

Research Article

Vibration-induced Thermal Fault Analysis and Optimisation of Induction Motors Using Artificial Intelligence

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Abstract

Induction motors play important roles in modern industrial operations due to their robustness, simplicity, cost-effectiveness and low maintenance. However, they are vulnerable to mechanical vibrations, which can reduce performance, generate excessive heating, and cause premature failure. This research explores the main sources of vibration such as bearing defects, mechanical imbalance, misalignment, rotor eccentricity, and environmental factors and their contribution to thermal faults in induction motors. The aim is to develop an intelligent diagnosis system capable of detecting thermal faults triggered by vibration using artificial intelligence. An autoencoder-based anomaly detection model was implemented to detect abnormal vibration patterns linked to overheating. Vibration data was sourced from an open-access industrial dataset. Preprocessing included data cleaning, feature scaling using min-max normalisation, and time-series reshaping using sliding windows. The dataset was divided into training and testing sets. Only healthy data was used for training, allowing the autoencoder to learn the standard operational behaviour of the motor. The model architecture included encoder and decoder components, built using TensorFlow and Keras. It was trained over 30 epochs using the Adam optimiser and Mean Squared Error (MSE) as the loss function. Validation was performed on 20% of the data, while additional testing used unseen faulty data to assess the model's diagnostic performance. The model achieved strong results, with a True Positive Rate (TPR) of 91.2%, False Positive Rate (FPR) of 6.1%, Precision of 92.4%, Recall of 91.2%, and an F1-score of 91.8%. Learning curve analysis demonstrated stable training and generalisation. Reconstruction error histograms confirmed the reliability of the anomaly detection threshold of the model. This study confirms that vibration plays an important role in causing thermal faults and shows that AI-driven diagnostic can effectively identify early warning signs. The proposed system is non-intrusive, scalable, and well-suited for real-time deployment. This makes it valuable for predictive maintenance and operational optimisation of induction motors. This approach supports the transition towards more intelligent and sustainable industrial systems.

Keywords

Induction Motor, Vibration Analysis, Thermal Faults, Autoencoder, Artificial Intelligence, Predictive Maintenance

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1. Introduction

Induction motors (IMs) are integral to modern industrial operations due to their robustness, simplicity, cost-effectiveness, and low maintenance. Their consistent performance over a wide range of functions, from mining, electric vehicles, Heating, Ventilation and Air-conditioning (HVAC) systems to manufacturing makes them a preferred choice for both light and heavy-duty applications. Their widespread adoption is largely attributed to mechanical reliability and efficiency [1]. Despite these advantages, induction motors are vulnerable to mechanical vibrations which can cause thermal and significant operational issues. These vibrations may result from rotor imbalance, bearing defects, loosened mechanical parts, rotor or stator core damage, misalignment, and external environmental influences like structural resonance and foundation instability [2]. Whilst such faults may initially seem minor, they often accumulate over time, leading to overheating, performance degradation, and in severe cases, system failure. One major consequence of persistent vibration is vibration-induced thermal failure, wherein continuous mechanical excitation produces excessive heat within motor components [3]. Contributing factors include elevated mechanical stress, unbalanced magnetic pull, and increased friction. These disturbances disrupt thermal equilibrium, degrade insulation, accelerates material fatigue, impair efficiency of energy conversion, reduce motor reliability, and increase power consumption. As industries strive to minimise maintenance cost and maximise productivity, early and accurate detection of these thermal anomalies is important. Traditional fault detection methods such as thermal imaging, the use of vibration meters, routine physical inspection although useful, have shortfalls. They often require system downtime, are time-consuming, and prone to human errors. Advanced methods using contact-based instruments or wired sensors complicate system integration and increase operational costs. Moreover, many existing approaches fail to detect early-stage or weak vibration patterns that precede failure [4]. This study seeks to address a critical gap, that is the absence of non-invasive, intelligent, and data-driven system for reliably diagnosing vibration-induced thermal faults in induction motors [5]. Artificial intelligence (AI), especially Autoencoders (AEs)-based models, offer a promising solution [6]. These models can analyse large volumes of sensor data to learn normal vibration patterns and detect subtle deviations indicative of emerging faults. Through predictive modelling, AI can be leveraged not only to identify existing issues but also to anticipate future faults before they evolve into catastrophic failures. The primary objectives of this study are to identify and characterise the causes and impacts of vibration-induced thermal faults and to design and implement an AE-based anomaly detection framework. The model is trained and validated using real-world industrial vibration datasets collected under various operating conditions. The key innovation of this study lies in its development of a non-intrusive,

AI-based anomaly detection system that leverages unsupervised learning to identify early-stage thermal faults without requiring labelled fault data. Unlike conventional methods, the proposed Autoencoder model detects subtle abnormal vibration patterns by learning from healthy motor data, enabling early intervention. This approach ensures minimal system disruption and offers scalability for real-time monitoring, aligning with the goal of Industry 4.0, where data-driven technologies are reshaping how industrial equipment is optimised and managed [7].

1.1. Causes of Vibration in Induction Motor

1.1.1. Mechanical Imbalance

Induction motor vibration is primarily caused by mechanical imbalance [8]. This imbalance occurs when the center of gravity of the rotor or other rotating components deviates from the axis of rotation, resulting in uneven weight distribution. This, in turn, generates centrifugal force during motor operation and that will lead to vibration. There are several types of mechanical imbalances in induction motors. The first is dynamic imbalance and that refers to an uneven weight distribution perpendicular to the axis of rotation [9]. Then there is static imbalance. This involves uneven weight distribution along the axis [10]. Also, there is couple imbalance which combines imbalances in both static and dynamic planes to complicate the vibration patterns. Various factors contribute to mechanical imbalance. Manufacturing defects, such as errors in machining or assembly, can result in inherent imbalances. Over time, normal wear and tear may cause component degradation to exacerbate the imbalance. External impacts or collisions can deform motor parts, while improper reassembly or balancing after repairs can introduce further imbalances. Environmental factors, like erosion or corrosion, can disrupt weight distribution and cause material loss. The effects of mechanical imbalance can be significant [11]. Increased vibration leads to higher noise levels, which result directly from the vibrational forces. Moreover, imbalance forces cause the motor to consume more energy to maintain performance, whilst reducing efficiency. Long-term imbalance may cause premature wear of bearings and other components, potentially leading to catastrophic motor failure.

1.1.2. Misalignment

Misalignment is a major contributor to vibration in induction motors [12]. It occurs when the motor shaft or bearings are not properly aligned with the driven equipment or its foundation. This misalignment leads to uneven loading and tension on motor components, causing vibrations during operation. These vibrations can result in premature wear, reduced efficiency, and, in severe cases, cause catastrophic motor failure. There are three types of misalignments. These

are angular, parallel, and mixed misalignments. Angular misalignment arises when the motor shafts are at an angle to each other rather than running parallel [13]. On the other hand, parallel misalignment occurs when the shaft centers are offset despite being parallel [14]. Combined misalignment involves both angular and parallel misalignment, resulting in more complex issues [15]. Several factors can cause misalignment. Improper installation is a common cause, often due to setup errors. Over time, it may also result from foundation settling, equipment shifts, or natural wear of components. Thermal expansion can further contribute, as uneven heating causes parts to expand at varying rates. In addition, maintenance errors such as improper reassembly or misalignment after repairs can intensify the problem. The consequences of misalignment are many and can significantly affect motor performance. It induces vibrations that compromise motor stability and are often accompanied by increased noise and energy consumption. This reduces operational efficiency and accelerates wear on important components such as seals and bearings. If unaddressed, misalignment can eventually lead to motor failure, particularly in high-demand or precision-driven applications.

1.1.3. Bearing Faults

Bearings are essential parts of induction motors, playing a vital function in reducing friction, support rotating shafts, and facilitating smooth operation. They also serve as important interfaces between stationary and rotating parts, while accommodating both radial and axial loads with marginal resistance. Common bearing faults include defects in the inner and outer races, rolling element (balls), and the cage (retainer). These faults can significantly compromise motor stability, leading to increased vibration, uneven load distribution, elevated friction, and eventually premature wear and reduced motor lifespan. Figure 1 presents a sectional view of a rolling-element bearing. The outer race forms the outermost ring, providing a smooth track for the rolling elements. The balls, typically made from steel or ceramic, rotate between the inner and outer races to reduce friction and enable smooth rotation.

The retainer or cage holds the balls in place, ensuring uniform spacing and preventing direct contact, thereby reducing wear and promoting operational stability. Bearings may develop problems over time due to various factors such as lubrication failure, poor maintenance, excessive mechanical loads, contamination, or misalignment. These conditions disrupt uniform load distribution, creating localised stress concentrations that can lead to surface damage. Over time, this manifests as pitting, spalling, or cracking, all of which compromise the bearing's structural integrity. Such degradation is a primary contributor to vibration anomalies and thermal buildup in the motor. Vibrations originating from damaged bearings can propagate to surrounding components, further increasing mechanical stress and noise levels. Initial signs of bearing failure usually include elevated operating temperatures, irregular noises, and increased energy consumption. If not properly addressed, these issues can escalate into severe mechanical failure. The most common bearing defects involve the outer race, rolling elements, and inner race, as shown in Figure 2. These failure modes are important indicators in condition monitoring and serves as targets in predictive maintenance strategies.

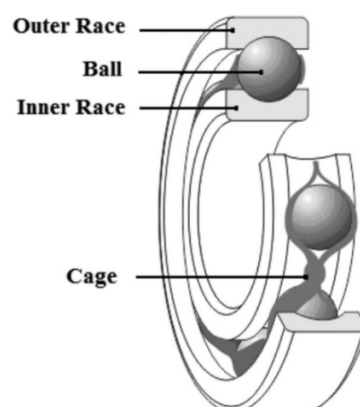


Figure 1. A Sectional View of a Rolling-element Bearing. Source [16].

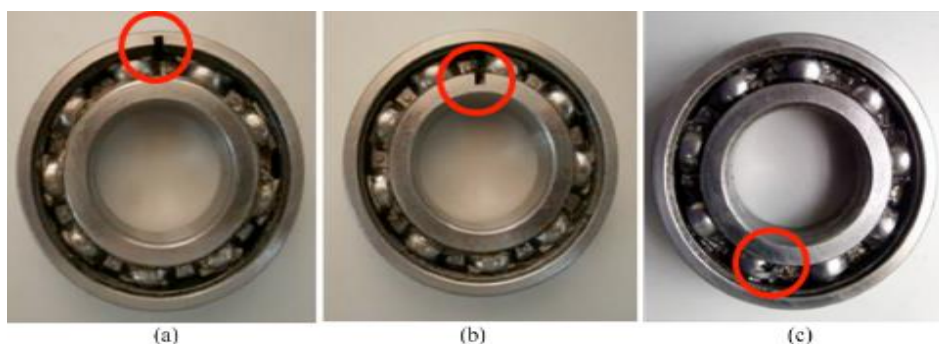


Figure 2. Images Illustrating Rolling Bearing Faults: (a) Outer Race Fault, (b) Inner Race Fault, and (c) Ball Fault. Source [17].

An outer race fault in a rolling bearing occurs when the outer ring becomes worn or damaged, typically due to contamination, excessive load, or lubrication failure [18]. If left unaddressed, this defect can cause uneven contact between the rolling components and the raceway, resulting in increased vibrations and potential bearing failure. An inner race fault refers to damage or wear on the inner ring of the bearing, often caused by misalignment, heavy loading, or insufficient lubrication [19]. This damage interferes with the bearing's smooth rotation, leading to uneven wear, elevated friction, and eventual failure. A ball fault involves damage to the rolling elements (balls) within the bearing, such as cracks, wear, or surface pitting [20]. This can result from improper lubrication, contamination, or excessive loads, leading to poor rolling contact and increased vibrations that can significantly reduce the lifespan of the bearing.

1.1.4. Rotor Eccentricity

When the centerline of a rotor deviates from its optimal position, rotor eccentricity occurs [21]. This misalignment is a significant cause of vibration problems in induction motors. The resulting variation in rotor position leads to an uneven distribution of magnetic flux and an irregular air gap. As the rotor rotates, these inconsistencies generate vibrations that can adversely affect motor performance. Eventually, such vibrations can cause early wear on components, reduce efficiency, and, in severe cases, lead to catastrophic motor failure. There are various types of rotor eccentricity. The dynamic eccentricity involves a time-varying offset of the rotor's centerline [22]. The static eccentricity refers to a constant, non-changing misalignment [23]. Axial eccentricity is the offset along the rotor's axis, while radial eccentricity involves an offset in the radial direction [24].

1.1.5. Stator and Rotor Core Damage

The stator and rotor cores are important components in induction motors, providing magnetic pathways for current flow [25]. Damage to these cores can significantly disrupt the magnetic field, causing imbalance magnetic forces that lead to vibrations. The integrity of the stator and rotor cores can be compromised by several factors. Electrical issues, such as overheating, power surges, or poor insulation, can degrade core materials [26]. Mechanical damage may result from impacts, excessive vibrations, or worn bearings. Also, environmental exposure including moisture or corrosive substances can lead to corrosion, further weakening the cores. Furthermore, normal wear and tear during motor operation also contributes to gradual degradation, increasing the risk of core-related faults and associated vibrations.

1.1.6. Loose and Worn-out Parts

Induction motor vibration can result from the deterioration of mechanical parts as the motor ages. As time passes by, components such as shafts, bearings, mountings, fasteners,

and couplings may worn out or loosen, creating uneven stresses that lead to vibration [27]. When these parts fail, the motor's performance and integrity are compromised. The loosening and wear of motor parts are caused by several factors [28]. Continuous operation gradually wears down parts, while overloading due to excessive mechanical or electrical demands further intensifies degradation. Poor maintenance practices, such as infrequent inspections or ignoring early warning signs, increases the likelihood of failure. Furthermore, environmental factors like temperature fluctuations, moisture, and corrosive substances can accelerate component wear. Manufacturing defects, such as the use of inferior materials or faulty construction, also contribute to premature failure.

1.1.7. Environmental Causes

Environmental conditions play a significant role in the vibration dynamics of induction motors and can greatly influence vibration-related issues [29]. External factors such as resonance, mounting problems, and foundation defects can impose additional stress on the motor, resulting in unstable operation and increased vibration. One of the most critical environmental factors is the motor foundation [30]. Foundation issues can lead to misalignment, often caused by settling or movement of the foundation. A poorly designed foundation, lacking sufficient mass or rigidity, may exacerbate vibration problems by failing to properly absorb and dissipate mechanical energy. Neglected foundation integrity can result in cracks or shifts, further increasing vibration and compromising motor function.

1.2. Effects of Vibration on Induction Motors

1.2.1. Reduced Motor Efficiency

Vibrations negatively impact the conversion of mechanical energy into useful work, causing excessive energy loss in the form of heat. As friction increases, a greater portion of mechanical energy is dissipated as heat rather than contributing to productive output, directly reducing motor efficiency. This inefficiency not only impairs motor performance but also raises energy consumption, as more power is required to maintain the same output level. Several factors contribute to this reduced efficiency. One primary cause is increased friction between moving components, which generates heat and results in energy loss [31]. Vibrations can also disrupt magnetic flux and current flow, leading to electrical losses that further degrade efficiency and increase operational costs [32]. Also, vibrations accelerate bearing wear, which in turn intensifies friction and amplifies energy loss [33]. Worn bearings not only reduce efficiency but also increase maintenance requirements and the risk of equipment failure [34]. Furthermore, uneven rotor movement caused by vibrations impairs energy transfer, compounding the inefficiency and escalating energy loss [35]. These issues create a negative feedback loop, where rising vibration levels intensify the very

conditions that caused them, leading to progressively worsening performance.

1.2.2. Increased Energy Consumption

In industrial environments, the increased energy consumption of induction motors due to vibration is a major concern. Vibration raises operational costs, lowers efficiency, and contributes to negative environmental impacts. It causes mechanical energy to be lost as heat rather than converted into useful work, further intensifying energy consumption and related economic challenges. Given the widespread reliance on induction motors, addressing this issue is necessary. Vibration-induced energy losses arise from both mechanical and electrical sources. Mechanically, vibrations generate friction between motor components, converting valuable mechanical energy into heat and reducing overall efficiency [36]. Electrically, vibrations cause fluctuations in magnetic flux and increase current flow, which further diminishes efficiency and raises energy usage [37]. These combined mechanical and electrical disturbances significantly impair performance, driving up energy consumption and highlighting the importance of effective vibration management.

1.2.3. Premature Wear and Tear

Vibration-induced damage in machinery can result in decreased motor reliability, increased maintenance costs, and reduced components lifespan. Gradually, vibrations cause wear and tear that considerably impacts the motor's durability and efficiency. A number of factors contribute to vibration-induced early degradation. One of the causes is mechanical fatigue, triggered by repetitive stress cycles from continuous vibrations [38]. This stress gradually leads to material fatigue, often appearing as cracks that, if left unchecked, may result in catastrophic failure. In addition to fatigue, vibrations increase frictional wear. As components vibrate, friction increases, generating heat that accelerates deterioration. Excessive vibrations can also produce impact loads, which strike surfaces with force, causing further damage and faster wear of components. Another essential factor is lubrication breakdown. Vibrations disrupt the lubricant films essential for reducing friction and wear between moving parts [39]. As these films break down, friction increases, leading to faster component deterioration. Together, these factors create a vicious cycle of accelerated wear, posing significant risks to machinery performance and durability. Induction motor components are particularly vulnerable. Bearings, for example, wear out faster due to increased friction. Vibration can cause shaft deflection, elevating stress levels and promoting fatigue. Gears experience uneven loading and misalignment, leading to faster degradation. Seals also suffer under vibration stress, resulting in fluid leaks and contamination that compromise motor integrity.

1.2.4. Motor Failure

Vibration significantly affects the operational integrity of

induction motors and can lead to a range of issues that may ultimately cause failure. One of the most critical consequences of vibration is bearing wear [40]. Excessive vibration increases heat and friction. This accelerates bearing deterioration and leads to premature failure. Persistent vibration also degrades motor winding insulation, increasing the risk of short circuit or ground faults that can impair performance. Furthermore, vibration induces mechanical stress on components such as the rotor, stator, and shaft [41], potentially causing material fatigue and structural failure. Long-term vibration may cause misalignment between the motor and the connected equipment, further increasing wear and reducing efficiency. Furthermore, it can loosen electrical connections, leading to overheating, intermittent contact or short circuits, and increased resistance.

1.2.5. Noise Pollution

Vibration is closely linked to noise pollution, a growing environmental concern. Noise pollution refers to excessive or unwanted sound that disrupts the environment, and it encompasses more than just loudness [42]. Its impact depends on several factors, including frequency, duration, and unpredictability. As its core, noise is a manifestation of vibration. Sound waves are vibrations transmitted through materials such as water or air. When object vibrates, it causes surrounding air particles to move, producing sound waves perceived as noise. This fundamental relationship explains why many sources of vibration inevitably contribute to noise pollution. Vibration-induced noise is generated by a range of everyday and industrial activities. Industrial machinery such as the heavy duty motors used in factories or construction sites produce large vibrations that are audible as noise [43]. Similarly, transportation systems like cars, trains, and airplanes contribute to noise pollution both directly and by causing nearby structures to vibrate. Common building systems also play a role. Heating, Ventilation, and Air Conditioning (HVAC) units, elevators, and plumbing can generate significant indoor noise due to vibration.

1.2.6. Structural Damage

Induction motors are well known for their reliability and efficiency in industrial applications. However, they inevitably generate vibrations during operation. While some vibration is normal, if left unmanaged, can significantly compromise the structural integrity of the motor. Vibrations in induction motors can lead to various forms of structural damage [44]. Repeated vibration cycles can cause wear on structural components, resulting in cracks that may expand over time. Vibrations may also loosen bolts, welds, and other fasteners, weakening the entire assembly. Also, continuous vibration speeds up material fatigue and degradation, increasing the risk of premature failure. One particularly critical issue is resonance, which occurs when the motor's operating frequency matches the natural frequency of its supporting structure, amplifying vibrations to potentially dangerous levels [45].

1.3. Related Works on Vibration-induced Thermal Analysis in Induction Motors

The impact of magnetic and mechanical rotor eccentricity on induction motor vibration was examined by [46], revealing links to excessive heating, reduced performance, and bearing failures. Eccentricity-induced vibrations were common across sectors, accelerating wear and shortening motor lifespan. A mathematical model incorporating magnetic eccentricity, rotor offset, and gyroscopic forces was developed to predict and mitigate vibration-related heating. The study emphasised aligning rotor angles to reduce static eccentricity and proposed early detection and monitoring as key strategies to prevent motor defects.

Advanced methods to reduce vibration-induced heating in induction motors using Finite Element Approach (FEA), Experimental Modal Technique (EMT), and Vibrational Analysis (VA) was investigated by [47]. These techniques were used to detect structural distortions, predict vibration velocity, and minimise friction buildup. The study emphasised identifying vibration sources and making structural adjustments to improve thermal management, reliability, and durability.

Dahifale highlighted the role of vibration analysis in diagnosing failures in three-phase induction motors [48]. Vibration was identified as a key cause of overheating, friction, mechanical stress, and reduced efficiency. Factors such as overloading, single-phasing, and bearing defects contributed to high vibration levels, leading to wear, bearing failures, and safety risks. The study stressed the need for advanced vibration analysis methods such as frequency spectrum and motor analysis to detect issues early, prevent overheating, and reduce downtime.

The impact of harmonic currents on vibration, electromagnetic force, and noise in permanent magnet synchronous motors for electric vehicles were performed by [49]. The study found that harmonic induced vibrations significantly contributed to overheating by increasing friction, mechanical stress, and heat generation. These effects led to reduced efficiency, premature wear, demagnetisation, and bearing failures. The study underscored the importance of controlling harmonic currents and minimising vibration to maintain the reliability, efficiency, and thermally stable operation of Permanent Magnet Synchronous Motors (PMSMs) in electric vehicles.

The use of vibration signals to diagnose induction motors faults, identifying vibration as a key cause of overheating was examined by [50]. Faults, such as broken rotor bars and rotor eccentricity increased friction, leading to excessive heating, mechanical stress, and reduced efficiency. The study also analysed electromagnetic forces under normal and faulty conditions. To address these issues, the researchers developed a fault diagnosis system using a One-Dimensional Dilated Convolutional Neural Network (1D-DCNN). This system enabled early fault detection and intervention, helping to

prevent overheating, reduce downtime, and maintain safe, continuous motor operation.

Impact of unbalanced voltage on IMs across different efficiency classes was investigated by [51]. The study found that higher-efficiency IMs experienced more pronounced vibrations, leading to increased friction, heat generation, and mechanical stress. Mathematical models were developed to predict active power under unbalanced voltage conditions, and results were validated through simulations and laboratory tests. Compared with industry vibration standards, findings indicated that high efficiency IMs are more vulnerable to vibration-related issues. The researchers recommended implementing protection mechanisms to prevent overheating and highlighted the importance of addressing voltage unbalance to ensure reliable motor operation.

The effects of magnetic vibrations on squirrel-cage induction motor stators, linking them to supply voltage distortion was examined by [52]. These vibrations increased friction, causing excessive hating, mechanical stress, and reduced efficiency. They researchers proposed a mathematical model of the excitation process and used finite element software to simulate motor behaviour under distorted voltage. The results showed that magnetic vibrations also elevated power consumption and acoustic noise. The study emphasised the importance of combining acoustic, mechanical, and electromagnetic analysis, especially for medium and high power alternating current motors, to better understand and reduce vibration-induced heating.

Prasad and Singh investigated the link between excessive heating and vibration-induced resonance in ageing induction motors [53]. Mechanical issues like misalignment and wear were identified as key sources of vibration, leading to increase friction, mechanical stress, and heat generation. This heat caused electrical faults, insulation breakdown, and overheating, resulting in reduced efficiency, winding damage, and bearing failure. To address these issues, the researchers developed numerical and experimental methods to detect and mitigate both electrical and mechanical faults.

Vibration characteristics of a 1140 V/75 kW variable-frequency motor, revealing that vibration was a major cause of overheating was explored by [54]. Factors such as temperature fluctuations, magnetostriction of silicon steel sheets, and frequency variation increased electromagnetic forces and energy losses. This led to excessive heating, reducing motor efficiency and performance. Vibration-induced stress, friction, and heat accelerated component wear, causing insulation failure, winding damage, and bearing issues. These issues resulted in premature ageing, increased maintenance costs, and frequent breakdowns. The study emphasised the role of controlling vibration to prevent overheating and ensure reliable motor operation.

A structured method to assess vibration frequency components for detecting bearing faults was presented by [55]. The study found that vibration-induced friction and mechanical stress generated heat, leading to premature motor wear,

reduced efficiency, and a higher risk of failure. Vibration analysis played a key role in identifying early signs of misalignment and bearing issues, enabling timely corrective actions to prevent overheating and minimise energy loss. The researchers also offered practical guidelines for implementing vibration-based monitoring in industrial settings, including optimal measurement directions and frequency ranges for detecting specific faults.

Gundewar and Kane [56] reviewed diagnostic techniques for identifying faults in induction motors, highlighting vibration as a contributor to excessive heating. Vibration-induced issues such as misalignment, imbalance, and bearing faults, led to friction, mechanical stress, and heat buildup. The study highlighted both conventional and advanced methods, including vibration-based diagnostics and motor current signature analysis. It also explored AI-based techniques such as Genetic Algorithm (GA), Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Fuzzy Logic (FL). The importance of condition monitoring was stressed, especially in electric vehicles, where vibration related faults can cause early wear, reduce efficiency, and system unreliability. Effective diagnostics were deemed vital for minimising downtime.

The behaviour of stator end windings in induction motors was analysed with a focus on vibration as a cause of excessive heating [57]. This heating increases the risk of motor failure, early wear, and reduced efficiency. The study emphasised the need to detect vibrations in the end windings to prevent damage caused by friction, mechanical stress, and heat. Structural analysis and impact tests revealed that looseness in the stator end windings intensified vibration heat generation. The findings highlighted the importance of secure winding structures to enhance motor reliability and thermal stability.

A study to monitor the health of induction motor bearings for early fault detection, aiming to reduce accidents and economic losses was performed by [58]. They developed a nonlinear vibration model with six degrees of freedom to analyse bearing behaviour under varying load conditions and radial clearances. The study proposed key indicators for tracking clearance angles, which were essential for effective maintenance and condition monitoring. These findings were relevant in wind turbine systems, where vibration-induced faults can lead reduced efficiency, premature bearing wear, and an increased risk of system failure due to overheating.

A system to predict and reduce vibration in Switched Reluctance Motors (SRMs), addressing vibration-induced issues such as misalignment, imbalance, and bearing faults was developed by [59]. The approach integrated three modules. That were, a digital controller and drive circuit, electromagnetic field, and mechanical components. The system enabled real-time vibration prediction and monitoring by combining electromagnetic forces with the structural model. Tested on a 12/8 poles, 1.5 kW SRM drive system test bench, the method aligned with experimental results. It allowed for optimised

structural design and control strategies, helping to minimise vibration-induced faults, improve efficiency, and enhance the reliability of SRMs.

The study by [60] examined how vibration levels in induction motors vary under different operating conditions, such as speed and load. It found that excessive vibrations amplified electromagnetic forces, leading to significant heat generation and thermal issues. These problems were further aggravated by harmonic distortions in electrical signals, largely influenced by Pulse Width Modulation (PWM) frequency in inverters. The interaction between electromagnetic forces, vibrations, and signal harmonics created a feedback loop of overheating. This cycle eventually reduced the efficiency of the motors, increased the risks of damage, and shortened their lifespan.

A comprehensive method for detecting bearing faults, introducing envelope analysis to classify current spectrum anomalies linked to localised faults was presented by [61]. This technique was tested on both operational and non-operational motors in a laboratory setting. The system enabled real-time data acquisition and fault diagnosis by integrating the results with vibration analysis and single board computer technology. This study identified vibration as a cause of excessive heating in induction motors.

2. Methodology

2.1. Design of an Autoencoder-based Fault

Classification System

Artificial Neural Network (ANN) can handle multivariable interactions, model complex relationships, and learn from data. In this study, an ANN was applied to thermal analysis of an induction motor, with vibration considered as the primary causal factor. This approach enabled precise predictions of thermal behaviour and abnormal detection. The ANN model was developed through a series of systematic steps as depicted in figure 3.

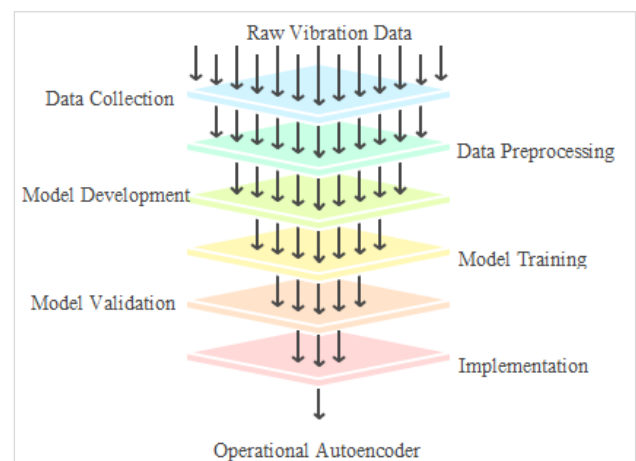


Figure 3. ANN-based Autoencoder System Design.

2.1.1. Data Cleaning

The vibration data was cleaned by removing duplicates, inconsistencies, and errors to ensure accuracy. This step was important, as even minor irregularities could compromise data integrity and hinder effective machine learning model training.

2.1.2. Feature Scaling

Min-max normalization was applied to scale feature between 0 and 1, ensuring all input variables contributed equally to the learning process. The normalisation formula is based on:

$$x_{\text{scaled}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

where x_{scaled} is the new normalised value, typically between 0 and 1, x is the original value of the feature before scaling, x_{\min} is the minimum value of the feature in the dataset, and x_{\max} is the maximum value of the feature in the dataset.

2.1.3. Time-series Reshaping

To capture temporal dependencies, the data was structured into overlapping time windows. A sliding window approach was used to train the model with sequences of past observations, enabling it to learn trends and patterns over time.

2.1.4. Splitting Data for Training and Testing

The dataset was split into training and test sets. The training set included only normal (healthy) machine operations to help the autoencoder learn typical behaviour, while the test set contained both normal and faulty conditions to evaluate the model's ability to detect anomalies.

2.2. Development of the Autoencoder Model

The autoencoder was implemented using TensorFlow and Keras. Its architecture included defined hidden layers, neurons, optimisation methods, loss functions, and activation functions. The AE enabled unsupervised learning by compressing data and extracting high-level features for deep model development.

2.2.1. Autoencoder Architecture

The architecture of the AE as shown in figure 4 was adopted from [62], where X stands for the input layer's data, Z for the hidden layer's data, and X' for the output layer's reconstructed output data. The encoder and the decoder are the two main parts of the AE. The input data is compressed into a lower-dimensional latent representation, which is then used by the decoder to recreate the original data.

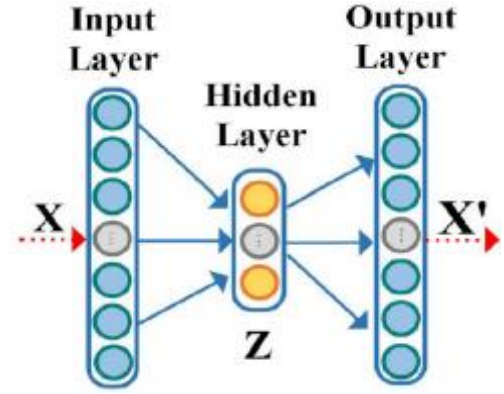


Figure 4. Autoencoder Architecture.

An AE uses an encoding function f to translate an input vector X to a code vector Z during the encoding step. The decoding stage converts the coding vector Z back to the output vector X' so that the input data can be rebuilt using a decoding function g . Through minimising the reconstruction error (L) between X and the reconstructed data X' , AEs fine-tune the network's weights (W). To optimise the network's settings, this reconstruction error serves as a loss function. The objective function of the AE can be written as follows:

$$\min_{\theta} J_{\text{AE}}(\theta) = \min_{\theta} \sum_{i=1}^n L(x_i, z_i) = \min_{\theta} \sum_{i=1}^n L(x_i, g_{\theta}(f_{\theta}(x_i))) \quad (2)$$

where n is the total number of training data points, z_i represents the i th dimension of the output data, and x_i represents the i th dimension of the training sample. The reconstruction error (L) between the input and output data is given as:

$$L(x, z) = \sum_{i=1}^n \|x_i - z_i\|^2 \quad (3)$$

The mapping function for the encoder is expressed as:

$$y = f_{\theta}(x) = s(Wx + b) \quad (4)$$

where s is an activation function, b is the bias factor, W is the weight matrix, and x is the input vector. Also, the mapping function for the decoder that performs the inverse operation is expressed as:

$$z = g_{\theta}(y) = s(W'y + b') \quad (5)$$

where s represents the activation function (ReLU or sigmoid), W' represents the decoder's weight matrix, b' represents the decoder's bias vector, z represents the reconstructed form of the original input vector x , and y represents the encoder's compressed representation.

2.2.2. Training Parameters of the Vibration-based Autoencoder

Training parameters for the autoencoder model used in vibration-based thermal detection and optimisation were carefully selected and customised for optimal performance, as shown in Table 1.

Table 1. Training Parameters of the Autoencoder Model.

Parameters	Vibration-based Autoencoder
Optimiser	Adam
Initial Learning Rate	0.00100
Final Learning Rate	0.00005
Batch Size	128
Regularisation Term (L2)	0.00050
Epochs Trained	30
Best Validation Loss	0.01020
Gradient at Last Epoch	0.00021

2.2.3. Loss Function and Optimisation Algorithm

The loss function was minimised using the Adam optimiser. Reconstruction loss was calculated using the Mean Squared Error (MSE) as follows;

$$MSE = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \quad (6)$$

where n is the number of data points or observations being considered, X_i is the original (true) value of the i th data point, \bar{X} is the predicted or reconstructed value of the i th data point by the model, $(X_i - \bar{X})^2$ is the squared difference between

the actual and predicted values, and $\sum_{i=1}^n$ is the summation

over all n th data points to compute the total squared error, and the inverse of n is the average of the total squared error, giving the mean squared error.

2.3. Training of the Vibration Autoencoder Model

2.3.1. Training of the Vibration-based Autoencoder

The AE was trained on the preprocessed vibration datasets. The data was normalised between 0 and 1 using Min-max scaling to ensure consistency as:

$$\text{Min - max scaler} = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (7)$$

where $\max(x)$ and $\min(x)$ stand for the feature x 's maximum and minimum values, respectively. The model was trained over 30 epochs with a batch size of 128, using 80% of the data for training.

2.3.2. Evaluation During Training

The reconstruction loss (MSE) was monitored during training to evaluate model performance. Early stopping was applied to halt training when validation loss ceased to improve for 10 consecutive epochs to avoid overfitting.

2.4. Validation and Testing of the Vibration-based Autoencoder Model

2.4.1. Validation Strategy and Metrics

Validation was performed on 20% of the dataset to assess generalisation capability. The Mean Squared Error (MSE) was used as the primary metric. Additionally, accuracy and F1 score were computed after thresholding the reconstruction error to classify fault vs. normal conditions.

2.4.2. Testing with Unseen Data

To evaluate the robustness of the model, it was tested with unseen data containing various fault scenarios in the induction motor. The model successfully identified anomalies based on reconstruction errors above a pre-defined threshold.

2.5. Vibration-based Autoencoder Model Implementation and Programming

2.5.1. Tools, Libraries, and Environment Setup

The environment was set up using Anaconda and executed on a machine with GPU acceleration. The implementation was carried out in Python using the following libraries:

- 1) TensorFlow 2.x'; and
- 2) Keras.

2.5.2. Code Structure and Workflow Overview

The codebase was structured into the following modules:

- 1) data_preprocessing.py: normalization and reshaping of time-series data;
- 2) autoencoder_model.py: definition of the encoder, decoder, and full autoencoder;
- 3) train_model.py: training loop, early stopping, and model checkpointing; and
- 4) evaluate_model.py: reconstruction error analysis and visualisation.

2.5.3. Exploratory Data Analysis

The Exploratory Data Analysis (EDA) was used to identify patterns, anomalies, and relationships within the dataset to detect deviations and faults, and guide preprocessing and modelling strategies.

3. Results and Discussion

3.1. Examination of Vibration Signatures for Fault Detection in Bearing Housings

The resampled vibration signal waveforms for both faulty and healthy induction motor conditions are shown in Figures 5 and 6. These time-series signals (measured in g) were captured along the x, y, and z axes under load conditions ranging

from 2 Nm to 4 Nm. The x-axis represents lateral vibrations, the y-axis represents vertical motion, and the z-axis represents axial movement along the shaft. Figure 5 reveals irregular, high-amplitude ripples under faulty conditions. The x-axis anomalies indicate rotor imbalance, the y-axis suggest misalignment or bearing defects, and z-axis disturbances reflect thrust bearing faults or axial misalignment.

Figure 6 illustrates normal motor operation. The x and y axes waveforms display smooth, low-amplitude, and periodic patterns aligned with the motor's horizontal and vertical radial directions, indicating minimal mechanical disturbances, uniform load distribution, and balanced rotors. The z-axis shows stable, low-amplitude signals, confirming controlled axial thrust and proper rotor-stator alignment. This waveform stability across all three axes reflects steady-state performance and mechanical health.

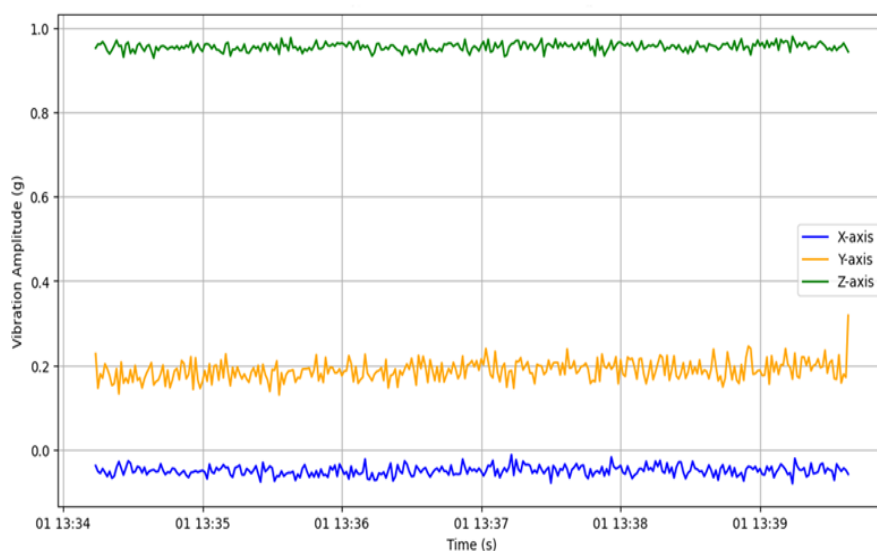


Figure 5. Resampled Vibration Signals of Faulty Condition.

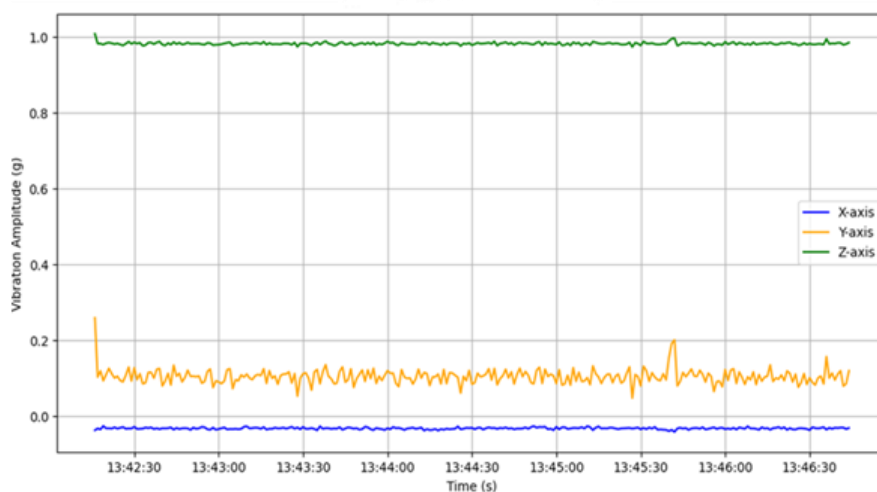


Figure 6. Resampled Vibration Signals of Healthy Condition.

3.2. Learning Curve for Vibration Signals

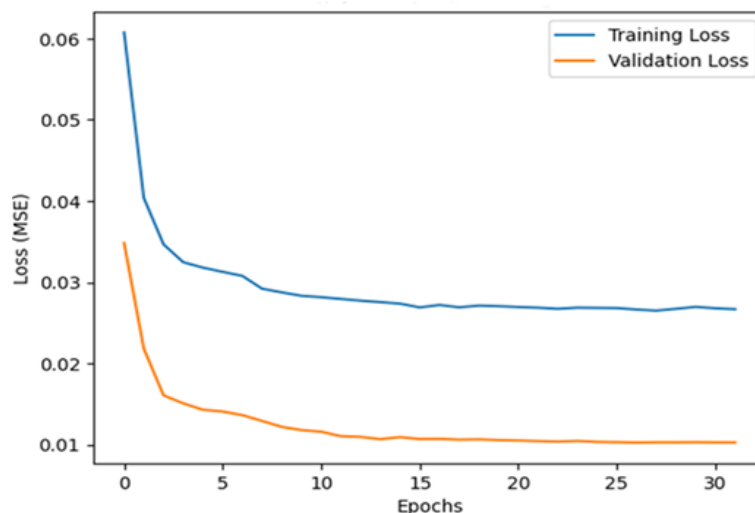


Figure 7. Learning Curve for Vibration Signals.

The learning curve for vibration signals is shown in figure 7. The autoencoder model was trained on vibration signals and demonstrated a strong ability to learn the underlying features of the data. Initially, the training loss started at approximately 0.062 MSE, with the validation loss following a similar pattern, beginning at around 0.035 MSE. By approximately the 10th epoch, the validation loss had significantly dropped and plateaued around 0.011 MSE, while the training loss stabilised slightly higher at around 0.027 MSE. The consistent gap between training and validation losses without any reversal or increase in validation loss indicates robust generalisation performance with no signs of overfitting. The minimal fluctuations in loss beyond epoch 10 suggest that the model had effectively captured the essential patterns in the vibration signals while avoiding the reconstruction of noise. Consequently, deviations from this learned baseline such as increased reconstruction errors can be reliably used to detect anomalous vibration behaviours, which are often early indicators of mechanical faults or imbalances. These results confirm the autoencoder's effectiveness in anomaly detection within vibration data, supporting its application in predictive maintenance strategies. This enables early intervention in machinery faults, contributing to enhanced operational safety and reduced downtime in industrial systems.

3.3. Fault Identification for Vibration Signals

The histogram of reconstruction deviations for vibration signals is illustrated in Figure 8. This provides informative insight into the autoencoder model's capability to identify faults within vibration data. Most of the data points show low

reconstruction errors, which indicates the model's effectiveness in accurately reconstructing normal vibration patterns under healthy operating conditions. The anomaly detection threshold was set at the 95th percentile (0.4858), designated by the red dashed line, and was established to distinguish normal signals from potential faults. This threshold serves as a boundary error below it is classified as normal, while those exceeding it are flagged as anomalous. The clear distinction between the densely populated low-error region and the sparse high-error region suggests that the autoencoder learned the normal behaviour of the system effectively but failed to reconstruct abnormal or faulty patterns. This is expected and desired in anomaly detection. The presence of higher reconstruction errors beyond the threshold likely corresponds to deviations caused by mechanical faults or irregularities in the system, confirming that the model can capture significant fault-related features. These results demonstrate the suitability of the autoencoder-based approach for fault identification in vibration monitoring systems. When deployed in real-time applications, this model can support early detection of mechanical issues, contributing to predictive maintenance strategies and reducing unplanned downtimes in industrial machinery. The effectiveness of the autoencoder model in detecting anomalies within the vibration signals was assessed by analysing the reconstruction errors. The AE was trained to learn a compressed representation of normal operating conditions. When exposed to faulty data, reconstruction errors increase significantly, allowing the identification of potential failures. The threshold for anomaly detection was determined using the 95th percentile for vibration signals.

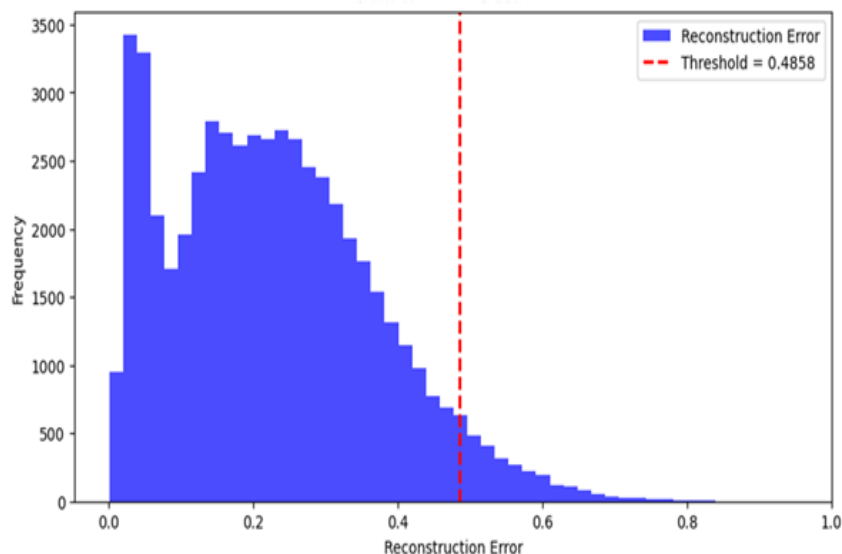


Figure 8. Histogram of Reconstruction Deviations for Vibration Signals at 95th Percentile Threshold.

3.4. Metrics for Vibration-based Autoencoder

Fault Analysis

Table 2 presents the metrics for the autoencoder fault analysis. The table shows the True Positive Rate (TPR), False Positive Rate (FPR), Precision, Recall, and F1-score for the vibration signals. To assess the developed autoencoder's capability for thermal analysis and optimisation of induction motors, a selection of diagnostic performance metrics was used. Using vibration datasets, metrics such as True Positive Rate (TPR), False Positive Rate (FPR), Precision, Recall, and F1-score were used. These metrics present important understandings into the model's ability to detect and classify anomalies that lead to overheating to enable predictive thermal regulation and enhance operational control. The autoencoder provided strong results on the vibration dataset, which supports vibration as causal agents of causing thermal generation. It achieved a TPR of 91.2% to show effective identification of vibration-induced thermal stress factors such as bearing degradation or misalignments. The FPR of 6.1% remains within acceptable bounds, given the naturally higher changeability of vibration data, which can influence thermal signatures. A Precision of 92.4% and Recall of 91.2% further exhibit the model's capability in identifying mechanical anomalies that could lead to temperature increase. The F1-score of 91.8% validates the model's ability to generalise well on vibration-based indicators of overheating to reinforce its role in comprehensive motor health assessment. Each metric shows an important role in justifying the model's ability to perform real-time thermal optimisation. TPR and Recall quantify how well the model detects true sources of thermal deviation, FPR prevents false alerts that could lead to inefficient maintenance, and Precision confirms the reliability of alerts issued. The F1-score integrates all these metrics to

evaluate overall stability and generalisation. The autoencoder demonstrated high performance to confirm its effectiveness as a tool for thermal analysis, fault detection, and operational optimisation of induction motors. It proposes a non-intrusive, smart approach to early detection of overheating. Thereby, supporting predictive maintenance strategies and extending the motor's operational lifespan.

Table 2. Metrics of the Vibration-based Autoencoder Fault Analysis.

Parameters	Vibration Signals (%)
True Positive Rate (TPR)	91.2
False Positive Rate (FPR)	6.1
Precision	92.4
Recall	91.2
F1-Score	91.8

4. Conclusions

This study proved the effectiveness of using a vibration-based autoencoder model for the thermal analysis and optimisation of induction motors. The study began by identifying and detailing key sources of vibration in induction motors, such as misalignment, mechanical imbalance, bearing faults, loose or worn-out parts, rotor eccentricity and rotor core damage, and environmental influences. These sources were shown to significantly contribute to excessive heating and mechanical stress in motors, eventually decreasing efficiency and resulting in premature failure. To address the matter, an unsupervised learning approach using an autoencoder was designed and implemented. The model was trained

on healthy vibration signals and tested on faulty datasets to detect anomalies that signify early-stage faults responsible for thermal degradation. Through systematic data preprocessing (cleaning, normalisation, and time-series reshaping), the autoencoder effectively learned the normal operational behaviours of induction motors. Results from the model showed a high capacity for distinguishing between healthy and faulty conditions. The training and validation loss converged smoothly to indicate strong generalisation. The model's fault detection capability was further confirmed by the distribution of reconstruction errors and by statistical metrics such as a True Positive Rate of 91.2%, a low False Positive Rate of 6.1%, and an F1-score of 91.8%. These findings underscore the autoencoder's strength in identifying vibration-induced anomalies that lead to overheating. Therefore, the developed autoencoder system serves not only as a reliable tool for identifying faults linked to vibration but also as a non-intrusive and intelligent solution for predictive maintenance. The model enhances operational safety, reduces unplanned downtime, and extend the lifespan of induction motors by facilitating early fault detection. The research contributes significantly to the field of smart diagnostics and thermal management in industrial motors.

Abbreviations

AE	Autoencoder
ANN	Artificial Neural Network
AC	Alternating Current
MSE	Mean Squared Error
TPR	True Positive Rate
FPR	False Positive Rate
EDA	Exploratory Data Analysis
GPU	Graphics Processing Unit
HVAC	Heating, Ventilation, and Air Conditioning
L2	Regularisation Term
ReLU	Rectified Linear Unit
X, Y, Z axes	Cartesian Coordinate Axes

Author Contributions

Daniel Kumi Owusu: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Writing – original draft, Visualization

Christian Kwaku Amuzuvi: Supervision, Validation, Writing – review & editing

Joseph Cudjoe Attachie: Supervision, Project administration, Writing – review & editing

Data Availability Statement

The datasets that were used for this work are available at: <https://data.mendeley.com/datasets/ztmf3m7h5x/6>

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Salman, A. E., Ahmed, N. Y., Saad, M. H. Machine Learning-based Fault Diagnosis for Three-Phase Induction Motors In Ventilation Systems. *Australian Journal of Mechanical Engineering*. 2025, 23(2), 263-276. <https://doi.org/10.1080/14484846.2023.2281027>
- [2] Garcia-Calva, T., Duque-Perez, Ó., Romero-Troncoso, R. J., Morinigo-Sotelo, D., Martin-Diaz, I. Detecting Particle Contamination in Bearings of Inverter-Fed Induction Motors: A Comparative Evaluation of Monitoring Signals. *Machines*. 2025, 13(4), 1-21. <https://doi.org/10.3390/machines13040269>
- [3] Meyyappan, K., Vujosevic, M., Wu, Q., Malatkar, P., Hill, C., Parrott, R. Vibration-induced Failures In Automotive Electronics: Knowledge-based Qualification Perspective. *Journal of Electronic Packaging*. 2018, 140(2), 1-12. <https://doi.org/10.1115/1.4039301>
- [4] Ullah, I., Khan, N., Memon, S. A., Kim, W. G., Saleem, J., Manzoor, S. Vibration-Based Anomaly Detection for Induction Motors Using Machine Learning. *Sensors (Basel, Switzerland)*. 2025, 25(3), 1-21. <https://doi.org/10.3390/s25030773>
- [5] Chikwendu, O. C., Emeka, U. C., Obiuto, N. C. Digital Twin Applications for Predicting And Controlling Vibrations In Manufacturing Systems. *World Journal of Advanced Research and Reviews*. 2024, 25(1), 1-9. <https://doi.org/10.30574/wjarr.2025.25.1.3821>
- [6] Behrouzi, S., Dix, M., Karampanah, F., Ates, O., Sasidharan, N., Chandna, S., Vu, B. Improving Visual Defect Detection and Localization in Industrial Thermal Images Using Autoencoders. *Journal of Imaging*. 2023, 9(7), 1-14. <https://doi.org/10.3390/jimaging9070137>
- [7] Hughes, L., Dwivedi, Y. K., Rana, N. P., Williams, M. D., Raghavan, V. Perspectives On The Future of Manufacturing Within The Industry 4.0 Era. *Production Planning and Control*. 2022, 33(2-3), 138-158.
- [8] Al-Haddad, L. A., Jaber, A. A., Hamzah, M. N., Fayad, M. A. Vibration-current Data Fusion and Gradient Boosting Classifier for Enhanced Stator Fault Diagnosis In Three-phase Permanent Magnet Synchronous Motors. *Electrical Engineering*. 2024, 106(3), 3253-3268. <https://doi.org/10.1007/s00202-023-02148-z>
- [9] Pakula, S. Method for Vibration Suppression In Rotarymachines Using Multiple Automatic Ball Balancers. *Journal of Sound and Vibration*. 2025, 596(10), 1-19. <https://doi.org/10.1016/j.jsv.2024.118683>
- [10] Kumar, R. R., Andriollo, M., Cirrincione, G., Cirrincione, M., Tortella, A. A Comprehensive Review of Conventional and Intelligence-based Approaches for the Fault Diagnosis and Condition Monitoring of Induction Motors. *Energies*. 2022, 15(23), 1-36. <https://doi.org/10.3390/en15238938>

- [11] Cogburn, A., Bhattarai, P. Impacts on the Grid-Side Voltage Due to the Current Unbalance Amplification Caused by Induction Motors, In *IEEE Texas Power and Energy Conference*. IEEE, College Station, TX USA, 2024; pp. 1-6. <https://doi.org/10.1109/TPEC60005.2024.10472266>
- [12] Ruiz-Sarrio, J. E., Biot-Monterde, V., Madariaga-Cifuentes, C., Navarro-Navarro, A., Antonino-Daviu, J. A. On the Utilization of Radial Vibration Transient Signals for Induction Machine Misalignment Diagnosis, In *IEEE International Conference on Electrical Machines*. IEEE, Torino Italy, 2024; pp. 1-6. <https://doi.org/10.1109/ICEM60801.2024.10700185>
- [13] Verucchi, C. J., Giraldo, E., Meira, M., Ruschetti, C. R., Bossio, J. M., Bossio, G. R. Efficiency Assessment of Induction Motors Drives Operating Under Shaft Misalignment Conditions. *Advances in Electrical and Electronic Engineering*. 2020, 18(3), pp. 142-152. <https://doi.org/10.15598/aece.v18i3.3596>
- [14] Rahmawan, H. A., Widjianto, B. L., Indriawati, K. and Ariefianto, R. M. Advancing Fault Diagnosis for Parallel Misalignment Detection in Induction Motors Based on Convolutional Neural Networks. *Electrics, Electronics, Communications, Controls, Informatics, and Systems*. 2023, 17(2), pp. 66-71. <https://doi.org/10.21776/jeeccis.v17i2.1655>
- [15] Demetgul, M., Zihan, M., Heider, I., Fleischer, J. Misalignment Detection On Linear Feed Axis Using Sensorless Motor Current Signals. *International Journal of Advanced Manufacturing Technology*. 2023, 126(5), pp. 2677-2691. <https://doi.org/10.1007/s00170-023-11258-8>
- [16] Tribonet, "Rolling Element Bearings Types and Selection". Available from: <https://tribonet.org> [Accessed 26 October 2024].
- [17] Liu, X., Chen, G., Wang, H., Wei, X. A Siamese CNN-BiLSTM-based Method for Unbalance Few-shot Fault Diagnosis of Rolling Bearings. *Measurement and Control (United Kingdom)*. 2024, 57(5), 551-565. <https://doi.org/10.1177/00202940231212146>
- [18] Bentrach, W., Bessous, N., Sbaa, S., Pusca, R., Romary, R. A. Comparative Study between the Adaptive Wavelet Transform and DWT Methods Applied to A Outer Raceway Fault Detection In Induction Motors Based on the Frequencies Analysis. In *International Conference on Electrical Engineering*, IEEE, Istanbul, Turkey, 2020; pp. 1-7. <https://doi.org/10.1109/ICEE49691.2020.9249925>
- [19] Kumar, R., Anand, R. S. Bearing Fault Diagnosis Using Multiple Feature Selection Algorithms with SVM. *Progress in Artificial Intelligence*. 2024, 13(2), 119-133. <https://doi.org/10.1007/s13748-024-00324-1>
- [20] Toma, R. N., Prosvirin, A. E., Kim, J. M. Bearing Fault Diagnosis of Induction Motors Using A Genetic Algorithm and Machine Learning Classifiers. *Sensors (Switzerland)*. 2020, 20(7), 1-19. <https://doi.org/10.3390/s20071884>
- [21] Prudnikov, A. Y., Bonnet, V. V., Loginov, A. Y. Virtual Model of An Induction Motor With Rotor Eccentricity, In *Institute of Physics Conference Series: Earth and Environmental Science*, MDPI AG, Basel, Switzerland, 2020; pp. 1-6. <https://doi.org/10.1088/1755-1315/548/3/032017>
- [22] Archana, P., Praveen, K. N. Investigation of Dynamic Eccentricity in Switched Reluctance Motors: A Fusion of Finite Element Analysis and Machine Learning, In *IEEE Control Instrumentation System Conference: Guiding Tomorrow: Emerging Trends in Control, Instrumentation, and Systems Engineering*, IEEE, Manipal, India, 2024; pp. 1-6. <https://doi.org/10.1109/CISCON62171.2024.10696578>
- [23] Ma, C., Gao, Y., Degano, M., Wang, Y., Fang, J., Gerada, C., Zhou, S., Mu, Y. Eccentric Position Diagnosis of Static Eccentricity Fault of External Rotor Permanent Magnet Synchronous Motor As An In-Wheel Motor. *IET Electric Power Applications*. 2020, 14(11), 2037-2043. <https://doi.org/10.1049/iet-epa.2019.0617>
- [24] Petryna, J., Duda, A., Sułowicz, M. Eccentricity In Induction Machines - A Useful Tool for Assessing Its Level. *Energies*. 2021, 14(7), 1-26. <https://doi.org/10.3390/en14071976>
- [25] Marcolini, F., De-Donato, G., Capponi, F. G., Caricchi, F. A. Comparative Study of Stator Winding Technologies for Coreless Axial Flux Permanent Magnet Machines, In *International Conference on Electrical Machines*, IEEE Xplore, Torino, Italy, 2024; pp. 1-7. <https://doi.org/10.1109/ICEM60801.2024.10700133>
- [26] Baraškova, T., Kudelina, K., Shirokova, V. New Opportunities in Real-Time Diagnostics of Induction Machines. *Energies*. 2024, 17(13), 1-16. <https://doi.org/10.3390/en17133265>
- [27] Borse, D., Tungikar, V. B., Patil, D. R. Failure Investigation of Induction Motor Bearing of Electric Vehicle Due to Manufacturing Defect, In *International Conference on Advances in Materials Processing and Manufacturing Applications*, Springer, Singapore, 2020; pp. 145-153. https://doi.org/10.1007/978-981-16-0909-1_15
- [28] Martin-Diaz, I., Garcia-Calva, T., Duque-Perez, Ó., Morinigo-Sotelo, D. Imbalanced Diagnosis Scheme for Incipient Rotor Faults in Inverter-Fed Induction Motors. *Applied Sciences (Switzerland)*. 2024, 14(16), 1-15. <https://doi.org/10.3390/app14167237>
- [29] Choudhary, A., Jamwal, S., Goyal, D., Dang, R. K., Sehgal, S. Condition Monitoring of Induction Motor Using Internet of Things, In *Proceedings of Recent Advances in Mechanical Engineering*, Springer, Singapore, 2020; pp. 353-365. https://doi.org/10.1007/978-981-15-1071-7_30
- [30] Jang, I. S., Kim, W. H. Study on Electromagnetic Vibration Analysis Process for Permanent Magnet Motors. *IEEE Transactions on Applied Superconductivity*. 2020, 30(4), pp. 1-6. <https://doi.org/10.1109/TASC.2020.2976070>
- [31] Mousaei, A., Peng, H. A New Control Method for The Steadiness of Electric Vehicles With 2-Motor In Rear and Front Wheels. *International Journal of Emerging Electric Power Systems*. 2024, 25(4), 541-554. <https://doi.org/10.1515/ijeeps-2023-0121>

- [32] Ibragimov, M., Akbarov, D., Fayziyev, M., Beytullaeva, R., Nimatov, K., Safarov, K. S. Analysis of The Methods of Diagnosing Asynchronous Motors According To Vibration Indicators. *IOP Conference Series: Earth and Environmental Science*. 2023, 1142(1), 1-11.
<https://doi.org/10.1088/1755-1315/1142/1/012031>
- [33] Noorazzmy, M. H., Sadiq, M. I., Sabri, M. A. M., Mohamed, I. F., Salleh, H., Muhallal, H. A., Ghopa, W. A. W. Investigation of Vibrational Response of Bio-Lubricants and SAE40 for Journal Bearing Application. *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*. 2024, 123(2), 214-230.
<https://doi.org/10.37934/arfmts.123.2.214230>
- [34] Chen, Y., Zhang, H., Li, X., Xiao, S., Gu, F., Shi, Z. Effects of Wear on Lubrication Performance and Vibration Signatures of Rotor System Supported by Hydrodynamic Bearings. *Lubricants*. 2023, 11(3), 1-29.
<https://doi.org/10.3390/lubricants11030107>
- [35] Lee, H., Son, S., Jeong, D., Sun, K. H., Jeon, B. C., Oh, K. Y. A Finite Element Model of an Electric Motor with An Unbalanced Rotor for Vibration Data Generation. *International Journal of Precision Engineering and Manufacturing-Smart Technology*. 2024, 2(1), 47-56.
<https://doi.org/10.57062/ijpem-st.2023.0122>
- [36] Aguayo-Tapia, S., Avalos-Almazan, G., Rangel-Magdaleno, J. J., Ramirez-Cortes, J. M. Physical Variable Measurement Techniques for Fault Detection in Electric Motors. *Energies*. 2023, 16(12), 1-21.
<https://doi.org/10.3390/en16124780>
- [37] Mavlonov, J., Ruzimov, S., Tonoli, A., Amati, N., Mukhitdinov, A. Sensitivity Analysis of Electric Energy Consumption in Battery Electric Vehicles with Different Electric Motors. *World Electric Vehicle Journal*. 2023, 14(2), 1-16. <https://doi.org/10.3390/wevj14020036>
- [38] Czerlunczakiewicz, E., Majerczak, M., Bonato, M. Fatigue Simulations for Automotive Components Undergoing Vibration Loadings: Effect of Nonlinear Behaviour. In *Procedia Structural Integrity*, Elsevier B.V., 2023; pp. 743-753. <https://doi.org/10.1016/j.prostr.2024.03.080>
- [39] Morgan, W. J., Chu, H. Y. An Unsupervised Vibration Noise Reduction Approach and Its Application in Lubrication Condition Monitoring. *Lubricants*. 2023, 11(2), 1-20.
<https://doi.org/10.3390/lubricants11020090>
- [40] Kobenkins, G., Rilevs, N. The Influence of Bearing Bore Wear on Power Indicators of the Traction Motor Gear Unit. In *IEEE International Conference and Exposition On Electric and Power Engineering*, Iasi, Romania, 2024; pp. 528-532.
<https://doi.org/10.1109/EPEi63510.2024.10758112>
- [41] Horváth, K., Zelei, A. Simulating Noise, Vibration, and Harshness Advances in Electric Vehicle Powertrains: Strategies and Challenges. *World Electric Vehicle Journal*. 2024, 15(8), 1-17. <https://doi.org/10.3390/wevj15080367>
- [42] de-Hoz, L. McAlpine, D. Noises on How the Brain Deals with Acoustic Noise. *Biology*. 2024, 13(7), 1-15.
<https://doi.org/10.3390/biology13070501>
- [43] Hassan, I. U., Panduru, K., Walsh, J. An In-Depth Study of Vibration Sensors for Condition Monitoring. *Sensors*. 2024, 24(3), 1-33. <https://doi.org/10.3390/s24030740>
- [44] Seventekidis, P., Karyofyllas, G., Giagopoulos, D., Parametric Study on Structural Damage Classification with Numerically Simulated Vibration Data. *Journal of Physics: Conference Series*. 2024, 2647(2), 1-8.
<https://doi.org/10.1088/1742-6596/2647/2/022004>
- [45] Kang, H., Kook, J., Lee, J., Kim, Y. K. A Novel Small-Scale Bladeless Wind Turbine Using Vortex-Induced Vibration and a Discrete Resonance-Shifting Module. *Applied Sciences (Switzerland)*. 2024, 14(18), 1-16.
<https://doi.org/10.3390/app14188217>
- [46] Goroshko, A. V., Zembytska, M. V., Paiuk, V. P. Induction Motor Vibrations Caused by Mechanical and Magnetic Rotor Eccentricity. *Journal of Engineering Sciences*. 2024, 10(1), 66-77. [https://doi.org/10.21272/jes.2024.11\(1\).d8](https://doi.org/10.21272/jes.2024.11(1).d8)
- [47] Sri, R. P., Kapu, V., Dhananjay, R. K., Alsaif, F. Induction Motor Structure Design to Reduce Vibrations with Numerical (FEA) and Experimental (VA) Techniques. *IEEE Access*. 2024, 12(1), 40894-40904.
<https://doi.org/10.1109/ACCESS.2024.3374785>
- [48] Dahifale, V., Keskar, M., Kakyalia, V., Rodge, S., Karve, G. M. Fault Detection of 3-Phase Induction Motor Using Vibration Analysis. *International Journal For Multidisciplinary Research*. 2023, 5(5), 1-9.
<https://doi.org/10.36948/ijfmr>
- [49] Wang, L., Wang, X., Li, N. and Li, T. Modelling and Analysis of Electromagnetic Force, Vibration, and Noise In Permanent Magnet Synchronous Motor for Electric Vehicles Under Different Working Conditions Considering Current Harmonics. *IET Electric Power Applications*. 2023, 17(7), 952-964.
<https://doi.org/10.1049/elp2.12315>
- [50] Liu, X., Hong, J., Zhao, K., Sun, B., Zhang, W., Jiang, J. Vibration Analysis for Fault Diagnosis in Induction Motors Using One-Dimensional Dilated Convolutional Neural Networks. *Machines*. 2023, 11(12), 1-17.
<https://doi.org/10.3390/machines11121061>
- [51] Donolo, P., Pezzani, C., Bossio, G., de-Angelo, C., Donolo, M. Vibration Magnitude Analysis on Induction Motors of Different Efficiency Classes Due to Voltage Unbalance. *IEEE Transactions on Industry Applications*. 2023, 59(3), 2913-2918.
<https://doi.org/10.1109/TIA.2023.3237218>
- [52] Ermolaev, A., Erofeev, V., Plekhov, A., Titov, D. Magnetic Vibration in Induction Motor Caused by Supply Voltage Distortion. *Energies*. 2022, 15(24), 1-11.
<https://doi.org/10.3390/en15249600>
- [53] Prasad, K. V. S. R., Singh, V. Numerical Investigation and Experimental Modal Analysis Validation to Mitigate Vibration of Induction Machine Caused due to Electrical and Mechanical Faults. *Journal of Electrical Engineering and Technology*. 2022, 17(4), 2259-2273.
<https://doi.org/10.1007/s42835-022-01049-8>

- [54] Su, Z., Luo, L., Liu, J., Li, Z., Luo, H., Bai, H. Research on Vibration and Noise of Induction Motor under Variable Frequency. *Symmetry*. 2022, 14(3), 1-19.
<https://doi.org/10.3390/sym14030569>
- [55] Tabasi, M., Ojaghi, M., Mostafavi, M. Vibration Analysis As Useful Domain for Detection of Bearing Fault Signals In Induction Motors. *International Journal of Engineering, Transactions B: Applications*. 2021, 34(8), 2010–2020.
<https://doi.org/10.5829/ije.2021.34.08b.22>
- [56] Gundewar, S. K., Kane, P. V. Condition Monitoring and Fault Diagnosis of Induction Motor. *Journal of Vibration Engineering and Technologies*. 2020, 9(4), 643-674.
<https://doi.org/10.1007/s42417-020-00253-y>
- [57] Prasad, K. V. S. R., Singh, V. Looseness Identification of Stator End Windings of Induction Motor By Modal Test. In *IEEE International Conference on Power Electronics, Drives and Energy Systems*, Jaipur, India. 2020; pp. 1-5.
<https://doi.org/10.1109/PEDES49360.2020.9379438>
- [58] Xu, M., Feng, G., He, Q., Gu, F. and Ball, A. Vibration Characteristics of Rolling Element Bearings With Different Radial Clearances for Condition Monitoring of Wind Turbine. *Applied Sciences (Switzerland)*. 2020, 10(14), pp. 1-19.
<https://doi.org/10.3390/app10144731>
- [59] Ling, X., Tao, J., Li, B., Qin, C., Liu, C. A Multi-physics Modeling-Based Vibration Prediction Method for Switched Reluctance Motors. *Applied Sciences (Switzerland)*, 2019, 9(21), pp. 1-16. <https://doi.org/10.3390/app9214544>
- [60] Zeng, D., Zou, J., Xu, Y. Analysis for the Vibration Characteristics of The Induction Machine In Different Operating Status, In *22nd International Conference on Electrical Machines and Systems*, Harbin, China, 2019; pp. 1–5. <https://doi.org/10.1109/ICEMS.2019.8922317>
- [61] Areias, I. A. D.S., Borges da Silva, L. E., Bonaldi, E. L., de Lacerda de Oliveira, L. E., Lambert-Torres, G., Bernardes, V. A. Evaluation of Current Signature In Bearing Defects By Envelope Analysis of The Vibration In Induction Motors. *Energies*. 2019, 12(21), pp 1-15.
<https://doi.org/10.3390/en12214029>
- [62] Berahmand, K., Daneshfar, F., Salehi, E.S., Li, Y., Xu, Y., 2024. Autoencoders and their applications in machine learning: a survey. *Artificial Intelligence Review*, 57(2), p. 1-52.
<https://doi.org/10.1007/s10462-023-10662-6>

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