], an assessment found that axial electromagnetic flux, current, and voltage monitoring were all Heat, infrared, vibration, and sound sensors, as well as sensors for chemical analysis of motor oil [25] had all been considered. A large number of these are being used now as we speak. Rather than a Using new magnetic flux sensors to monitor stator-rotor air-gap flux and leakage flux is a novel approach. The most recent details on this method can be found. These additional methods, together with partial-discharge analysis, are presented, even though vibration analysis was included. Recent years have seen a surge in interest in non-invasive in-operational techniques like current analysis, and more especially current harmonics. Experiments using inferential sensors that use current analysis tend to be accurate, and machine physics has yielded typical frequency responses for various defects. Because induction motors spin, many of the signals that point to current or future issues with these devices are periodic. Consequently, frequency-domain analysis has played a significant role in the detection of motor problems for a really long time. Previous approaches relied on Fourier transforms, while newer ones take a look at signals across the frequency and temporal domains as well.

3. Proposed System

Condition monitoring induction motors is a challenging process that engineers and researchers, especially those working in industrial settings, have encountered. Unlike other condition monitoring methods like chemical, vibration, acoustic emission, and thermal monitoring all of which require expensive sensors or specialized equipment current monitoring does not require any extra sensors. Modern monitoring methods can identify a wide range of issues with induction motors, including but not limited to: load, air gap eccentricity, rotor, bearing, and short winding.

3.1 Preprocessing

Cepstrum analysis is a non-linear signal processing method that takes the integral derivative of the logarithm of the absolute value of the input signal's DFT. This document provides a detailed outline of the techniques needed to achieve the cepstrum analysis of an input signal. For the creation of the term "cepstrum," the first four letters of the word "spectrum" were reversed, representing the spectrum of wavelengths [26]. We are able to separate the impulse response from the excitation forces by cepstrum analysis, a vibration analysis specialist. It is possible to express the fault signal $d(j)$ as follows, presuming that it is composed of two convoluted sequences, $a(j)$ for the excitation function and $m(j)$for the basic wavelet:

$$d(j) = a(j) * m(j) \tag{1}$$

It is possible to express (1) in terms of frequencies as:

$$D(\sigma) = A(\sigma).M(\sigma) \tag{2}$$

Obtaining the magnitude spectrum of the given signal requires taking the absolute value of $D(\sigma)$, which may be expressed as:

$$|D(\sigma)| = |A(\sigma)|.|M(\sigma)| \quad (3)$$

The expression (3) expressed as a logarithmic form is:

$$log|D(\sigma)| = log|A(\sigma)|.log|M(\sigma)| \quad (4)$$

From its frequency domain form, the signal is transformed into a linear sum of its components using the logarithmic function [22]. It can now obtain the equation for the cepstrum analysis that intends to use IDFT to (4):

$$g(j) = IDFT(log|A(\sigma)|.log|M(\sigma)|) \quad (5)$$

The inverse Fourier transform of linear spectra converts the signal back to its original form in the time domain, which the author named the "quefrency" domain (the term "frequency" is derived from it). There is another form that the cepstrum analysis equation can take:

$$g(j) = K^{-1}[log|K\{d(j)\}|] \quad (6)$$

Real, power, complex, and phase cepstrum analyses are only a few of the many options available for this type of investigation. According to its original definition, the power cepstrum $g_b(j)$ is what cepstrum analysis is all about.

$$g_b(j) = |K^{-1}[log|K\{d(j)\}|^2]|^2 \quad (7)$$

A definition for the complicated cepstrum would be:

$$g_g(j) = K^{-1}[log|K\{d(j)\}|] + n2\pi h \quad (8)$$

Unwrap the imaginary part of the complex logarithmic function is an operation that can only be performed with the integer h. It was the real cepstrum analysis that we used to preprocess the fault signals; it is obtained by taking the real component of (6) or by setting the phase to zero in the complex cepstrum equation. In other words, the real cepstrum analysis could be expressed as:

$$g_q(j) = real(K^{-1}[log|K\{d(j)\}|]) \quad (9)$$

3.2 Feature Extraction

3.2.1 ICA

The application of ICA allows for the statistical transformation of multivariate random signals into signals with completely independent components. It was recently shown that the approach can differentiate between mixed signals and independent ones. To say that one component is independent, it means that the data transmitted by that component cannot be deduced from the data transmitted by other components. The combined probability of two independent quantities can be calculated by multiplying their probabilities, according to statistical interpretation. One way to represent a generic ICA model is as

$$d = Ew \tag{10}$$

with A being an unknown full-rank matrix called the mixing matrix, and w and d being the data matrices representing the independent components and the measured variables, respectively. Finding an approximation for the mixing matrix E or the independent component matrix s given the measured data matrix d is the primary obstacle of independent component analysis (ICA) [27]. The real problem of ICA is to find a separation matrix S that, taking into account the following, makes the components of the reconstructed data matrix $\widehat{w}$ as independent as possible:

$$\widehat{w} = Sd \tag{11}$$

Requiring that components be independent of one other is equivalent to assuming that they do not follow a normal distribution [23]. Thus, it is possible to determine the independent variables that, when applied to the vector Sd, maximize a non-Gaussianity yardstick. Here, there is a fast fixed-point approach to minimize or maximize the fourth-order cumulant in order to determine the ICA. Statistical independence is more rigorous than uncorrelation and requires first transforming the measured variables into uncorrelated variables with unit variances. So might hear this pre-whitening process referred to as sphering.

3.2.2 PCA

Typically, m is smaller than l, and PCA takes an input set of m-dimensional vectors $D_i = (d_i(1), d_i(2), \ldots., d_i(h))^I$ and uses linear transformations to create new vectors w_i by

$$W_i = Z^I D_i \tag{12}$$

Z is an orthogonal matrix with size $h \times h$, and z_t is the eigenvector of the sample covariance matrix.

$$G = \frac{1}{l}\sum_{i=1}^{y} D_i D_i^I \tag{13}$$

To rephrase: PCA initially fixes the eigenvalue problem

$$\tau_i z_i = G z_i, t = 1, \ldots., h \tag{14}$$

Being an eigenvalue of G, τ_i corresponds to the eigenvector z_i. To get the components of w_i, we first estimate z_i, and then we apply the orthogonal transformations of d_i.

$$W_i(t) = z_t^I D_i \tag{15}$$

This new structure is defined by its principal components.

By sorting the eigenvectors in ascending order, we can use the first few to reduce the number of primary components in w_i. Therefore, PCA has the ability to reduce the number of dimensions. Among the characteristics of PCA features are: With minimal mean squared error, the initial principal components give a respectable estimate of the initial inputs. Furthermore, the variances of $w_i(t)$ increase in a progressive manner, and they are uncorrelated.

3.3 To Model Train

3.3.1 CNN-CLSTM

Deep learning methods, especially convolutional neural networks (CNNs), have shown remarkable success on a number of computer vision tasks, such as rotor fault, air gap eccentricity fault, short winding fault, load fault, bearing fault, etc. An example of CNN architecture is a stack of fully connected layers followed by several iterations of the convolution and pooling layers. At different points throughout a CNN's training process, convolutional layers perform the local feature extractor function. In the first stage of a CNN, for instance, layers extract important details including edges, counters, and gradients [24]. Data required for image classification at a high level is fed into the networks via convolutional layers later on. On the other hand, max-pooling operations reduce the feature resolution. The FC layers are then used to perform a non-linear transformation on the image features. Classification of CNN and accompanying convolutional processes can be 2D, 1D, or 3D, depending on the data complexity. Similarly, max-pooling processes can be categorized as either 2D, 1D, or 3D. Although 1D and 2D convolution are also applicable for computing spatial information, 3D convolution may learn features in both the spatial and temporal dimensions. 3D convolution is the best method for image and video analysis problems since it gives information about both space and motion. Through the use of a convolution kernel $S(d,l,i)$with dimensions $(e \times p \times g)$, the 3D convolution output $U(d,l,i)$can be generated for a specific image cube $T(d,l,i)$according to Equation (12).

$$S(d,l,i) = \sum_{t=-e}^{e} \sum_{n=-p}^{p} \sum_{\mu=-g}^{g} T(t,n,\mu).S(d-t,l-n,i-\mu) \qquad (12)$$

An all-connected layer, a ConvLSTM block, and a softmax classifier layer are the three components that comprise the proposed model. In order to execute the non-linear transformation of features between the layers, the 3D convolution blocks are followed by Rectified Linear Unit (ReLU) activation functions. A second max-pool layer feeds data into an 18-unit ConvLSTM layer [28]. Output from the ConvLSTM layer is fed into the final fully linked layer. The softmax layer precedes the fully-connected layer and sorts the output from various induction motor issues (such as rotor, short winding, air gap, load, bearing, etc.). While LSTM excels at dealing with temporal data, it loses spatial data essential for modeling the spatial-temporal data involved in fault diagnosis in induction motor because full connections in input-to-state and state-to-state transitions do not consider spatial data. The Convolutional Long Short-Term Memory (ConvLSTM) algorithm solves this issue by substituting convolution operations for the LSTM's state-to-state transition operations. Multiple articles have now argued that ConvLSTM is effective for tasks that require human intervention. Equations (13)–(18) explain the key mathematical computation and illustrate the internal elements of the ConvLSTM layer.

$$K_i = \omega(S_{dk} * D_i + S_{mk} * M_{i-1} + p_k) \qquad (13)$$

$$T_i = \omega(S_{dt} * D_i + S_{mt} * M_{i-1} + p_t) \qquad (14)$$

$$C_i = \omega(S_{dc} * D_i + S_{mc} * M_{i-1} + p_c) \qquad (15)$$

$$G_i = G_{i-1} \ominus K_i + C_i \ominus T_i \qquad (16)$$

$$V_i = \omega(S_{dv} * D_i + S_{mv} M_{i-1} + p_v) \quad (17)$$

$$M_i = tanm(G_i) \ominus V_i \quad (18)$$

Here are the definitions of the various terms used in the equations: input feature map D_i, hidden state M_i, cell output G_i, input gate T_i, forget gates K_i, and output gate V_i. from one to six. Signs $*$ and $\odot$ denote the convolution operator and Hadamard product, respectively. The 2D convolutional kernels S_{dt} & S_{mt}, S_{dv} & S_{mv}, S_{dc}& S_{mc}, and S_{dk} & S_{mk}represent the input gates, output gates, input modulation gates, and forget gates, respectively, and their hidden states.

4. Result and Discussion

Various methods for diagnosing faults in a single-phase induction motor's bearings, stator, and rotor are specified in this proposed. These approaches rely on sound waves. The single-phase induction motor was examined in five different states: healthy, with shorted main and auxiliary winding coils, with damaged rotor bar and faulty squirrel cage ring, and with bad bearing.

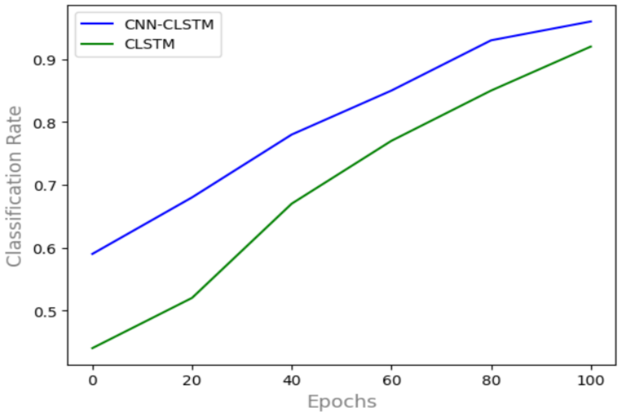

Fig. 1. Classification Rate of the Proposed CNN-CLSTM Model and CLSTM Model

Fig. 1 displays the categorization rates for the two models. Faster convergence and a higher classification rate are characteristics of the CNN-CLSTM model, according to the comparison. Since DBN models experience fluctuations when learning, it's possible that the architecture isn't stable enough to acquire a model that accurately performs the classification task.

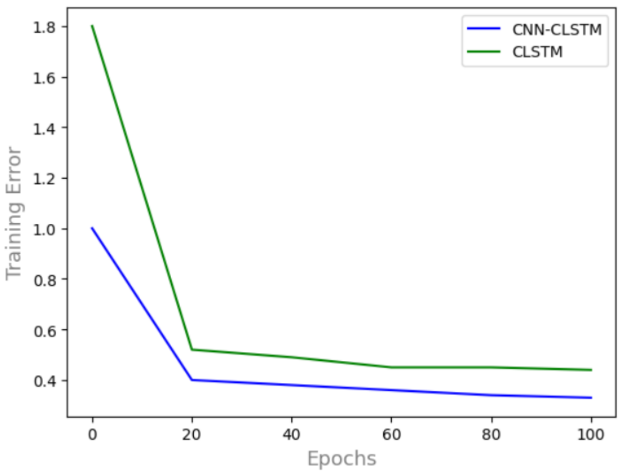

Fig. 2. Training Error With the Epochs

Figure 1 displays the training error. We have achieved the lowest loss compared to other models with our CNN-CLSTM training model.

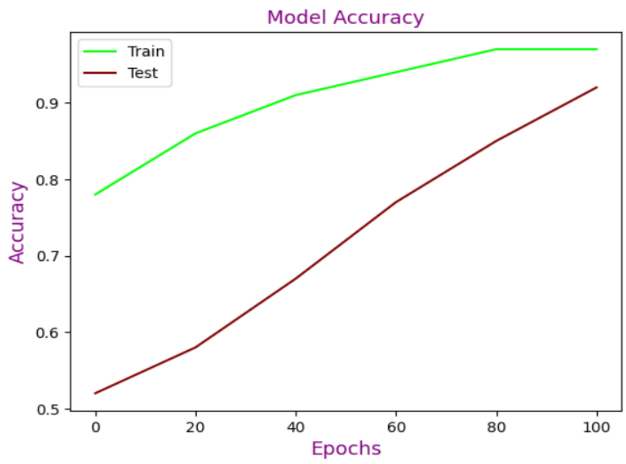

Fig. 3. Vibration Accuracy

The accuracy of the model's validation is shown in figure 3. The suggested model performs better on the vibration dataset during testing, suggesting it has poor generalizability when faced with current signals.

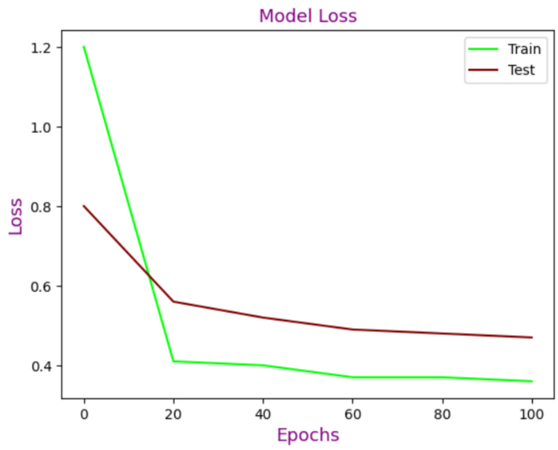

Fig. 4. Vibration Loss

There is a difference in model loss between the training and testing sets, suggesting a modest overfitting issue in the current signals, even though the suggested model achieves faster convergence in those signals.

5. Conclusion

The induction motor could vibrate if its alignment, balance, or clearances are off. Bearings are the most prone to failure and fault development when continuously subjected to fatigue loading. These defects cause the vibration signature to shift over time. When diagnosing mechanical issues like stator rotor rub or bearing faults, vibration monitoring techniques are a lifesaver. The most typical issues with induction motors, as well as innovative diagnostic methods based on advanced signal processing and their applications in EV systems are covered in this review article. The evaluation also identifies possible research gaps and opportunities to make a contribution based on its results in the field of condition monitoring. The Cepstrum analysis is a non-linear signal processing technique that is employed for data preparation. It is the integral derivative of the logarithm of the absolute value of the DFT of the input signal. Through the application of ICA, a signal with components that are statistically fully independent of each other can be transformed from a multivariate random signal. During the training process, the CNN-CLSTM algorithm considers all of the available parameters. While both the CNN and CLSTM models get an average accuracy of 97.38%, the suggested method consistently outperforms them.

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