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Research Article

Data Fusion-Based Multiple Fault Diagnosis of Rotating Machines Using Transfer Learning

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Abstract:

This study presents a fault diagnosis system, which uses data fusion together with transfer learning and multi-modal sensors (vibration, acoustic and temperature) to diagnose faults in rotating machinery. The system achieved an impressive overall accuracy of 99% on the combined dataset, as it utilised pre-trained convolutional neural networks (CNN), specifically ResNet50, adapted to the fault diagnosis task. The proposed system performed exceptionally well for fault classification and had particularly strong results for a number of the fault classes. For example, the inner race fault class had an outstanding recall of 1.00, demonstrating robust detection capabilities, and the outer race fault class had strong precision and recall with 0.98 and 0.98. The healthy class had outstanding precision and recall performance with values very close to 1.00. Having access to multiple sensor data sources helped to improve not only the overall classification accuracy but also the ability of the model to generalise to different operational conditions and provide consistent performance across those conditions. The presented results show the capabilities of data fusion and transfer learning for fault diagnosis and provide a scalable and effective solution for real-time, actionable data for monitoring machinery, with relatively low requirements for data labelling. The system presented has great potential to improve fault detection for industrial fault detection systems by improving reliability and reducing downtime.

1. Introduction

In the industrial sector, rotary machinery is an essential power transmission device that finds extensive application in energy, navigation, aircraft, and industrial machinery [1,2]. The nonviolent and strong process of spinning equipment significantly impacts the dependability of the entire mechanical system. Researching and applying rotating equipment fault diagnosis and health maintenance is crucial to guarantee the security and dependability of tackle systems. However, it is difficult to identify and diagnose fault characteristics because revolving equipment failures are characterised by coupling, unpredictability, and complexity. As artificial intelligence advances, clever algorithms offer a fresh method for automatically identifying and detecting faults [3,4].

In clever algorithms, convolutional neural networks are a crucial advancement. The first CNN was a one-dimensional (1D) CNN for voice recognition called the time delay neural network [5,6]. Regarding 1D CNN, the model's input, the convolution kernel's vectors, and the feature map are all 1D, as is the output. Concrete fractures were detected using a vision-based technique based on CNN's deep architecture [7]. For structural visual inspection, a quicker region-based CNN was built to identify many types of faults simultaneously in quasi-real-time [8].

Intelligent techniques have also been used to diagnose rotating equipment faults (Tang et al., [9]). Feng et al. used a cardinal twin-driven approach for gear health evaluation and a novel vibration indicator to study gear wear [10]. Taking into account a lack of defect training examples. Presented simulation-driven techniques and machine learning models and summarised the literature on dynamic simulation and gear defect modelling [11]. Using a endured parameter model to acquire enough training data allowed for the identification of the gear operating state [12]. A “two-stage diagnostic has been proposed for small sample fault identification of bearing and gearbox, utilising CNN to identify bearing damage through simulation and experiment [13], as the defective data is always significantly smaller than normal data in practice. Grasshopper optimisation was used to optimise the support vector data description and the support vector” machine.

Regarding the drawbacks of conventional CNN and recurrent neural networks, a feature fusion structure that combines CNN with a self-attention mechanism was presented for intelligent gearbox and bearing problem diagnostics [14]. A grey wolf optimiser and weight-based selection method were added to the CNN to create an ensemble model for gearbox and hob defect diagnostics. To classify hydraulic piston pump faults, a deep normalised CNN model was constructed. The technique used the synchro-squeezed wavelet transform's strength and introduced the Bayesian algorithm [15]. A deep residual network-based fused diagnostic approach for nuclear power plant (NPP) rotary machinery was proposed. The fast Fourier transform (FFT) converted vibration data into frequency data. The 3D maps were created through the combination of 2D reconstructed feature maps, which served as multiple sensor fusion equipment [16].

1.1 Role of Data Fusion and Transfer Learning in Fault Detection

Detection systems use data fusion together with transfer learning to enhance their detection accuracy while increasing their operational efficiency in diagnosing faults within rotating machinery. The process of data fusion combines data from multiple sensors, which include vibration, temperature, and acoustic signals, to provide a complete assessment of machine health status. The system increases its capacity to find faults through its ability to handle data that contains noise, together with missing information. Transfer learning enables models to handle new fault detection tasks with only minimal available labelled data by utilising pre-existing knowledge from related domains. The system decreases training time requirements while enhancing model performance across various machine types and environmental conditions by eliminating the need for large training datasets. The fault diagnosis system uses these two methods to create a system that can handle all user needs while providing permanent protection against machine faults in rotating equipment.

Wireless Sensor Networks collect information about the physical world, and they can acquire all types of environmental data. The network performs further data processing tasks on the information that it has collected. There are several nodes spread out in a variety of topologies that make up the WSN topology. Deployment might be sparse, dense, specialised, or random. Because WSN is developing so quickly, it may be used in a wide range of applications. In other domains, such as data science, where vast volumes of data need to be handled, WSN is crucial. Studies have employed machine learning methods to categorise this massive volume of data from various sensors.

The prediction outcomes from each sensor are then combined using ensemble learning methods. The issue of choosing the incorrect models is reduced by this method of combining the machine learning algorithms' prediction outputs [17]. In WSN, decision fusion has been crucial for multiclass classification issues. There are several sensor nodes in WSNs, which can be dispersed throughout the network or remain stationary. Direct or indirect communication between these nodes is required. Decisions about the sensor data are made at a central node where the data is combined. The accuracy of the data is an issue if the sensors are dispersed. Local sensors cannot address problems with data accuracy. A fusion rule is therefore required to fuse only trustworthy data. To determine whether or not the data are correct, a choice synthesis regulation has been developed to examine the detection of limited device data and the false alarms created [18]. The forest image classification technique was created by the authors in [19] using an estimation classifier and the belief function fusion methodology. The categorisation of photos from remote sensing was addressed, and information was gathered from the forests. This categorisation problem is addressed using a belief function theory. The target's distance was determined using the distance estimation model classifier. The WSN distributes sensors, classifies sensing data, and transmits the binary findings to the fusion centre. A threshold is established to get precise local sensor detections, and the final choice is reached by comparing the detections with the threshold. The optimum decision fusion rule is used to address the decision fusion problem in cooperative WSNs. The Neyman-Pearson sense is used to generate this ideal fusion rule. “The decode-and-forward relaying is used for the channels in the optimum decision fusion rule. Numerous methods have been put forth in the literature to address this decision problem, and two algorithms—the category similarity weight-based TOPSIS intuitionistic fuzzy decision algorithm and the data distribution-based IFS construction algorithm—are used to construct the multi-attribute decision fusion model based on the Intuitionistic Fuzzy Set” IFS [20]

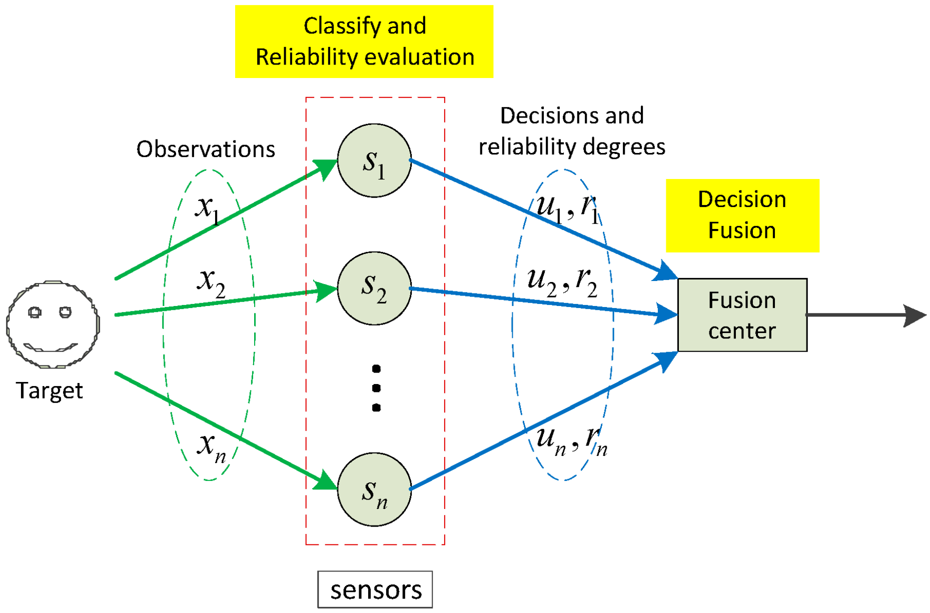

Figure 1: System model of the proposed decision fusion approach **Diagnosis**

Figure 1 shows the design of a decision-level data fusion system that tracks multiple faults in rotating machinery systems. The process begins with multiple heterogeneous sensor observations $x_1, x_2, \ldots, x_n$ acquired from the target system. The observation data undergoes independent processing through dedicated classifiers $S_1, S_2, \ldots, S_n$, which execute local classification and reliability assessment tasks.

Each sensor generates a decision output. u_i along with an associated reliability degree r_i, which quantifies the confidence level of the local prediction. The framework employs decision-level fusion because it takes local decisions together with their reliability scores to a centralised fusion centre instead of processing raw sensor signals. The fusion centre aggregates the weighted decisions using a reliability-aware fusion rule to produce the final global classification outcome. The system architecture establishes multiple protections against sensor noise and sensor errors while enhancing the system's ability to identify faults and maintain higher levels of system dependability. The framework uses reliability degrees to determine how much trustworthy sensor decisions impact the final diagnosis in the fusion process.

The proposed structure operates effectively in distributed industrial settings where accurate and stable multi-fault detection needs multiple-sensing technologies to work together.

1.2 Fundamentals of Data Fusion in Fault Diagnosis

This study aims to investigate four significant issues with data-driven approaches to fault classification by analysing data from a Pratt & Whitney commercial dual-spool turbofan engine. Among the four problems examined here are the following. [21] Is it possible to describe the complexity of defect categorisation using self-organising maps beforehand? [22] Can data-driven classification approaches be implemented in memory-constrained digital electronic control units, and do data reduction strategies enhance fault classification performance? [23] When may classification performance be enhanced by adaptive boosting, an incremental fusion technique that gradually merges somewhat inaccurate classifiers into accurate” ones? [24] How might classifier fusion topologies be created to increase the overall accuracy of diagnosis? This study examines many classifiers, including a "physics-based single fault isolator, k-nearest neighbor, principal component analysis, support vector machines" probabilistic neural networks, and Gaussian mixture models.[25] Since these methods work with enormous amounts of data and are typically computationally costly, use the multiway partial least squares approach to minimise the data set. Smaller memory needs and increased diagnostic accuracy are further advantages of this. Adaptive boosting is used to increase the performance of the classifiers that are relatively incorrect. These outcomes are contrasted with those of other fusion structures and the classifiers alone [26]. Demonstrate that fusion, which works best when merging classifiers that are moderately incorrect, lowers the variability in diagnostic accuracy.

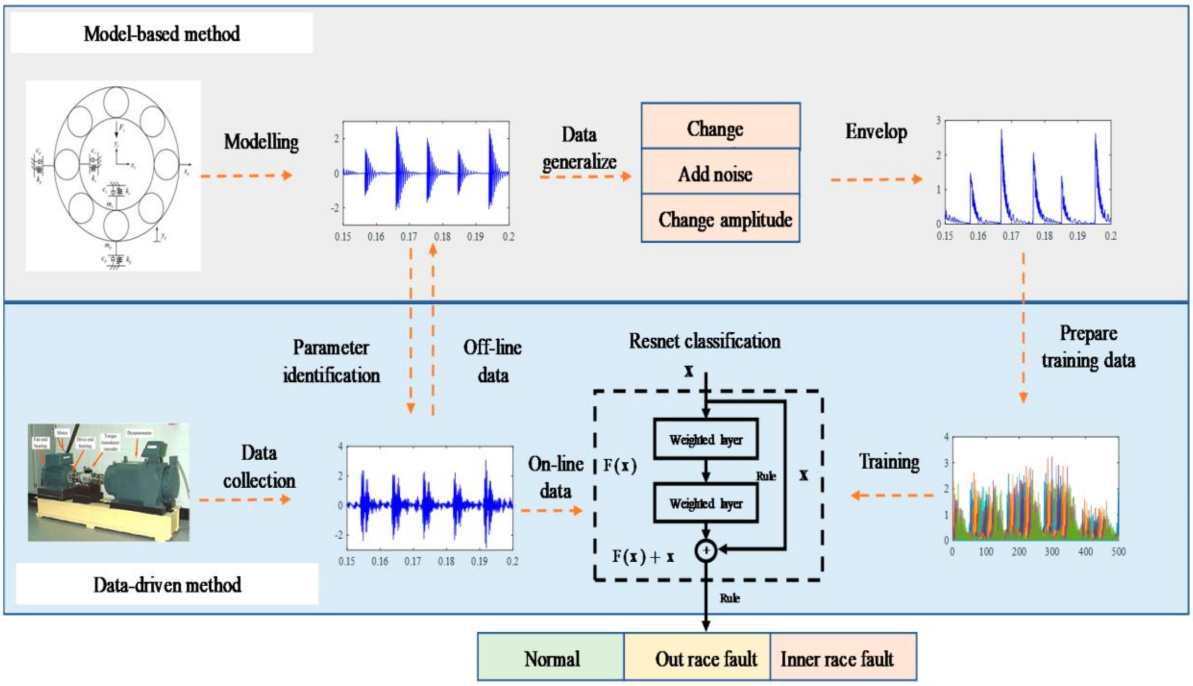

Figure 2: The ResNet classifier framework for defect detection with model-based data augmentation

The complete fault diagnosis system, which combines two approaches: model-based data augmentation and data-driven deep learning classification (Figure 2). The upper section illustrates the model-based approach, where physical system modelling is performed to simulate representative fault signals. The synthetic signals undergo controlled modifications, which include noise addition and amplitude variation, and signal generalisation to create multiple fault patterns. The procedure of envelope analysis is used to enhance defect-related frequency components, which are required for training data preparation. The lower section of the system conducts data-driven operations through its collection of actual sensor measurements from rotating machinery, which operates under various conditions. The system conducts parameter identification and signal preprocessing to create both structured online and offline datasets. The ResNet-based classifier receives these datasets as input, which includes weighted layers that perform hierarchical feature extraction and fault discrimination tasks. The combination of synthetic model-generated signals with actual measured data improves training diversity while solving data shortage problems. The hybrid architecture enables systems to generalise across multiple operational environments while accurately classifying three different states: normal operation, outer race fault, and inner race fault.

1.3 Fault Diagnosis using Transfer Learning

The industrial industry is being propelled towards an inevitable digital and intelligent transformation by powerful and sophisticated computer, sensing, measuring, and communication technology. It has fully embraced Industry 4.0, the fourth industrial revolution, which aims to empower robots with intelligence, enable precise self-perception, and enable autonomous decision-making in the production process [27,28,29]. "One of the most important carriers for the manufacturing sector in such a trend and revolution is industrial equipment, which has been devoted to producing financial gains, including cost reduction, energy conservation, efficiency improvement, and quality improvement. In the meantime, the IE must deliver long-term services and is usually required to do impossible tasks in a challenging operational environment [30,31,32]. The health state of IE must be tracked and diagnosed promptly to guarantee the safety and dependability of the industrial environment. This may minimise equipment downtime, create planned maintenance, boost financial gains, and prevent catastrophic events [33, 34].

The intricacy and dynamic nature of manufacturing processes, which invariably result in deterioration, failure, and damage, made it extremely difficult to accurately diagnose IE faults promptly. Since many governments and organisations have identified timely and accurate IFD as a major priority, academia and industry researchers have focused more on it in recent decades. Fortunately, because artificial intelligence technologies are developing so quickly, particularly in deep learning and transfer learning, many intelligent algorithms have been created by engineers and researchers to solve a variety of real-world issues in industrial settings. The intelligent fault diagnosis of Internet Explorer has also advanced significantly because of these algorithms. In artificial intelligence, deep learning is a subfield of machine learning that generally refers to methods that learn higher-level representations from raw inputs, such as pixel-based images, audio files, text documents, etc., using “hierarchical architectures, such as Deep Neural Networks, Deep Belief Networks, Recurrent Neural Networks, Convolutional Neural Networks, and Graph Neural Networks [35, 36, 37]”. Deep learning technology has proven to be a promising tool in many manufacturing applications because of its exceptional advantages in processing large amounts of data, discriminative feature learning, effective pattern recognition, and building intelligent models by mapping relationships between industrial data and IE health conditions in an end-to-end manner [38, 39]. Deep learning technology does have several limitations, though, which hinder its advancement and use in difficult real-world scenarios.

1.4 Challenges in Diagnosing Multiple Simultaneous Faults

An electrochemical reaction with oxygen is used in a solid oxide fuel cell device to transform hydrogen energy into electrical power [40]. Because of its “low greenhouse gas emissions, high power output efficiency, usable residual heat, and fuel flexibility, SOFC systems are used in auxiliary power units and stationary power generators” [41]. The short life, low dependability, and high cost of SOFCs prevent their widespread use [42]. By quickly identifying and isolating defects and maintaining systems in the proper state interval, fault detection algorithms and sophisticated control techniques can address the issues [43]. As required, fault tolerance control has evolved by fusing a management approach with a problem diagnostic algorithm [44]. Suggested a fault-tolerant way to regulate the temperature and power of the SOFC stack. An approach to fault-tolerant SOFC control was put out by Wu and Gao [45]. A fault-tolerance control system was suggested by Wu and Gao [46] to reduce SOFC expenses and increase efficiency. To put it briefly, improved management and problem-solving techniques can reduce maintenance expenses and increase system longevity [47].

Since fault diagnosis informs future operations, it is essential to have fault tolerance control. Building fault detection algorithms is a popular research topic to guarantee the efficacy of the control strategy and lower the risks of accidents and efficiency losses in SOFC systems [48]. Frequently, fault diagnosis occurs concurrently or independently [49]. One flaw type is examined at a time using the procedure. The fault detection algorithm must predict many failure types simultaneously since the system may have multiple independent defects that manifest simultaneously [50]. The majority of SOFC-independent fault diagnostics are based on data and models [51]. The actual SOFC system, which might be a physical or black-body model, serves as the basis for the SOFC model in model-based approaches. The distance between the projected model and the SOFC system is calculated, and the SOFC model shows the system's predicted normal operating condition [52]. Lastly, a distance residual analysis looks for problems with the system. Although the model-based approach has proven effective, the complexity of real systems makes it challenging to build a systematic physical model, which makes it more difficult to apply a defect detection technique based on the physical model. Defect diagnosis based on data is becoming more popular. There is not much talent involved in this process. By gathering a certain amount of data and determining the basic system features, the data-based approach may be able to identify failure patterns and anticipate difficulties [53]. Techniques for detecting faults have been developed, including support vector machines, supervised self-organisation maps [54], artificial neural networks, fault tree analysis, and principal component analysis. SOFC tests are included in the overview.

2 Literature Reviews

Zhang Yi et al. (2024) [55] stated that a key part of industrial equipment is rotating machinery, and as bearings and gears are fundamental components of rotating machinery and frequently fail under adverse operating conditions, resulting in major "property losses and serious personal safety issues, fault identification of these components is crucial. It is difficult to guarantee the stability and dependability of fault diagnostic results by extracting the characteristics of a single data set, as fault data for gears and bearings are frequently sparse in actual conditions. This research suggested a defect diagnostic approach that integrates data fusion and transfer learning approaches to address the issues. First, this approach converts two types of fault signals into recurrence plots and Gramian angular difference fields. Two-dimensional pictures from various sensor data are then fused using a U-shaped feature fusion dual discriminator generative adversarial network. The influence of single data on the stability and dependability of defect detection is resolved by its feature fusion module, which fully fuses the characteristics of the two pictures. Additionally, to address the small sample issue, Transfer Learning training is conducted using open-source datasets. Lastly, the fused pictures are classified using the "Dual-Branch Dempster-Shafer Classifier", a decision-level information fusion classifier.

Gawde Shreyas et al. (2023) [56] looked at production, and rotating machinery is essential. Unexpected breakdowns of poorly maintained equipment might result in industrial closures. Predictive maintenance is one area where the fourth industrial revolution is manifesting. The major challenge of predictive maintenance, which all maintenance engineers face, is defect detection and prediction. The majority of bibliometric literature review studies concentrate on rotating equipment fault diagnostics, often on a single failure type. However, the literature on "multi-fault diagnosis using multi-sensor data" in rotating machinery has not been systematically examined. The research on "multi-fault diagnosis using multi-sensor data fusion" of industrial rotating machines using ML and DL techniques is covered in this study. Studies from the "Web of Science" and "Scopus" databases over the past ten years were examined using a hybrid bibliometric approach. Both quantitative and qualitative methods are used in the literature research process, including network analysis, classic bibliometrics, and a novel technique called ProKnow-C that intelligently filters findings to choose the most pertinent studies.

Jigyasu Rajvardhan et al. (2024) [57] explored non-invasive techniques for fault detection in offshore wind turbines to overcome the limitations of conventional sensor-based monitoring. In this context, a thermography-based approach combined with deep learning has been proposed for reliable condition monitoring. The method utilizes thermal images to classify multiple fault conditions, including stator, rotor, and cooling fan faults. To enhance feature representation, deep features are extracted from multiple pre-trained networks such as AlexNet, ResNet, and EfficientNet, and fused using a Serial-Based Feature Fusion (SBFF) technique. Furthermore, a Hybrid Feature Selection (HFS) method integrating statistical approaches like Chi-square, ANOVA, and Kruskal–Wallis is employed to reduce redundancy and computational complexity. The final classification is performed using shallow learning classifiers (e.g., SVM, KNN, Decision Tree) with Bayesian hyperparameter optimization. The proposed framework eliminates the need for segmentation and clustering while achieving very high classification accuracy (up to 100%), demonstrating its effectiveness and computational efficiency for fault diagnosis in offshore wind turbine systems.

Hu Zhiqiang et al. (2021) [58] expressed that Smart sensors and deep learning advances enable sophisticated systems for diagnosing and tracking machine health. The accuracy of bottom-up classification methods depends on their capacity to identify standard sensor measurements that lack both extreme values and false data. Data-driven diagnosis techniques can automatically identify important issue patterns from sensor measurements. The effectiveness of diagnosis becomes restricted when industrial environments produce noisy sensor inputs, and devices experience operational failures. The study developed a deep learning and data fusion-based multisensory framework for rotating equipment failure detection, which integrates vibration measurements and thermal imaging technologies. The proposed strategy shows two main benefits, which include improved diagnostic performance and better ability to handle background noise compared to single-sensor systems. The researchers performed three case studies to test the proposed method for diagnosing multiple faults in rotating equipment. The system performance and dependability assessment process examines three types of data, including normal sensor data, data that contains different noise levels, and data that shows sensor abnormalities, which include bias and stuck failures. The findings demonstrate that in a complex working environment, the proposed data fusion technique performs well diagnostically in identifying machine health concerns.

Huang Min et al. (2020) [59] said that predictive maintenance of mechanical equipment might significantly increase machine service life and save labour costs for detecting mechanical difficulties by utilising multi-source sensor data derived from the IoTs in conjunction with artificial intelligence and big data processing technology. This is why research in this field is more important than ever before. This research provided a comprehensive overview and discussion of fusion models and strategies for multi-source sensing data. As a first step, they examine and compare the Hierarchical fusion model with the Dual Boards of Workrooms synthesis model. Following this, several fusion methods based on DL and NN are compared to Dempster-Shafer indication theory and its uses in mechanical fault diagnosis and fault prophecy. The results show that improving mechanical defect prediction and detection might be possible with additional study and the construction of an intelligent fusion model that integrates the advantages of many fusion approaches. However, this approach is not without its challenges.

Guo Sheng et al. (2019) [60] found that operational and maintenance cost reductions, together with enhanced system reliability and effective production schedule management, require precise defect information. Recent research has produced multiple deep learning methods that diagnose defects in rolling element bearings. The majority of them use data as their foundation while disregarding the established knowledge that has been used to solve problems. In the meantime, operational factors that significantly affect vibration signals, including load and rotation speed, are also disregarded. Changes in operating conditions or bearing type may result in a reduction in accuracy. This research suggested a "multitask convolutional neural network with information fusion-based rolling element-bearing defect diagnostic and localisation" method to tackle these issues. The suggested method combines vibration signals, operational circumstances, and domain knowledge into a three-dimensional input that CNN can effectively handle. Next, a multitask CNN with dynamic training rates is built to complete two tasks at once: localisation and defect diagnostics. To illustrate the efficacy and precision of the suggested method, experimental data on two rolling element-bearing test beds with various bearing types and operating circumstances are provided and contrasted with current state-of-the-art techniques.

Luwei Kenisuomo C et al. (2018) [61] examined complex spinning machinery that must be provided to prevent catastrophic failures in various industrial processes. Enhancing the mean-time-to-repair of malfunctioning equipment has the potential to significantly increase availability, according to reliability engineering. However, rotor-related anomalies are difficult to detect and diagnose, which often hinders an efficient "maintenance decision-making mechanism. Prior studies have tried to address these limitations by using principal components analysis to determine the properties of polycoherent composite spectra produced at different machine speeds. Even if the observations were crucial, the linear nature of the PCA-based classifications used may or may not restrict their use to real-world machine vibration data, which is usually linked to varying degrees of non-linearities caused by flaws. Additionally, machine health classifications would be done by hand because the PCA-based flaws classification system used in earlier studies might not self-learn. A comprehensive literature search on data fusion techniques in rotating machine condition monitoring comprised the first part of the research. The research's later sections focus on using the pCCS features to investigate a simplified two-staged artificial neural network classification method that may lead to the automatic classification of rotating machine" faults. This is based on the potential of pCCS features.

Zeng Ruili, et al. (2017) [62] stated an engine's vibration signal contains a wealth of information about its status, fault identification based on this signal is a successful non-disassembly way for diagnosing engines. Three vibration sensors were positioned at various test locations to gather vibration data on the engine running procedure, to gather many pieces of information for this study. For engine fault detection, a technique combining Dempster-Shafer evidence theory and support vector data description was created. This method uses Dempster-Shafer evidence theory to classify the information from the three vibration sensors in detail, while support vector data description is used to" identify the data from a single sensor. According to the experimental findings, employing three sensors improves fault detection accuracy compared to utilising just one. The suggested approach may use multi-complementary sensor data, which would improve fault detection reliability and lower uncertainty in problem identification.

Zhang, Li, and Hongli Gao (2016) [63] expressed that a single sensor signal cannot fully and precisely convey the status of a ball screw, which has a complicated structure and vast distribution range. “Multi-sensor data fusion” is “typically superior to a single signal. A prominent method, multi-sensor data fusion using neural networks has its limitations due to local optimum problems. A deep learning-based multi-sensor data fusion approach for ball screws is proposed in this study. Deep learning, the evolution of classical neural networks, incorporates both supervised and unsupervised learning. Solving optimization issues becomes easier with it. Using parallel superimposition on signal frequency spectra, the proposed deep learning-based multi-sensor data fusion approach can adaptively mine accessible defect features and automatically determine the ball screw's deterioration situation. The next step is to use the fused data to create deep belief networks. Throughout the seven deterioration phases, the test gathers vibration data from ball screws using five acceleration sensors strategically positioned throughout the test bed. They show that the suggested fusion method works well for measuring the ball screw's corrosion level. The last use of neural network-based multi-sensor data fusion is in determining the extent of degradation. Due to its superior monitoring accuracy” deep learning-based multi-sensor data fusion is the way to go over neural network-based fusion.

Yunusa-Kaltungo, et al. (2015) [64] stated that now many indistinguishable (comparable mechanisms and setups) "as installed" machines on most industrial sites because of equipment standardization, which is a cost-effective way to rationalize maintenance parts. Perhaps because the dynamic behaviors of such “identical machines usually differ due to changes in their underlying flexibilities, a different study is sometimes required for each machine during problem identification. Analysis is often performed at separate measurement locations for different speeds, which further complicates the fault identification process because many rotating equipment operates at different speeds. Therefore, this study suggested a simplified vibration-based fault diagnosis method that could be applicable for fault detection irrespective of foundation flexibilities or operating speeds by experimentally modeling a comparable real-world situation involving two identically configured "as installed" rotating machines with different foundation flexibilities. Two experimental rigs were used, each with a different foundation flexibility, to independently model several typical rotor-related problems. Computed utilizing the data combination technique, composite higher-order spectra (composite Bi spectrum and composite Tri spectrum) were then utilized for defect identification and diagnosis using aggregated data and principal component analysis. So, regardless of the rotational speeds and foundation flexibilities, this research emphasized the significance of the suggested problem detection technique for improving the dependability of identical "as installed" spinning machinery.

Table 1: Approach to Literature Reviews

S.no.	Authors/ Year	Techniques Used	Research Gaps	Outcomes
1.	**Zhang Yi, et al. (2024)**	Improvements in rotating equipment defect detection by data fusion, transfer learning, recurrence plots, dual-branch Dempster-Shafer classifier, U-shaped feature fusion dual discriminator GAN, and Gramian angular difference fields.	The need for an improved model explains the ability and durability in actual industrial settings, the restricted scalability to large systems, and real-time application issues.	The study solves two main challenges which include limited available data and uncertain model performance through its implementation of data fusion and transfer learning methods which enhance the reliability and stability of defect detection results in rotating machines.
2.	**Gawde**	This mixed bibliometric	There hasn't been a	The research examines

	Shreyas, et al. (2023)	method uses network analysis, traditional bibliometrics, and ProKnow-C to find important studies on multi-fault diagnosis and multi-sensor data fusion in rotating machinery.	complete investigation of rotating equipment multi-fault detection which uses multiple sensor data fusion together with machine learning and deep learning techniques.	extensive literature regarding multi-fault diagnosis which uses multi-sensor data fusion methods to diagnose faults in rotating equipment. The research presents important trends and various methods which researchers have developed during the past ten years.
3.	**Mian Tauheed, et al. (2022**	A feature fusion method that uses vibration and heat data, a Hilbert transform, dimensionality reduction by neighborhood component analysis, relief algorithm feature selection, and SVM classification.	Better multi-sensor fusion methods that use different sensor data (like vibration and heat) to help find problems in rotating machinery more quickly and accurately. These methods should have fewer dimensions and be more accurate.	The proposed multi-sensor feature fusion method achieves better fault classification results than all current fusion methods and individual sensor systems. This strategy takes vibration and heat data into account.
4.	**Huo Zhiqiang, et al. (2021)**	The research applies deep learning together with data integration from vibration sensors and thermal imaging systems to enhance its ability to detect problems in rotating machinery while handling increased levels of noise and sensor-related disturbances.	There exists a requirement for advanced multi-sensor fusion systems which possess the capability to handle both noisy sensor data and corrupted sensor data within complex industrial environments to enhance their ability to identify and diagnose problems in rotating machinery systems.	The research demonstrates that using vibration measurements together with thermal imaging and deep learning and data fusion methods achieves better defect detection results in rotating machinery because the system can handle both noisy environments and sensor malfunctions.
5.	**Huang Min, et al. (2020)**	It looks at Hierarchical and JDL fusion models, deep learning and neural network-based fusion systems, and Dempster-Shafer evidence theory in finding and predicting mechanical defects.	The need for intelligent fusion models has increased, which involve multiple fusion methodologies to boost mechanical defaults forecast and detection and to overcome the underlying issues in complex industrial settings.	The research results show that intelligent fusion models which use multiple fusion methods can enhance mechanical defect prediction and detection for complex industrial systems.

3 Background study

The convolution technique is quite computationally intensive and displays considerable temporal complexity, but a CNN can extract features from high-dimensional input. When it comes to online defect detection in equipment with high sampling frequencies, fault diagnosis systems using CNNs fall short. Using two-level transfer learning to integrate heterogeneous data from several sources, this study demonstrated a fault-detecting approach. This method aims to achieve real-time defect diagnosis by utilizing external domain data and multi-source heterogeneous information, integrating it via a two-tier transfer mechanism, and avoiding convolutional methods. The overarching objective is to facilitate the transition from convolutional to deep neural networks by developing a network model for feature extraction from screenshots, determining how to feed those features into a deep learning model from one-dimensional sequence signals, and so on. After the two-level transfer, the defect detection model combines the features of one-dimensional sequence signals with screenshots, skipping convolution procedures and keeping time complexity low. A gearbox dataset and a bearing dataset are used to validate the efficacy of the suggested technique.[65].

4 Research Gaps

Lack of comprehensive methods integrating multiple sensor data for fault diagnosis in rotating machines.
Insufficient utilization of transfer learning to address the challenge of limited labeled data in fault diagnosis tasks.
Current models frequently struggle to extend to various operating settings, which restricts their usefulness in practical situations.
Current fault diagnosis systems face challenges in handling complex fault patterns and differentiating between similar fault signatures across machine components.

5 Research Objectives

To develop a data fusion approach that integrates data from multiple sensors to enhance fault detection accuracy.
To apply transfer learning techniques to improve the model's ability to diagnose faults with limited labeled data.
To design a robust diagnostic model that can generalize across diverse operating conditions and machine types.
To investigate the effectiveness of the proposed model in identifying and classifying a wide range of fault types with high accuracy.

6 Research Methodology

The method proposed in this research combines transfer learning with data fusion methods to identify multiple operational failures in rotating equipment. The initial stage of enhancing fault detection accuracy involves the acquisition of data from multiple sensors which include temperature and sound and vibration measurement devices. The raw data undergoes preprocessing through noise reduction and normalization and feature extraction processes to create high-quality training materials for the model. The transfer learning framework enables improved fault classification through its ability to work with situations that contain limited authorized data. The framework starts with pre-existing deep learning models and enhances them through the application of new data sources which the system has received. The system uses domain adaptation techniques to achieve better performance across various operating conditions.
The research approach being proposed here for data fusion-based multiple fault diagnosis of rotating machines based on transfer learning is organized into several main phases, as shown in Figure 3. The process of data collection begins with the collection of both sensor data and benchmark datasets which include CWRU. The problem identification stage leads to data pre-processing that uses normalization and noise filtering together with feature extraction. The study then examines different methods which include feature fusion and transfer learning through ResNet model and domain adaptation and fault classification. The techniques enable fault diagnosis accuracy enhancement through successful data source integration and model performance improvement.
The final assessment is performed through a performance matrix before generating the output which validates the proposed framework's efficacy in diagnosing faults in rotating machinery.

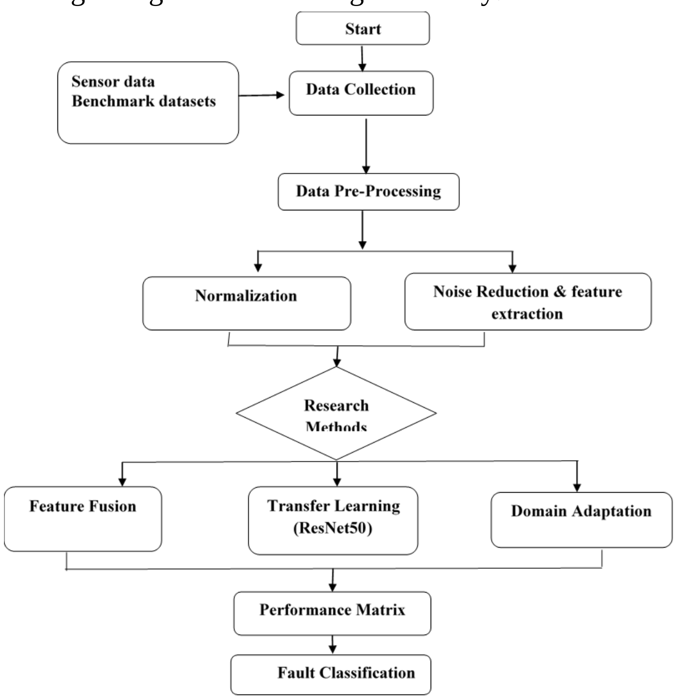

Figure 3: Proposed Research Methodology

6.1 Problem Identification

Rotating machinery serves multiple industrial applications which need dependable performance because equipment failures create operational downtime and result in financial losses. The machine defect identification process remains difficult because mechanical components interact with each other while equipment operates under changing conditions and multiple fault signals overlap. The traditional fault diagnosis methods rely on manually developed feature extraction methods which create classification systems that lack dependable performance and flexible operation capabilities. The majority of Machine Learning models require extensive labeled training data which industrial environments typically do not provide. Transfer learning provides a solution to this issue by enabling learning improvements through the application of pre-existing models to new learning environments. The use of data fusion techniques to merge information from multiple sensors enables more precise defect detection while creating an all-encompassing view of the system.

6.2 Problem Formulation

The proposed multi-fault diagnosis framework is formulated as a supervised multi-class classification problem based on fused multi-sensor representations. Let $X = \{x_1, x_2, ..., x_N\}$ denote the set of feature vectors extracted from vibration, acoustic, and temperature signals, where each $x_i \in \mathrm{R}^d$ represents a fused feature vector of dimensionality d.

Each sample is associated with a corresponding fault label $Y = \{y_1, y_2, ..., y_m\}$ representing distinct machine conditions such as Inner Race Fault, Outer Race Fault, Normal, Healthy, and General Faulty states. The objective is to learn a nonlinear mapping function $f: \mathrm{R}^d \to \mathrm{R}^m$ parameterized by θ, that estimates posterior class probabilities.

The predicted probability for class is obtained using the SoftMax Activation Function:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{m} e^{z_j}}$$

Model training requires the minimization of the categorical cross-entropy loss function which is defined as follows: The formula uses z_i denotes to represent the logit value which corresponds to class i while the total number of fault categories is represented by m:

$$L = -\frac{1}{N}\sum_{k=1}^{N}\sum_{i=1}^{m} y_{k,i}\log(\hat{y}_{k,i})$$

The expression $y_{k,i}$ shows the actual label through its representation in one-hot encoding. The optimal model parameters θ^* are obtained by solving the empirical risk minimization problem $\theta^* = \arg\min_\theta L$.The system uses this formulation to make decisions based on probabilities because it achieves better separation of overlapping fault signatures while maintaining system reliability across all operating conditions.

6.3 Data Collection

The fault diagnosis framework operates by collecting sensor data from vibration and acoustic and temperature sensors which it uses to monitor rotating machinery during various operational conditions. The researchers used both signals obtained from their experiments and publicly accessible benchmark datasets which included the Case Western Reserve University (CWRU) bearing dataset [66] and the Motor Current–Vibration Monitoring dataset [67] to validate their model and assess its performance across different domains. The unified dataset contains around 38200 data points which researchers have classified into five different operational states that include Inner Race Fault and Outer Race Fault and Normal and Healthy and General Faulty conditions. The system achieves balanced learning outcomes through proper distribution of each class. The dataset split established an 80 percent training set and a 20 percent testing set which ensured valid assessment of performance results. The dataset contains different types of data which enables testing at multiple load and speed conditions to verify generalization capabilities while showing the need for domain adaptation methods.

6.4 Pre-Processing

The acquired multi-sensor signals proceed through a structured preprocessing pipeline which guarantees high-quality input representation and backup diagnostic system reliability. The initial stage of signal denoising applies finite impulse response (FIR) low-pass filtering which operates according to the formula:

$$y(n) = \sum_{k=0}^{M} h_k\, x(n-k)$$

The operation uses x(n)to represent the raw sensor signal while $\boldsymbol{h_k}$ stands for filter coefficients and M denotes the filter order. The process reduces high-frequency noise components while maintaining essential spectral information which relates to faults. Statistical standardization removes scale differences that exist between different sensor types through the following process:

$$x' = \frac{x-\mu}{\sigma}$$

The process uses μ and σ to represent the mean and standard deviation of the signal. The process of normalization maintains numerical stability while stopping high-amplitude features from dominating and it speeds up model optimization times through faster convergence. The process of denoising and normalization leads to discriminative feature extraction which operates in time and frequency domains to create complete fault signatures. Time-domain statistical descriptors use Root Mean Square (RMS) which is defined as the following:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

and kurtosis, defined as:

$$\mathrm{Kurtosis} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4$$

The system calculates two measurements which assess how sound wakes and area active during sound testing. The Fast Fourier Transform (FFT) generates frequency-domain results which identify harmonic patterns and spectral energy distribution linked to inner and outer race faults

$$X(f) = \sum_{n=0}^{N-1} x(n)\, e^{-j2\pi f n/N}$$

The preprocessing framework increases the signal-to-noise ratio while creating better feature separation which enables effective feature fusion and transfer learning-based classification.

6.5 Methods

6.5.1 Feature Fusion

The process of feature fusion combines different sensor data streams to create a more accurate and diverse diagnostic system. Let $F_i \in \mathrm{R}^{d_i}$ denote the extracted feature vector from the i^{th} sensor modality. The fused representation F is obtained through weighted linear aggregation:

$$F = \sum_{i=1}^{n} \omega_i F_i$$

The equation determines the contribution weight for i^{th} sensor through the variable ω_i which satisfies the condition $\sum_{i=1}^{n} \omega_i = 1$. The weights may be either defined through empirical methods or determined through the training process. The fusion mechanism of the model enables it to identify cross-modal relationships which results in better differentiation of fault patterns that share similarities.

6.5.2 Transfer Learning

The researchers used transfer learning with pre-trained deep convolutional neural networks ResNet50 because lacked enough labeled fault data to train their models. The system starts with pre-trained weights for its initial convolutional layers which perform core feature extraction while the system tunes its last fully connected layers according to data from the unified fault database. The optimization objective is defined as:

$$\theta^* = \arg\min_{\theta} L(f(X;\theta), Y)$$

where θ denotes the trainable parameters X represents fused input features Y corresponds to ground-truth fault labels and $L(\cdot)$ is the categorical cross-entropy loss. The method improves two factors which include training performance and system capability to work with new data when there is little training material available.

6.5.3 Domain Adaptation

Industrial environments show different data distributions because their operating speed and load conditions and sensor placement practice their operations. The system uses Maximum Mean Discrepancy (MMD) to reduce distribution errors which exist between source domain Sand target domain T. The squared MMD distance is defined as:

$$\mathrm{MMD}^2 = \left\| \frac{1}{n_s}\sum_{i=1}^{n_s} \phi(x_i^s) - \frac{1}{n_t}\sum_{j=1}^{n_t} \phi(x_j^t) \right\|^2$$

The source domain and target domain feature representations are represented by x_i^s sand x_j^t. The feature mapping function is represented by ϕ (·). The number of source samples is represented by n_s and while the number of target samples is represented by n_t. The system achieves cross-domain feature distribution alignment through MMD minimization which enhances system performance under different operational conditions.

6.5.4 Fault Classification

The SoftMax function converts learned feature representations into probabilistic fault predictions during the final classification stage:

$$P(y_i \mid X) = \frac{e^{W_i^T X}}{\sum_{j=1}^{m} e^{W_j^T X}}$$

The equation describes the relationship between the Wi weight vectors and the m is the fault categories and X is the fused feature vector. The system uses its probabilistic implementation to produce standardized class outputs, which enable effective multiple class identification.

6.6 Performance Metrics

The proposed fault diagnosis model undergoes assessment through multiple assessment standards to guarantee its dependable performance and precise results. The precision metric calculates the percentage of correctly identified faults from all anticipated issues whereas accuracy measures the correctness of predictions. The model's actual defect detection capability gets tested through recall, which assesses its capacity to detect genuine defects while maintaining low false negative rates. The F1-score function calculates performance through its combined measurement of precision and recall results. To ensure real-time defect diagnosis, assessed computational efficiency to assess model speed and complexity. These measures define multi-source heterogeneous information fusion performance using two-level transfer learning.

Feature Fusion, Transfer Learning, Domain Adaptation, and Softmax Classification provide a complete defect detection and classification system. Sensor data is fused to improve accuracy. Transfer learning reduces training time by using pre-trained models. Operating environment generalization is made easier by domain adaption. Finally, the Softmax classifier accurately detects multi-class faults.

7 Results & Discussion

Table 2: Classification Performance of the Fault Diagnosis Model on Rotating Machinery Dataset

Class	Precision	Recall	F1-Score	Support
Inner Race Fault	0.98	0.98	0.98	12,528
Normal	1.00	1.00	1.00	12,528
Outer Race Fault	0.98	0.98	0.98	12,528
Accuracy		**0.99**		37,584
Macro Avg	0.99	0.99	0.99	37,584
Weighted Avg	0.99	0.99	0.99	37,584

The model provides excellent fault identification on the first dataset, which includes Inner Race Fault, Outer Race Fault, and Normal. Table 2 shows that Inner Race Fault and Outer Race Fault accuracy, recall, and F1-score values were 0.98, indicating extremely few incorrect positives or negatives. The model can detect healthy circumstances since the Normal class has flawless accuracy, recall, and F1-score values of 1.00. Overall accuracy across 37,584 test samples was 0.99, and macro average and weighted average were both 0.99, indicating that all classes performed similarly and well. These findings demonstrate that the model reliably detects defects and regular rotating equipment functioning
.

Table 3: Classification Performance of the Fault Detection Model on Dataset 2

Class	Precision	Recall	F1-Score	Support
Faulty	0.99	0.95	0.97	328
Healthy	0.95	0.99	0.97	288
Accuracy		0.97		616
Macro Avg	0.97	0.97	0.97	616
Weighted Avg	0.97	0.97	0.97	616

Table 3 shows that the defect detection model on Dataset 2 performed well, attaining 97% accuracy over 616 test samples. The model has a little greater accuracy (0.99), so it can differentiate Faulty instances nearly always, but its recall (0.95) is lower, so a few are missed. High recall (0.99) and accuracy (0.95) results indicate that practically all Healthy samples are properly recognised. The F1-score for both classes confirmed the model's precision/recall balance at 0.97. The model achieves dependable performance because it demonstrates repeated success in correctly identifying healthy and defective cases

Table 4: Classification Report for Combined Fault Diagnosis Dataset

Class	Precision	Recall	F1-score	Support
Faulty	0.99	0.95	0.97	328
Healthy	0.95	0.99	0.97	288
Inner Race Fault	0.98	0.98	0.98	12,528
Normal	1.00	1.00	1.00	12,528
Outer Race Fault	0.98	0.98	0.98	12,528
Accuracy		0.99		38,200
Macro Avg	0.98	0.98	0.98	38,200
Weighted Avg	0.99	0.99	0.99	38,200

The integrated fault diagnostic model performed well in multi-class defect classification, achieving 99% accuracy across 38,200 test samples. The model recognised virtually all fault samples in the Faulty class with a precision of 0.99 and a recall of 0.95. A minority of faulty samples were not detected. The Healthy class has an accuracy of 0.95 and a recall of 0.99, identifying most healthy samples with minimal false positives. The first dataset's Inner Race Fault, Normal, and Outer Race Fault classes separated fault types effectively with accuracy, recall, and F1-scores between 0.98-1.00. The macro-average of 0.98 and weighted average of 0.99 showed the model's classification is balanced and trustworthy across all fault types (Table 4). Combining these datasets produces a single model that effectively finds and classifies multi-source problems in rotating equipment for industrial use. As shown is Figure 4 confusion matrix.

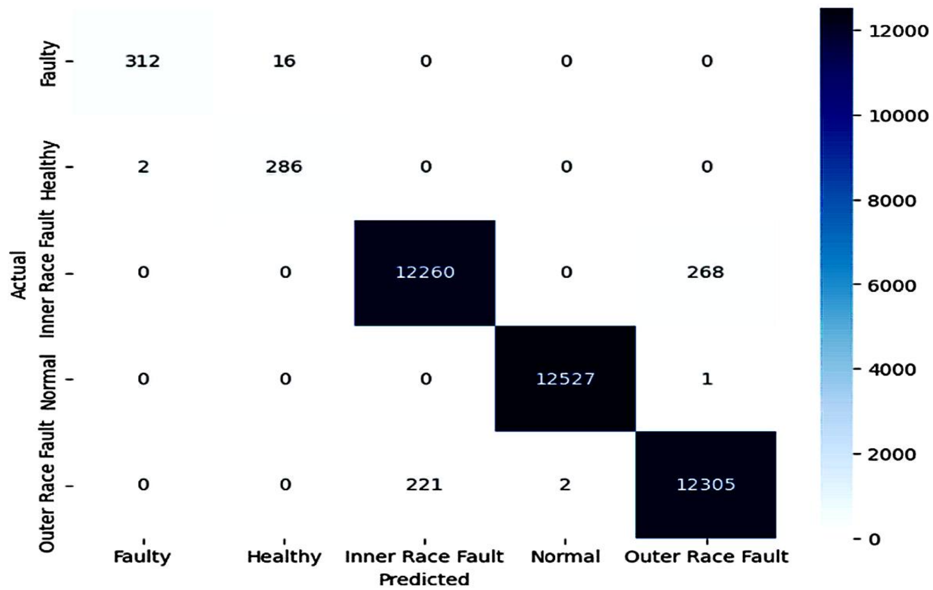

Figure 4: Confusion Matrix Analysis For Multi-Fault Analysis in Rotating Machines Using Combined Dataset.

The proposed multi-fault diagnosis system using transfer learning exhibits its performance results through testing, which uses a combined dataset as the testing method. The model demonstrates strong classification capability across five operational states: Faulty, Healthy, Inner Race Fault, Normal, and Outer Race Fault. The model achieved correct classification results by identifying 312 of 328 Faulty samples and 286 of 288 Healthy samples in the Faulty–Healthy category, which demonstrates its ability to identify real cases through both sensitivity and specificity measurements. The system showed minimal errors between the two classes because 16 Faulty samples were incorrectly identified as Healthy and 2 Healthy samples were predicted to be Faulty.

The model achieved high correct classification rates in bearing fault categories through the correct identification of 12,260 Inner Race Fault samples and 12,305 Outer Race Fault samples. The study observed only minor inter-class confusion between the two fault categories, which consisted of Inner and Outer Race faults. The study showed that 268 Inner Race Fault samples were misclassified as Outer Race Fault, while 221 Outer Race Fault samples were predicted as Inner Race Fault. These two defect types show their misclassification results from their vibration signatures and harmonic components, which create similar patterns to each other. The Normal class showed near-perfect performance because the model correctly classified 12,527 out of 12,528 samples, which proves its ability to separate healthy operating conditions from faulty states.

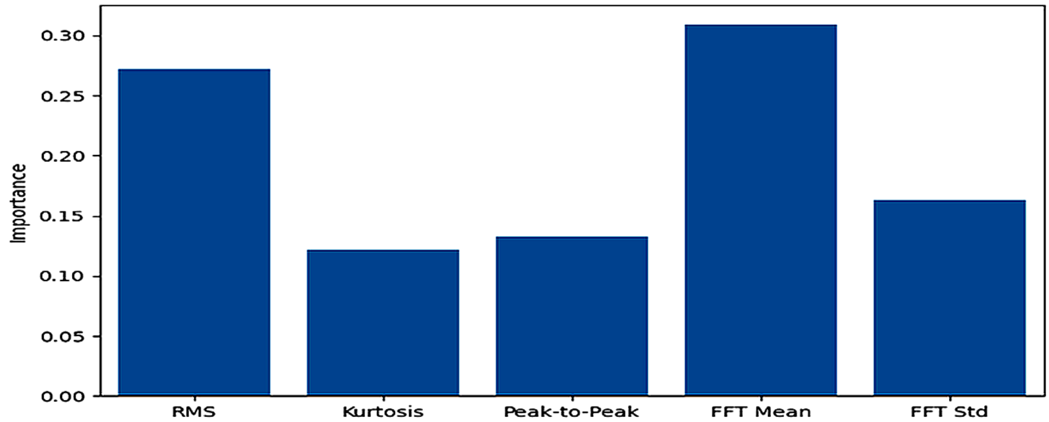

Figure 5: Feature Importance of Vibration and Frequency-Domain Parameters in Random Forest-Based Fault Diagnosis

Figure 5 demonstrates how vibration and frequency domain parameters affect the detection of various rotating machine faults. The highest FFT Mean value reached approximately 0.31, which proved that fault detection relies heavily on frequency-domain energy measurements. The RMS value of approximately 0.27 demonstrated the successful performance of both signal processing methods because it could differentiate between complete vibration energy levels that matched particular problem types. The Kurtosis measure showed a value of 0.12 while the Peak to Peak measurement showed a value of 0.13, which both proved important, but they showed lower impact than other dataset elements because fault types had less effect on advanced statistical measures. The FFT Standard Deviation attained a value of approximately 0.16, which showed fault type-related variation across all testing categories. The research findings demonstrate that frequency domain characteristics create effective transfer learning models that identify multiple faults in rotating equipment because these characteristics provide complete information when paired with time domain data.

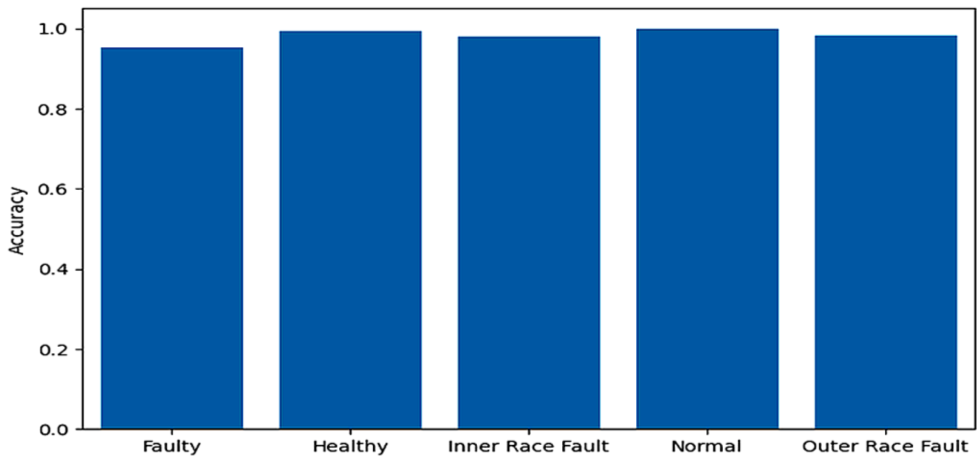

Figure 6: Class-wise Accuracy of Transfer Learning Model for Multi-Fault Diagnosis of Rotating Machines

Figure 6 shows how different time-domain and frequency-domain features impact fault classification accuracy through their various levels of significance. The FFT Mean parameter delivers its highest impact among all extracted parameters because it shows that average spectral energy serves as the main factor that identifies faulty conditions. The study demonstrates that frequency-domain features hold essential value because they enable the detection of harmonic elements that are associated with defects. The Root Mean Square (RMS) value of approximately 0.27 stands as the second most important feature, which demonstrates the total vibration energy present in the signal. The energy-based descriptors show their high capacity to distinguish between faulty conditions and normal operational states through their significant impact on system performance.

The comparison between Kurtosis and Peak-to-Peak amplitude shows that these two features have moderate importance according to their respective values of ~0.12 and ~0.13. The current dataset demonstrates that higher-order statistical features can identify impulsive behaviour and extreme signal conditions, but their effectiveness remains lower than that of spectral energy measurements. The FFT Standard Deviation value of approximately 0.16 demonstrates a significant impact because it shows that frequency dispersion and spectral variability help to identify faults. The research findings indicate that frequency-domain features, which include FFT-based metrics, provide better capacity to detect multiple faults during diagnostic assessments. The time-domain descriptors work together with existing features to improve their performance, which demonstrates the usefulness of the study's feature fusion method, that it proved through transfer learning experiments

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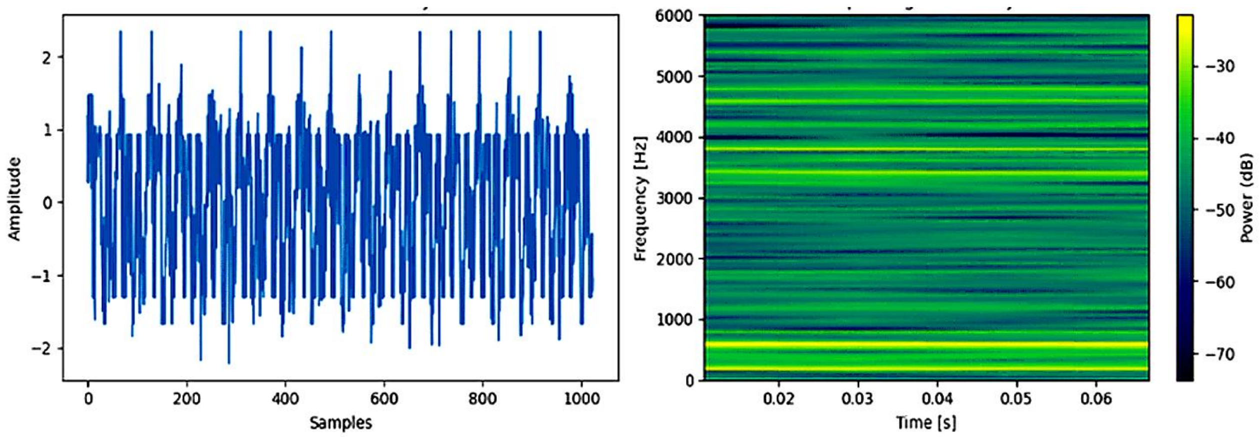

Figure 7: Time-Domain Vibration Signal and Spectrogram Representation of Faulty Rotating Machine Condition

The defective rotating machine condition is shown through its time-domain waveform and its spectrogram results, which appear in Figure 7. The vibration signal displays high amplitude changes that extend from -2.5 to 2.5 units because of mechanical failures that produce elevated vibration energy. The waveform shows unusual motion patterns that create unexpected sound explosions that result from faults in the rotating elements.

The entire frequency range, which reaches 6000 Hz, contains different energy patterns that the spectrogram displays. The faulty condition shows more intense spectral bands, which persist longer than the healthy operational signals because of harmonic excitation from mechanical impacts that occur repeatedly. The sustained high-energy regions that exist over time demonstrate that the detected frequency components stem from defects and not from random noise elements. The joint time–frequency analysis method reveals a better understanding of fault-induced resonance phenomena, which remain hidden when only analysing time domain data. The proposed data fusion and transfer learning framework for multiple fault diagnosis in rotating machinery requires both time-domain and frequency-domain features, according to these observations.

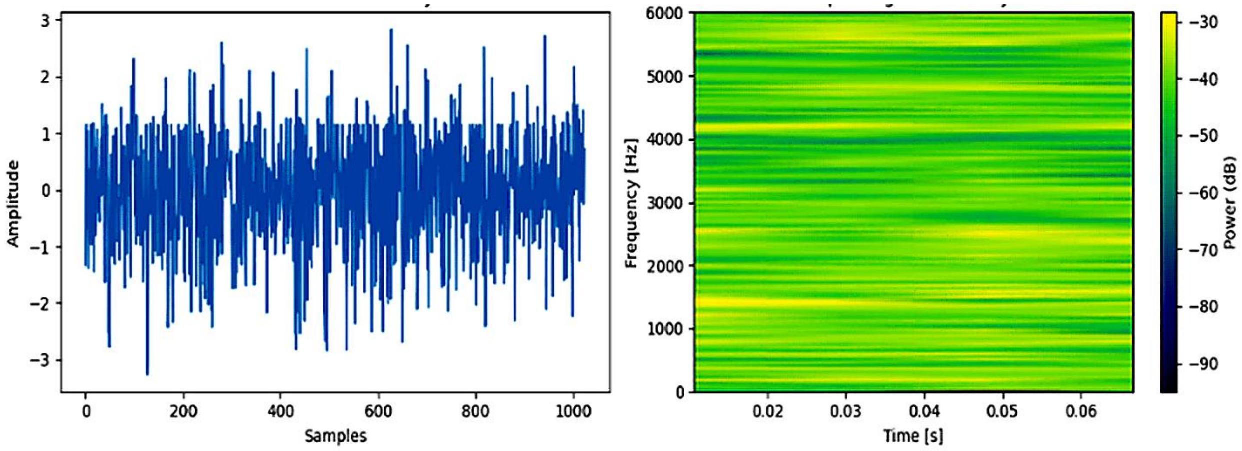

Figure 8: Time-Domain and Spectral Representation of a Healthy Rotating Machine Signal

The left plot in Figure 8 shows a healthy spinning machine's time-domain waveform. The amplitude oscillates symmetrically about zero, peaking at +3 to -3. The waveform is disorganised with no repeating spikes, suggesting no impact or fault oscillations. The spectrogram and frequency content change over time in the right pane. Energy is uniformly distributed throughout the frequencies of interest up to 6000 Hz. Power levels are modest, ranging from -90 dB to -30 dB for all frequencies, with no notable frequency bands. This indicates operational balance. Deviations should seldom be this large. Healthy machines have balanced oscillation amplitudes and modest spectral power. The findings provide a standard for data fusion-based transfer learning model fault detection.

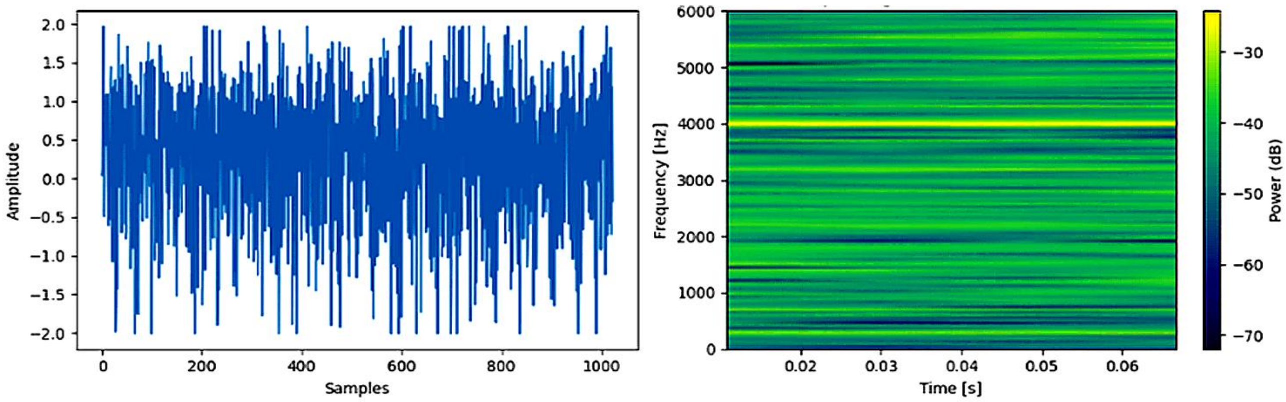

Figure 9: Time-Domain and Spectral Features of an Inner Race Fault in Rotating Machines

The inner race fault's time-domain waveform (left) in Figure 9 exhibits erratic oscillations between +2 and 2, but it has a denser collection of fluctuations than the healthy instance, indicating localized flaws are impulsive. The spectrogram (right) displays power concentrations as dark bands in frequency regions of importance at 1000, 3000, and 4500 Hz. When no fault effects were present, energy levels reached –30 dB, substantially higher than the healthy baseline, which stayed below –40 dB. The research results demonstrate that the study has found multiple hidden faults through its harmonic analysis of fault locations. The time domain oscillation density together with the spectrum characteristics enable health professionals to detect this medical condition. The research presents specific characteristics which exhibit clear unique patterns that can be used to identify faults in a system that combines data from various sources and uses transfer learning for its operations.

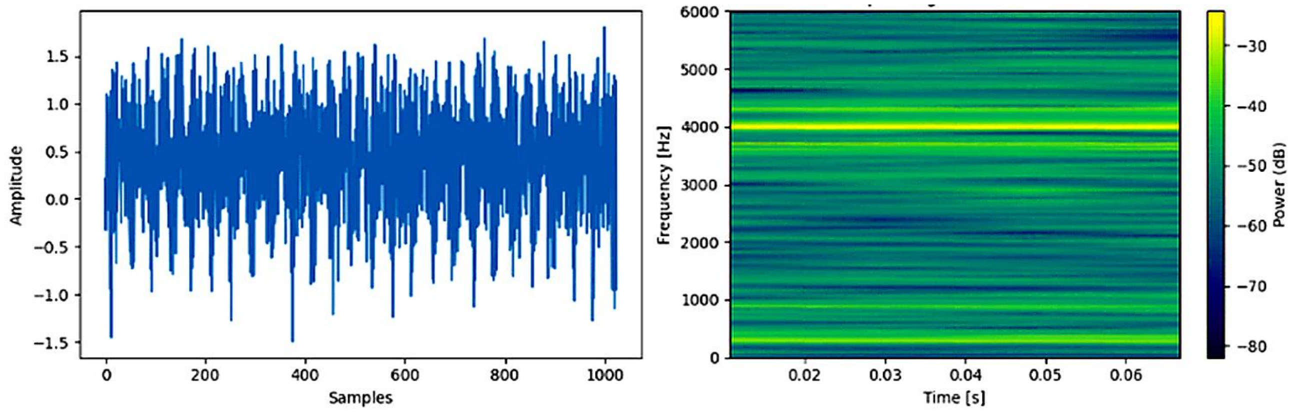

Figure 10: Time-Domain and Spectral Characteristics of a Normal Rotating Machine Signal

In contrast to faulty examples, the time-domain waveform of a typical machine signal (left) in Figure 10 fluctuates between +1.5 and 1.5 with near balance and no impulsive peaks. Constant frequencies of around 1000, 3000, and 4000 Hz are seen in the spectrogram (right), with the lowest amplitudes falling between –80 and –30 dB. These spectral bands are smooth, with greater knock sequences just above 35 dB, in contrast to inner race fault patterns. Frequency band dispersion and amplitude levels are both part of normal machine operation. These common operational reference signals may aid in the identification of malfunctions and fault detection when using data fusion and transfer learning to uncover different issue diagnoses.

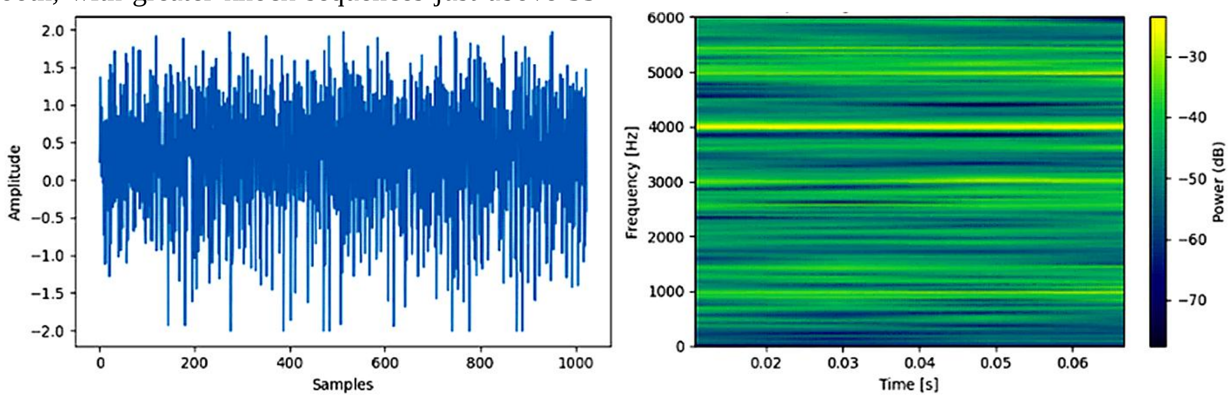

Figure 11: Time-Domain and Spectral Features of an Outer Race Fault in Rotating Machines

The outer race fault's time-domain waveform (left) is seen in Figure 11; it shares a dense pattern with the inner race fault, but the outer race 'e' faults cause a comparatively continuous periodicity. According to the spectrogram, the outer race fault has strong frequency responses at 1000, 3000, and 4500 Hz together with power values of around -30 dB. Accelerations were suggested by the fault's spectral bands, which were sharper and brighter than usual. In transfer learning-based fault detection and classification models, the outer race fault is distinguished from "healthy" and "Normal" by this significant increase in spectral energy and time-domain oscillations

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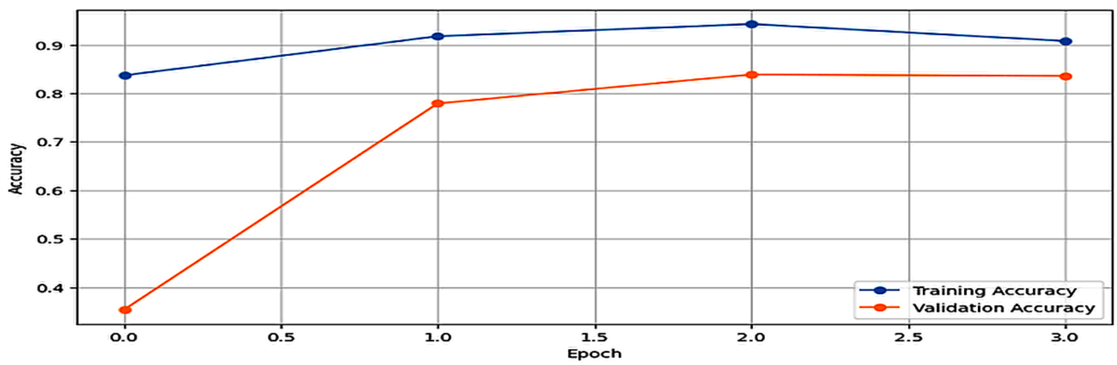

Figure 12: Training and Validation Accuracy Trends of ResNet50 for Multi-Fault Diagnosis in Rotating Machines

The performance of ResNet50 on fused vibration datasets is shown in Figure 12. With minor overfitting, the training accuracy starts at 83.5% (epoch 0), increases to 94.2% at epoch 2, and then drops to 90.5% at epoch 3. Beginning at 35.4% (epoch 0), validation accuracy sharply increases to 77.8% at epoch 1 and 83.6% by epochs 2 and 3. The decreased training-validation curve gap after epoch 1 indicates the model's improved generalisation when learning defect features from fused datasets. Data fusion and transfer learning can accurately identify a variety of rotating equipment defects, as shown by the consistently high training performance and convergent validation accuracy of 83%.

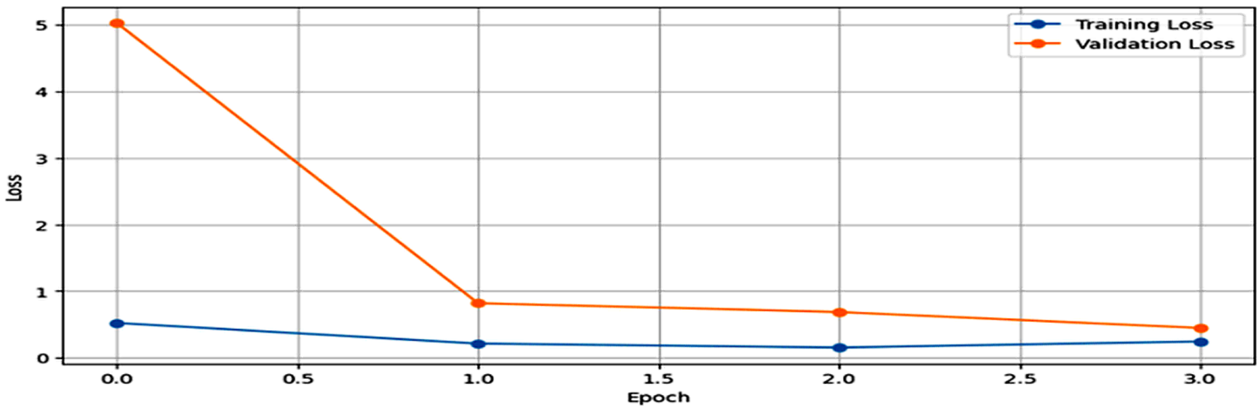

Figure 13: Training and Validation Loss Curves of ResNet50 for Fault Diagnosis in Rotating Machines

The convergence of ResNet50 is shown in Figure 13. At epoch 0, the training loss is 0.54 and the validation loss is 5.02. This implies early challenges with generalisation. By epoch 1, training loss lowers to 0.22 while validation loss drastically decreases to 0.85, demonstrating rapid fault-related feature learning. As training loss stabilises between 0.18 and 0.25 and validation loss decreases from 0.72 (epoch 2) to 0.45 (epoch 3), training and validation performance align better in subsequent epochs. The model learns fault-specific patterns and generalises effectively to unknown data, as shown by the low training loss and rising validation loss. This demonstrates how data fusion and transfer learning may stabilise the diagnosis of rotating machine problems.

8 Conclusion

This study demonstrates a fault diagnosis system for rotating machinery using a data fusion approach with ResNet50 as the base model by using transfer learning, The fusion of vibration and acoustic and temperature sensor data improved fault detection accuracy which achieved a total fusion accuracy of 99 percent. The data from various sensor types were combined using transfer learning which enabled us to improve the pre-trained model through weight usage because we had limited labeled data that contained all fault types thus our classifier performed better with different fault types which included an inner race fault and an outer race fault and no fault. The study achieved high precision and recall measurements throughout the research process because the inner race fault recall reached 1.00. Our results support the case for data fusion which enabled the model to generalize well under various operating conditions and successfully applied real-time intensity and reliability for fault detection. Our future research will enhance model robustness through class imbalance solutions that use SMOTE techniques and through investigation of CNN-LSTM hybrid models and through dataset expansion which will add more complex fault examples to our existing dataset. Future directions will also focus on optimizing systems for edge computing and applying to larger datasets in industrial contexts to enhance the field-scalability and applicability of our model which will enable industrial machinery to shift from traditional prognostics to advanced predictive maintenance systems.

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