

Efficient Method for Gearbox Fault Diagnosis Under Variable Speed Conditions Using WVD Based Time Frequency Information of Vibration Signals and Deep Learning

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Abstract – The gearbox fault diagnosis under variable speed remains one of key challenges in industrial domain due to the nonlinear and time-varying nature of vibration measurements. In this paper, a highly-efficient hybrid method that combines the Wigner-Ville Distribution (WVD) based time-frequency representation and deep learning model to improve the accuracy of fault detection is suggested. WVD converts the signals of vibration to rich time-frequency representations in which complex fault-based patterns are recorded. We use an Attention-Based Convolutional Neural Network (Attention-CNN) to be able to extract useful features out of these representations, with `_attention_` giving priority to the most pertinent areas. The features so extracted are further fed to an effective Random Forest (RF) model, and this effectiveness minimizes overfitting and maximizes the generalizability even across the changing speed settings. A comparative analysis of the proposed model is performed with vibration data of a publicly available gearbox fault dataset, which is outperforming the traditional techniques. The results show that the method is expecting 99.73 per cent accuracy, higher than the available methods of machine and deep learning. In addition to the above, a flexible measurement procedure is proposed to examine the fault diagnosis reliability under various loads to verify robustness in a real-life condition. The results support the fact that the suggested approach can enhance the gearbox condition monitoring and predictive maintenance approaches.

Keywords – Gearbox Fault Diagnosis, WVD-Based Time–Frequency, Vibration Signals, Deep Learning.

I. INTRODUCTION

Gearbox mechanisms are essential in various aspects of the industry in automotive, aerospace and manufacturing industries among others. Being the essential part of mechanical power transmission, the job of gearboxes is to provide balanced output in torque and speed which leads to the effective work of the machinery [1]. Nevertheless, gearboxes are vulnerable to several faults, which include tooth gears breakage, improper alignment, lack of oil, etc. These faults have the tendency to cause mechanical failures that are disastrous in the event that they are not detected earlier on hence costing an industrial organization money in terms of downtime, lower productivity, and creating safety hazards. It is therefore necessary to formulate reliable and accurate fault diagnosis methodologies of predictive maintenance and condition monitoring in gearboxes systems [2,3]. Traditional methods to fault diagnosis of gearbox mainly make use of time-domain, frequency-domain, and statistical signal processing-based methods [4]. Root mean square (RMS), measurement of the peak-to-peak value, and the measurement of kurtosis are considered time-domain analysis techniques that provide only slight knowledge of more complex vibration patterns. Periodic fault signals have a tendency of detection technique includes frequency-domain techniques such as Fast Fourier Transform (FFT) and spectral analysis, which demonstrate limited capabilities of representing the nonlinear, transient and non-stationary nature of gearbox failures [5]. An alternative method Wavelet Transform (WT) has also been utilized, and gives better time-frequency resolution. The fact that it uses predetermined basis functions and is susceptible to noise has a problem in proper identification of the changing fault patterns under changing operational conditions [6,7]. In order to surmount these

drawbacks, time frequency analysis methods have been given a great market in gearbox fault identification. Among them, the Wigner-Ville Distribution (WVD) can also be cited as an efficient approach to analyze non-stationary signals since it gives a high-resolution description of time and frequency simultaneously [8]. Relative to the traditional spectrogram-based schemes, the WVD has been found to be highly effective to extract transient event and the non-linear dynamics of vibration signals, and therefore suits the fault detection task in complicated mechanical systems. Raw time frequency representations are however not adequate in robust classification and thus to automate the fault detection process we have to rely on advanced feature extraction and machine learning to extract the desired feature so as to classify well and come up with effective solutions [9]. Cases of Deep learning have been defined as a useful fault diagnosis technique such that it can automatically generate meaningful patterns in raw data without the process of manual feature engineering. Specifically, CNNs have proved to perform awesomely when it comes to image-based image fault detection applications as they acquire hierarchy feature representations [10]. Nevertheless, typical CNN models might not perform well where long-dependency is expected as well as the ability to detect minute fault-related features using time frequency images. Within this challenge, one might add attention mechanisms to CNN architecture to concentrate on the most valuable parts of the input data to enhance the interpretability and overall classification performance of the given model. The machine learning algorithms like Random Forest (RF) can be additionally used to finalize the classification, whereby ensemble learning methods are used to increase the resistance to noisy data and filter against over-fitting [11,12]. In this study, we propose an advanced hybrid approach that integrates WVD-based time-frequency analysis with deep learning and machine learning techniques for gearbox fault diagnosis. To validate the effectiveness of the proposed approach, we conduct extensive experiments using a publicly available gearbox fault dataset, considering multiple load levels (0%, 30%, 60%, and 90%). The proposed model achieves a classification accuracy of 99.73%, significantly outperforming conventional machine learning and deep learning techniques, such as Support Vector Machines (SVM), standard CNNs, and Wide-Kernel CNNs. Additionally, the study introduces an adaptive evaluation framework to assess fault detection performance under varying operational conditions, ensuring robustness in real-world applications.

The Key Contributions of This Research are Expressed in the Following

Proposing an efficient hybrid method for extracting time-frequency features from vibration signals, where the Wigner-Ville Distribution (WVD) serves as a high-precision time-frequency analysis tool. This approach generates rich visual representations of gearbox vibration signals, enabling the identification of complex and nonlinear fault-related patterns with improved clarity and accuracy. Introducing an advanced algorithm based on an Attention-Based Convolutional Neural Network (Attention-Based CNN) for analyzing and extracting meaningful features from the generated visual representations. The integrated attention mechanism dynamically highlights the most informative regions within the time-frequency images, enhancing the recognition of long-term dependencies and improving the accuracy of fault-related feature extraction in real-world gearbox conditions. Developing a robust Random Forest (RF)-based classification framework, which leverages the extracted features from the Attention-Based CNN to achieve optimized fault classification. By employing random feature selection and aggregating multiple decision trees, this approach mitigates overfitting and enhances the model's generalization capability when dealing with noisy and variable data. Presenting an adaptive evaluation method for analyzing the model's performance under different load conditions, incorporating the impact of load and speed variations on vibration signals. This method adaptively assesses system behavior across various load levels, ensuring the reliability and stability of the proposed approach in real industrial environments.

The remainder of this paper is organized as follows: Section 2 reviews related works in gearbox fault diagnosis. Section 3 details the proposed methodology, including time-frequency feature extraction, deep feature learning, and classification techniques. Section 4 presents experimental results and performance analysis under different load conditions. Finally, Section 5 concludes the study and outlines future research directions.

II. RELATED WORKS

In [13] authors introduce a multibranch time-frequency spectrum segmentation network (TFSSN) model, which integrates an adaptive segmentation algorithm and a multipath fully connected attention (MPFCA) module to extract and fuse features from multiple meshing frequencies. Experimental results demonstrate that TFSSN effectively addresses overfitting in sparse fault sample scenarios, achieving superior accuracy (0.982) and F1 score (0.99) compared to conventional methods, thus advancing the robustness and precision of gearbox fault diagnosis.

In [14], the authors introduce a deep neural network (DNN)-based framework for monitoring gearbox conditions and forecasting potential failures. Six data-mining algorithms—k-nearest neighbors, least absolute shrinkage and selection operator, ridge regression, support vector machines, shallow neural network, and DNN—are utilized to model lubricant pressure. A comparative analysis shows that the DNN model delivers the highest accuracy. Computational findings demonstrate that prediction errors exhibit notable changes before gearbox failures, which are identified using an exponentially weighted moving average (EWMA) control chart.

In [15] authors propose a novel gear fault diagnosis method based on WSET-CNN-BKA-LSSVM. The Synchro extracting Transform (SET) is introduced to enhance and extract subtle features from gear vibration signals, particularly for rolling bearings. These enhanced signals are then processed by a Convolutional Neural Network (CNN) for further

feature extraction. Black Kite Algorithm (BKA) is used to dynamically optimize the kernel function parameters and the penalty factor of the Least Squares Support Vector Machine (LSSVM), and a solid fault diagnosis model is formed. The experimental outcomes revealed that the suggested model can attain a high diagnostic accuracy and computational efficiency. In [16], the authors offer a multiscale lifting wavelet contrast network, interpretable, uniquely designed toward fault diagnosis in planetary gearboxes. It involves the combination of an interpretable multiscale lifting wavelet network so as to extract an important set of features over fault signals. It also incorporates an interactive channel attention system to select feature maps depending on the frequency components to enhance their interpretability in addition to their accuracy. Besides, the loss of contrast of time-frequency contrast loss optimizes feature distribution within the time-frequency plane.

In [17], authors suggest a model of MTF-ECA-ResNeXt fault detection aimed at gearboxes. First, Markov Transition Fields can be used to convert collected vibration signals to two-dimensional feature maps. Such images are subsequently smashed via a pixel averaging algorithm and supplied into the ECA-ResNeXt neural network to discover the fault and classify it. The usefulness of the model is confirmed on the figures of Drivetrain Dynamics Simula gearbox. Moreover, noise resistance experiments and ablation experiments are carried out in order to measure overall robustness and generalizability of the method.

In [18], authors use transfer learning by implementing the VGG16 model used in image recognition to diagnose gears of wind turbines. Discrete wavelet transform converts time-domain vibration signals to two-dimensional time frequency maps. They then use the Efficient Channel Attention (ECA) module to minimize the loss of feature dimensionality as well as maximize channel-channel feature interaction that increases diagnostic accuracy. Through the transformed pictures, the model is entered in a deep transfer learning model, where the weights of migration and model structure are fine-tuned throughout the experiments.

In [19], the authors presented a complex deep learning-powered methodology in anomaly detection on industrial equipment. Vibrational analysis is a very important tool used by the system in making maintenance decision. Analysis of gearbox data begins with analysing the gearbox dataset and deriving relevant insights. Studying vibration characteristics of the machine, the researchers hope to identify the nature of potential defects and their levels of severity, so anomalies could be detected in early stages. Since the deep learning techniques are best used to isolate the fault signature in gearbox vibration signals, the vibration using deep learning is a suitable method when dealing with gearboxes.

In [20] In this respect, authors strive to minimize operational disturbances and financial losses using a new neural network model on the vibration data of the Gearbox Fault Diagnosis Dataset that can be found in Kaggle. The method includes the data preparation such as normalization and one-hot encoding after which a sequential neural network with multiple dense layers and dropout regularizing is developed. The model trained in the Adam optimizer in 50 epochs can achieve high accuracy when detecting the healthy or defective states of gears, which is better than using traditional machine learning methods.

In [21], In this respect, authors strive to minimize operational disturbances and financial losses using a new neural network model on the vibration data of the Gearbox Fault Diagnosis Dataset that can be found in Kaggle. The method includes the data preparation such as normalization and one-hot encoding after which a sequential neural network with multiple dense layers and dropout regularizing is developed. The model trained in the Adam optimizer in 50 epochs can achieve high accuracy when detecting the healthy or defective states of gears, which is better than using traditional machine learning methods. In [22], the authors introduce an unsupervised fault detection methodology named Frequency-wise Angular Filtering (UFAF) which aims at supporting the detection of faults found within a noisy vibration signal. UFAF is used to extract angular features to supply approximation of normal samples to be only used in model training stage.

The filtering procedure will be repeated in every epoch, which will be narrowing down to applying the high-quality normal samples. The results of the conducted experiments on the Spectra Quest gearbox dataset sets prove the high performance of the method with the contaminated signals as well proves the quality of angular features helping to identify normal and fault states.

III. PROPOSED METHOD

In the present paper, a powerful model on the diagnosis of the faults in the gearbox in the variable speed environment will be proposed which is operated on the basis of the time-frequent characteristic extractions of gearbox vibration signals collected on an automobile gearbox. In order to compare the performance of gearbox under mechanical stress at various speeds, the proposed method is specifically aimed at detecting fault under varying load conditions to determine the effectiveness of the system at various gearbox speed. In the suggested method, initial data are extracted to the publicly available database, and vibration transients are separated accordingly. These signals are then processed via visualization using time-frequency features extraction. The signals visualized are converted into spectral images in the form of Wigner-Ville distribution (WVD) so that visualization in left allows extraction of time-frequency patterns and interpretation. Such images of the Wigner-Ville distribution are finally processed using a convolutional neural network (CNN) to obtain valuable frequency-time patterns. Lastly, the features are extracted through a random forest algorithm with a gearbox fault classification. Random forest algorithm uses stochastic methods in feature and data selection, which is effective in preventing overfitting (i.e. overshadowing response to training data). Moreover, the random forest itself

will generate numerous decision trees but will combine the results; hence the error will be less, and the result will be more consistent and robust. The flowchart of the proposed approach is demonstrated in **Fig 1**.

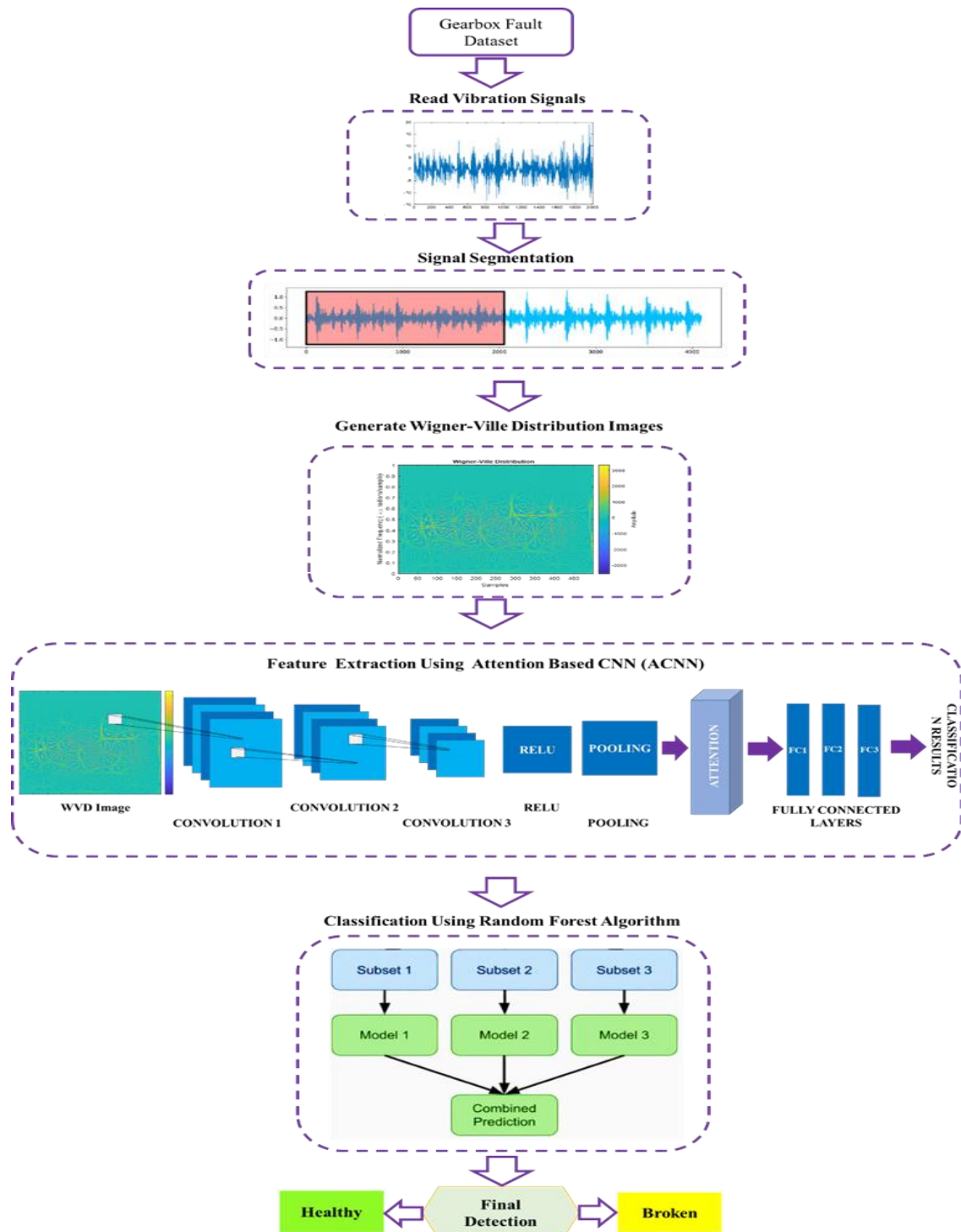


Fig 1. Flowchart of the Proposed Method.

Read Dataset and Data Preparation

For gearbox fault detection, this study utilizes vibration signals obtained from the Openai Gearbox Fault Database, which is also publicly available on Kaggle. This dataset contains vibration signals recorded under predefined conditions. The dataset includes two primary classes: (i) healthy gearbox and (ii) faulty gearbox with broken tooth. The healthy condition represents normal signals, while the broken-tooth condition represents fault signals. The signals are recorded under varying load conditions ranging from 0% to 90% torque. Torque refers to the applied load on the gearbox shaft. At higher

torque levels (lower speeds), greater force is required to transmit power, increasing the stress on the gears and other gearbox components. Conversely, at lower torque levels (higher speeds), less force is needed for power transmission, reducing the load on the gearbox. These variations in load directly impact the gearbox's lifespan, component wear, and overall transmission system efficiency. To evaluate the gearbox's response to mechanical stress across different speeds, this study conducts fault detection under load conditions of 0%, 30%, 60%, and 90%. The goal is to analyze the proposed system's performance under various operating speeds. **Fig 2** presents segments of vibration signals corresponding to healthy and faulty gearboxes under 0% and 90% load conditions. **Fig 2(a)** shows A vibration signal segment for a healthy gearbox under 0% load. **Fig 2(b)** represents A vibration signal segment for a faulty gearbox under 0% load. **Fig 2(c)** shows A vibration signal segment for a healthy gearbox under 90% load and **Fig 2(d)** represents A vibration signal segment for a faulty gearbox under 90% load.

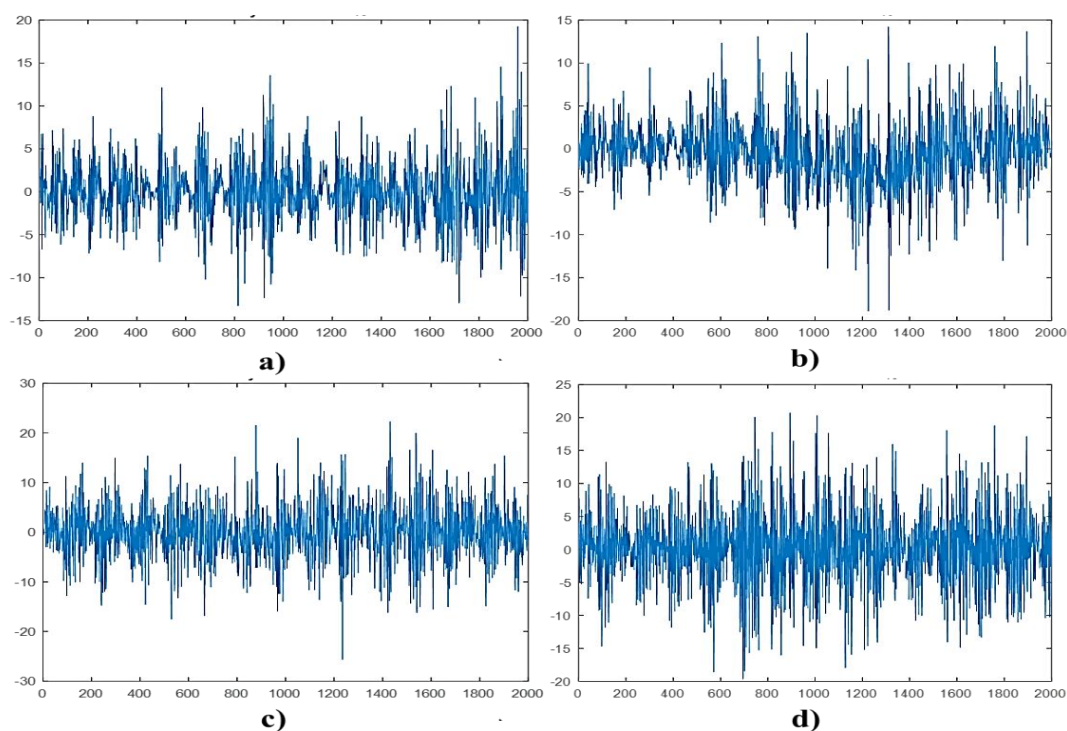


Fig 2. Vibration Signal Samples for Healthy and Faulty Gearboxes Under 0% and 90% Load.

The data to be prepared: the data-performance of a vibration signal is subdivided into sections of predetermined length allowing a time-frequency dimension characteristic to be extracted by analysis of a fault. The signal is cut into small pieces, which can be investigated more in detail and in this way, the peculiarities of the signal can be defined. This segmentation activity also increases the ability of identifying faults that might have occurred earlier helping to investigate each segment more closely. Fixed-size windowing is shown as an example of segmentation process in **Fig 3**.

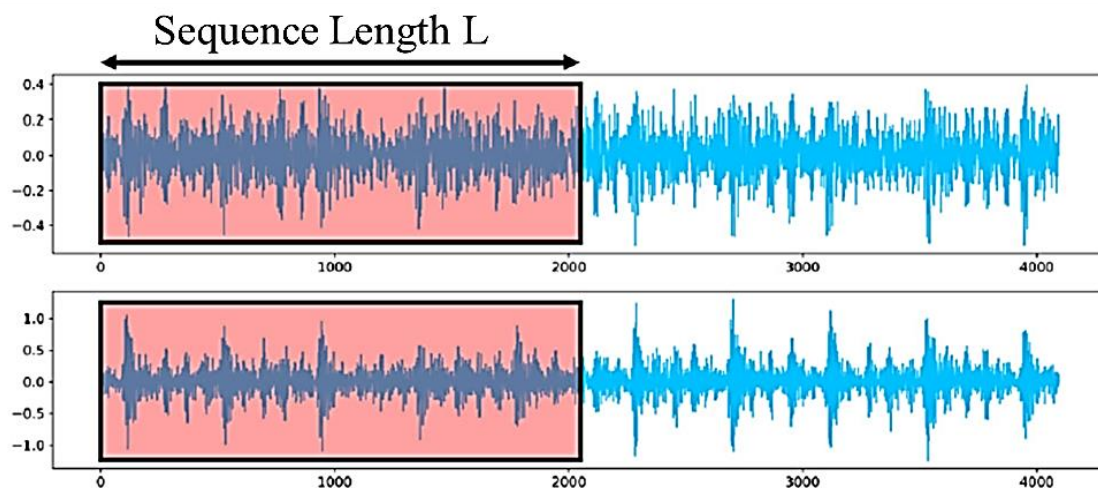


Fig 3. Example of Signal Segmentation Using Fixed-Length Windows.

Data Visualization Using Wigner-Ville Distribution (WVD)

Wigner-Ville transform or WVT is a mathematical method of processing non-linear and time-varying signals. It finds application especially in signal processing and dynamic systems analysis. This transformation makes it possible to make analysis of the time varying signal and therefore one can be able to make analysis on how a signal behaves with time. Wigner-Ville distribution carries the information about frequency in finer detail to each time point and is usually represented as a 2 dimensional function, with time on the horizontal axis and frequencies on the vertical axis. This indication enables one to observe the changes in frequency in the course of a signal.

The Wigner-Ville distribution function $w_x(t, f)$ at time T and frequency f is defined as follows:

$$w_x(t, f) = \int_{-\infty}^{+\infty} x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau \quad (1)$$

Where; $x(t)$ is the signal, $x^*(t)$ denotes its complex conjugate and τ represents the time delay variable.

The proposed method of analyzing the gearbox fault using Wigner-Ville distribution as a time-frequency analysis tool has been used to detect faults in gearbox based on the extraction of feature in vibration signals. Among the most important implications in this transformation would be the possibility to see how the frequency changes with time which is vital industrially and in the engineering field where abrupt changes and sudden alterations in the material behavior are important factors to be identified to mark faults. The application of the Wigner-Ville transform allows relating frequency drifts in the signal received and the changes in reception fluctuations over the time, which helps identify patterns related to faults. This transformation also gives statistical data on energy distribution of the signal which can be utilised by machine learning models to identify early stage faults in gearboxes. Looking at temporal dependencies, and energy changes in the signal would permit locating the origin of faults and determining type of faults particularly when the fault is developing with time. The Fourier transform derived based on spectrogram has some tremendous limitations in comparison to the Wigner-Ville that allows meaningful feature representation in the vibration signals. Whereas a spectrogram is limited to the general information on the frequency during a period of time, it cannot map the dynamic pacing of frequencies. Wigner-Ville distribution gives a two dimensional time frequency representation in contrast which allows a better analysis of the potential fluctuation in the frequencies.

It is especially useful in the case of the vibration signal, which is frequently prone to nonlinearities and different complexities. In addition, the Wigner-Ville transform has a nonlinear analysis ability, and hence more complex fault patterns can be detected such as due to structural modifications and gradual damage of gearboxes. **Fig 4** provides an example of segmented vibration signals and their respective Wigner-Ville distribution.

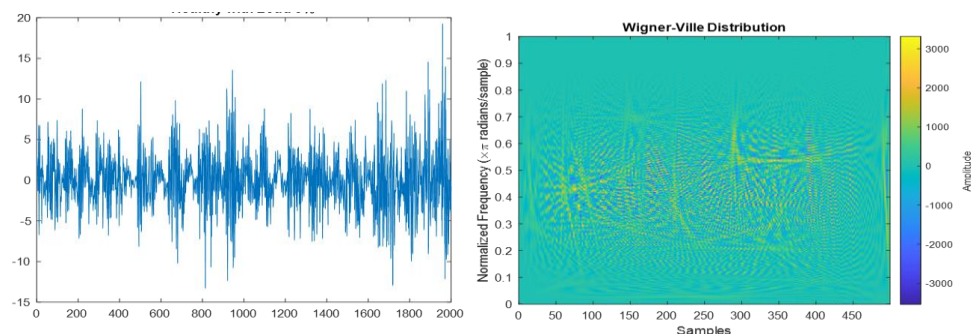


Fig 4. Example of Segmented Vibration Signal and Corresponding Wigner-Ville Distribution.

Feature Extraction Using Deep Convolutional Neural Network

Here, an attention-based convolutional neural network (ACNN) will be used to carry out feature extraction of time-frequency patterns that are visualized in visual representation of the Wigner-Ville transformation (WVD). As an input, the visualized information is supplied into the ACNN, through which, the network is shown to capture the spatial features on the visualized information. The convolutional neural networks (CNNs) can acquire complex features of images with convolutional layers, and wildly recognize time-frequency pattern about gearbox faults in Wigner-Ville distribution images. In addition, the ACNNs have the ability to detect multi-scale features, that is, they are able to identify the patterns at the various scales of the image.

The ACNN uses attention layers to enhance the accuracy of the model because it can highlight the most informative aspects in the input data. Moreover, such layers filter out the impact of noise and other irrelevant data and help to recover more interesting features. The attention operation enhances the model ability to identify long-term temporal dependence so that it can derive more complicated time-frequency relations. Lastly, through the different weights they give to different components of the signal, the attention layers allow the model to make more informed and precise decision. A very common neural architecture is deep convolutional neural networks (CNNs). There are two key differences in CNNs and traditional artificial neural networks (ANNs): input data type and model architecture. ANN classically works with numerical data, and the CNN mainly works with image data. A digital image consists of a lot of pixels, the number of

which depends on the width (w) and height (h) of the picture and its depth (d). Scaling of the images starts with these 3 parameters. The depth of an image varies depending on the color model employed. For example, in the RGB color space, which utilizes three distinct color channels, the image depth d is equivalent to three. The ACNN model architecture consists of convolutional, fully connected, and pooling layers in sequence. **Fig 5** illustrates the ACNN structure implemented in this study for gearbox fault diagnosis using vibration signal images.

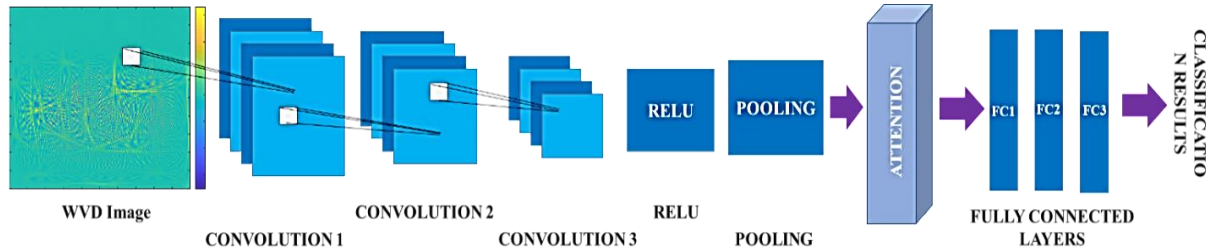


Fig 5. ACNN Architecture Used for Gearbox Fault Diagnosis.

In convolutional neural networks, filters (also known as kernels) are employed in convolutional layers to analyze and extract specific features from input images. The convolution process involves a mathematical transformation of each image pixel in conjunction with a kernel k , which is a $p \times p$ matrix. This operation is symbolized by the convolution operator $*$.

$$k * I_{x,y} = \sum_{i=1}^p \sum_{j=1}^p k_{i,j} \cdot I_{x+i-1,y+j-1} + b_1 \quad (2)$$

where b_1 represents the bias term. The pooling layer serves to reduce the image file size. It employs a function $\omega(\cdot)$ that examines each pixel along with its adjacent pixels, applying operations such as minimum, maximum, or average calculations. The resulting pixel from this function is then incorporated into a more compact image. For clarity, we can express this process as follows:

$$\omega(I_{x,y}) = \max_{i,j \in \{-1,0,1\}} I_{x-i,y-j} \quad (3)$$

Image resizing calculations can be represented by the formula $(w-k)/(s+1) \times (h-k)/(s+1)$, where s represents the kernel shift. These resizing layers may be applied multiple times before reaching the fully connected layer, which is positioned at the end of the model's structure. This architectural design includes several hidden layers and a single output layer. The attention module in the proposed ACNN is implemented as a weighting function $A(x)$, which modifies the significance of extracted features. The attention model can be formulated as follows:

$$A(x) = \sigma(W_2 \cdot \text{ReLU}(W_1 x + b_1)) + b_2 \quad (4)$$

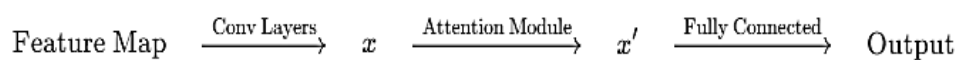
where:

- x represents the feature vector extracted from convolutional layers.
- W_1 and W_2 are weight matrices.
- b_1 and b_2 denote bias terms.
- ReLU (Rectified Linear Unit) is a nonlinear activation function, aiding the model in learning complex dependencies.
- σ is the sigmoid activation function, which normalizes attention weights between 0 and 1.

To obtain the refined features x' after calculating the attention weights it can be done as follows:

$$x' = A(x) \odot x \quad (5)$$

where $\odot$ denotes element-wise multiplication. This operation enhances important features while suppressing irrelevant information. The process is as follows:



The attention mechanism has a considerable effect of improving the model accuracy in classification and interpretability. It enhances detection of long-term temporal dependencies and makes multi-scale features extraction possible by assigning more weight to important regions. As a result, this method makes the model to be more accurate when examining the intricate patterns and minimizes noise in data. Image processing of time-frequency images based on

the Wigner Ville distribution have been in use in the industrial realm (such as gearbox faults detection), and the attention mechanism has found great utility in processing these images.

Classification Using the Random Forest Algorithm

Here, the Random Forest classifier is applied to diagnose the faults in gearboxes with data classification made possible by bootstrapping and aggregating procedures. These methods entail creation of subsets of the initial dataset, and then, this dataset is designated to separate classifiers. What this indicates is that each individual classifier will work on only a portion of the data, and develop the model using the subset allocated to it. The subsets are relections are based on the sampling with replacement, where each sample has a possibility to be picked at least twice. Using this classification method, the overfitting of the model will be minimized and hence resulting to the increased learning ability of the model and an advancement in the accuracy of the classifications of different sets of data [23]. **Fig 6** shows an overall operation of this technique.

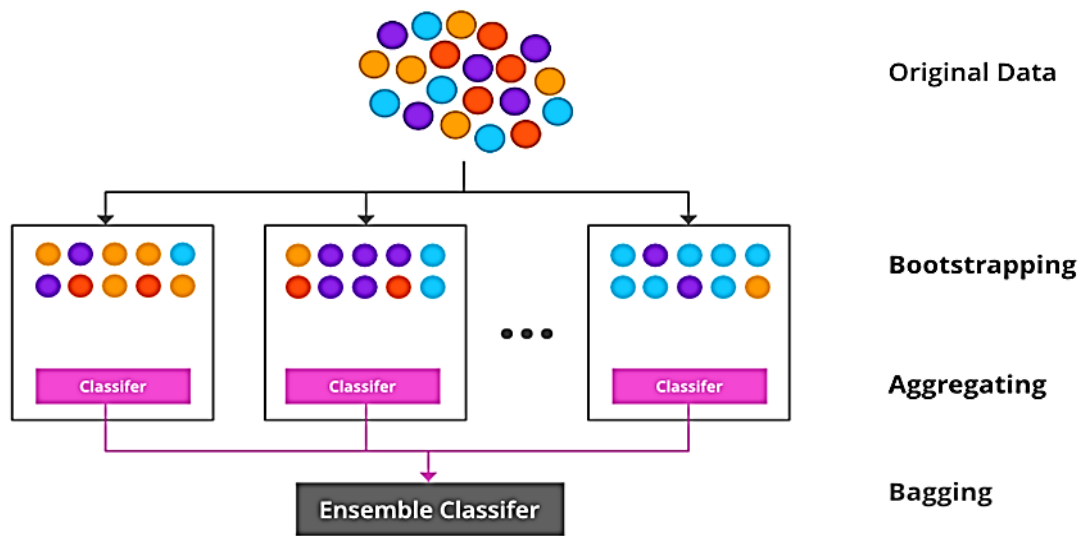


Fig 6. Classification Model Using the Random Forest Algorithm.

IV. EXPERIMENTAL RESULTS

In this part, the efficiency of the suggested procedure is verified by the accepted measures of performance, and its the classification accuracy rate is demonstrated in comparison with other known techniques. The model is constructed in MATLAB (2024a) and requires an NVIDIA graphic card with uninterrupted RAM of 6 GB to operate. In order to perform a performance assessment, the weighting of the gearbox by vibration signal is used to determine the state of a gearbox as being either healthy or faulty. The vibration signal is divided into the samples of 500 points each. The healthy and faulty set classes possess 160 partitioned vibration signs. In order to enhance the learning process, data augmentation is used, where the number of feature vectors per class is loaded to 640. Each vibration signal is then analyzed to extract the features of the signal through Wigner-Ville Distribution (WVD) and the resultant corresponding visual features generated. In order to perfect such images, a process of automatic cropping is used to shave unnecessary white spaces on the Wigner-Ville distribution images. The pictures are afterwards scaled down to 227*227*3 pixels, in order to concentrate on areas of interest within the Wigner-Ville distribution. In the course of simulations, Wigner-Wille distribution images are used to train a Convolutional Neural Network (CNN) of 70 percent. Based on every image, 1,000 features may be detected with the CNN and afterward discriminated with the Random Forest algorithm. Also, k-fold cross-validation (k=10) is applied to determine the classification accuracy by splitting all data into 10 subsets after each of them had been referred to as validation data once; the rest of the data are used in training. It should be mentioned that prior to dividing it into training and testing datasets, the dataset is shuffled randomly. The results, as presented in a form of a table, are the mean performance of the 70 independent runs of the experiment.

Evaluation Metrics

The following evaluation measures were used in this research to assess the model's classification performance:

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (6)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (8)$$

$$\text{F1 - score} = \frac{2PR}{(P+R)} \quad (9)$$

where:

TP (True Positives) refers to correctly identified faulty gearboxes.

FP (False Positives) represents non-faulty gearboxes incorrectly classified as faulty.

TN (True Negatives) indicates correctly identified non-faulty gearboxes.

FN (False Negatives) refers to faulty gearboxes misclassified as non-faulty.

Evaluation of the Proposed Method Under Different Load Conditions

Table 1 presents the performance of the proposed method across different load levels (0%, 30%, 60%, and 90%), based on Accuracy, Precision, Recall, and F1-score. The results indicate that the optimum performance was yielded at 90% load, with values of 99.78% (Accuracy), 99.90% (Precision), 99.60% (Recall), and 99.74% (F1-score). Conversely, the lowest performance was observed at 0% load. As the load increases, classification performance improves. This can be attributed to the fact that higher loads induce greater mechanical stress and vibrations in the gearbox, resulting in more pronounced fault patterns in the recorded data. At lower loads, some faults may remain subtle and difficult to detect. However, under higher loads, the effects of gear meshing interactions, friction, and wear become more pronounced, facilitating better fault recognition by the proposed model.

Table 1. Performance of the Proposed Method Under Different Load Conditions

Load	Accuracy	Precision	Recall	F-score
0	99.21	99.60	98.93	99.26
30	99.44	99.73	99.01	99.36
60	99.61	99.79	99.41	99.59
90	99.78	99.90	99.60	99.74

Evaluation of the Proposed Approach and Comparative Analysis

In this section, the performance of the proposed method is analyzed based on various evaluation metrics. First, the learning process of the Random Forest algorithm is assessed. **Fig 7** illustrates the learning curve of the Random Forest algorithm for different numbers of trees. As shown in this figure, increasing the number of trees enhances the learning process (i.e., accuracy) during training. The accuracy continues to improve until it converges to 100% when approximately 18 trees are considered.

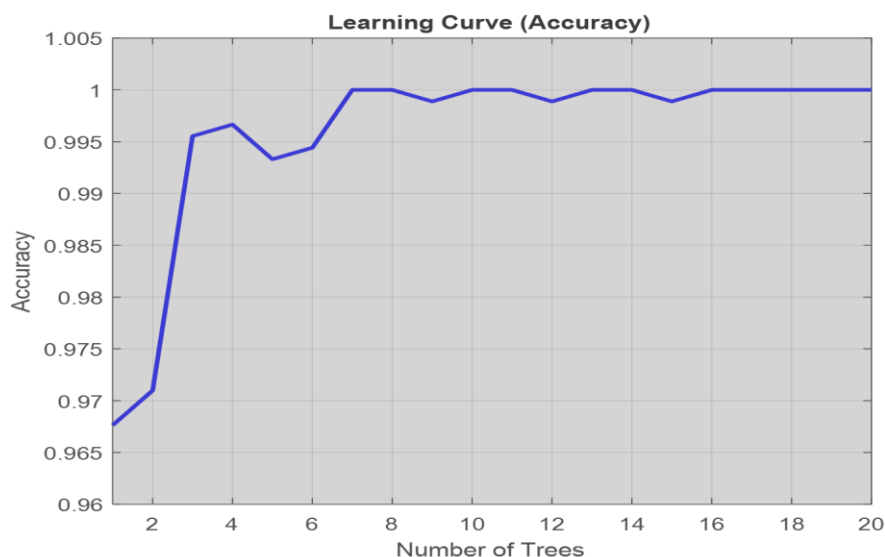


Fig 7. Learning Curve of The Random Forest Algorithm with Different Numbers of Trees.

Fig 8 presents the confusion matrix obtained from the simulation of the suggested approach for gearbox fault diagnosis using vibration signals. As observed, the proposed method demonstrates high accuracy in identifying gearbox faults. The values along the main diagonal of the matrix represent the number of correctly classified samples for each

class. Specifically, Class 1 (Healthy Gearbox) and Class 2 (broken Tooth Gearbox) are identified with accuracies of 100% and 99.4%, respectively. The classification error rate, indicated by the red values, is extremely low, which highlights the strong performance of the proposed method in detecting gearbox faults based on vibration signals.

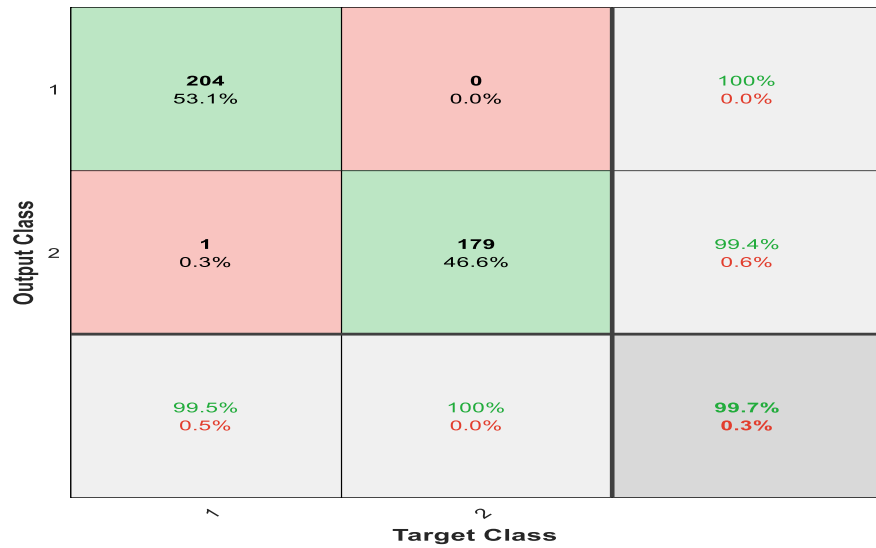


Fig 8. Confusion Matrix Obtained from The Classification of Test Data.

A Receiver Operating Characteristic (ROC) curve, which is built using two important metrics—True Positive Rate (TPR) and False Positive Rate (FPR)—can be used in machine learning to display the performance of a binary classifier at various decision thresholds. The TPR depicts the ratio of true positive results that are marked accurately by the model also known as sensitivity, or recall. The FPR on the other hand, which can be written in the following mathematical way, expresses the proportion of negative samples in false positive categorization:

$$\text{FPR} = \frac{\text{FP}}{\text{TN} + \text{FP}} \quad (10)$$

By plotting the two measures true positive rate (TPR) vs false positive rate (FPR) at each possible threshold, the relationship between the two will emerge. A good classifier should be on the top-left quadrant of the ROC chart since its values of TPR and FPR are big and small respectively. Conversely, a weak classifier is closer to the bottom-right corner, where TPR is low and FPR is high. A random classifier is positioned at the curve's diagonal, as it produces identical TPR and FPR values. **Fig 9** illustrates the ROC plot for the presented approach. As shown, the curve is positioned close to the top-left corner, indicating a high TPR and a low FPR. This result confirms that the proposed model is capable of accurately classifying gearbox faults with a high degree of precision.

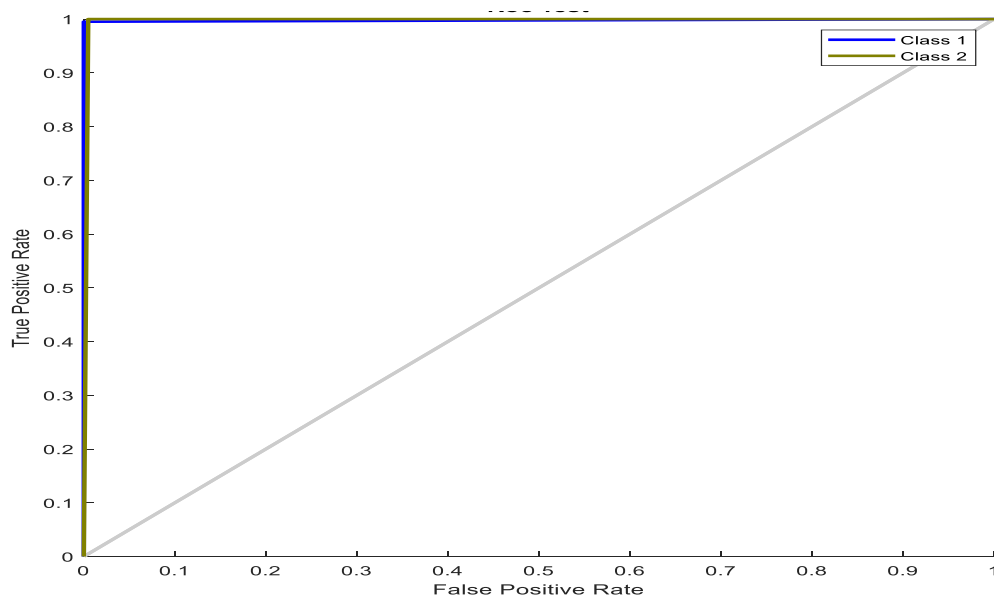


Fig 9. ROC Curve.

Fig 10 presents a relative evaluation of the proposed model against Support Vector Machine (SVM) [19], Deep Learning [19], Neural Networks [20], Wide-Kernel CNN [21], and UFAF [22], based on the F-score, Recall, and Precision metrics. As illustrated in this figure, the proposed approach achieves the highest performance, with scores of 99.74, 99.73, and 99.73 for Precision, Recall, and F-score, respectively. Additionally, after the proposed approach, the Wide-Kernel CNN [21] exhibits the best performance among the compared methods. The figure also highlights that the lowest Recall and F-score values belong to the SVM method [19], while the UFAF method [22] records the lowest Precision score.

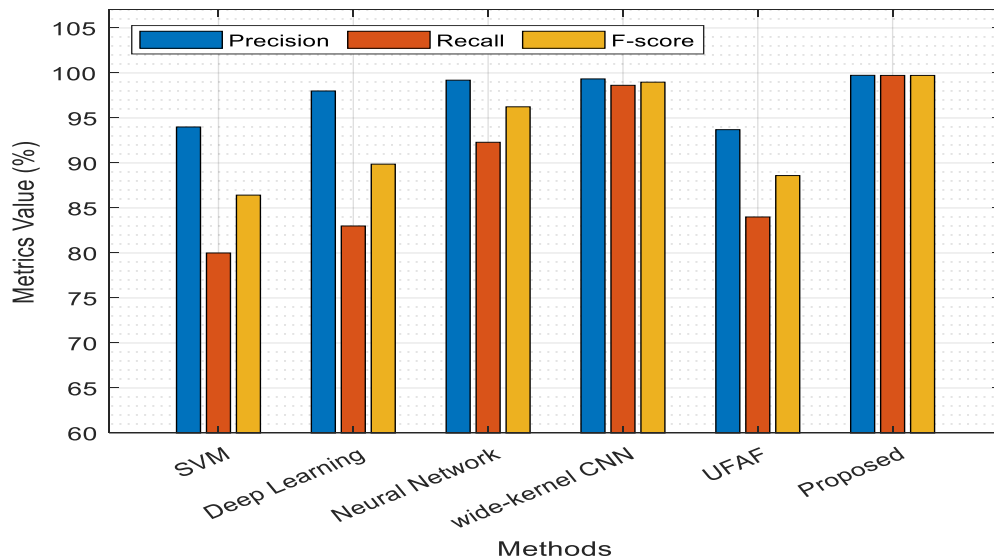


Fig 10. Comparison of the Proposed Method with Other Approaches Based on Precision, Recall, and F-Score.

Table 2 provides a comparative evaluation of the proposed approach against existing methods for gearbox fault detection. As observed, machine learning-based methods, such as SVM and deep learning, deliver acceptable performance, but their reported accuracy rates of 90.00% and 91.00%, respectively, are lower than those of other methods. The Wide-Kernel CNN, proposed by Van Den Hoogen et al. (2024), achieves an accuracy of 99.00%, while the UFAF method, introduced by Byun et al., records an accuracy of 89.20%. Additionally, the Neural Network approach, developed by Mayo, S. A. et al. (2024), attains an accuracy of 98.6%. In contrast, the proposed method, which integrates feature visualization via the Wigner-Ville Distribution (WVD), a Convolutional Neural Network (CNN), and Random Forest (RF), achieves the highest accuracy of 99.73%. These findings prove that the suggested method increases generalization capacity and classification accuracy in the detection of gearbox fault. The CNNs extraction of time-frequency features of the Wigner-Ville distributional images and the efficiency of the RF classifier in optimal decision making are to be credited with the increased efficacy of the suggested technique [23]. These findings underline the fact that the method suggested outshines the currently available ones and can be regarded as a highly effective classification technique to determine the fault in the industrial gearbox systems.

Table 2. Comparing The Suggested Approach Against Other Methods

Author	Method	Year	Ref	Accuracy
Ahmed, I. et al.	SVM	2023	[19]	90.00
Ahmed, I. et al.	Deep Learning	2023	[19]	91.00
Mayo, S. A. et al.	Neural Network	2024	[20]	98.63
Van Den Hoogen, J. et al.	wide-kernel CNN	2024	[21]	99.00
Byun, Y. et al.	UFAF	2024	[22]	89.20
Proposed	CNN-RF	-	-	99.73

V. CONCLUSION

This paper describes an effective approach to the diagnosis of gearbox faults created by varying speeds in conditions of time and frequency based on time and frequency analysis method based on Wigner-Vile Distribution (WVD), deep and machine learning. The suggested solution Between the raw vibration data, the proposed method will convert them into high-resolution time projections with frequency WVD high resolutions to permit the extraction of complex fault-concerning patterns. These forms are fed into an Attention-Based Convolutional Neural Network (Attention-CNN), that can improve the feature extraction by highlighting the most informative time points in the time frequency images. The

derived features are then categorized via a Random Forest (RF) classifier which strengthens the process of generalization and reduces the problem of overfitting. The publicly available gearbox fault data was validated experimentally under different load conditions (0%, 30%, 60% and 90%). As the results indicate, the proposed approach has a high classification of 99.73%, which exceeds the accuracy rates of conventional methods, which are Support Vector Machines (SVM), typical deep learning, and Wide-Kernel CNNs. Also, the research seeks to illustrate the effects of the load condition on the accuracy of fault detection and it is established that under a greater level of load, fault detection is more visible as a result of an elevated level of mechanical stress and vibration. The results support the fact that the suggested method is rather strong and reliable in an industrial context, and they provide a viable approach to predictive maintenance and condition monitoring. Additional signal processing methods and the real-time implementation could also be combined in the future work to support fault detection in more powerful operating conditions

CRedit Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Raied Qaied Ajmi, Layth Saleem Kamal and Ali Jasim Atiyah; **Methodology:** Raied Qaied Ajmi and Layth Saleem Kamal; **Software:** Layth Saleem Kamal and Ali Jasim Atiyah; **Data Curation:** Raied Qaied Ajmi and Layth Saleem Kamal; **Writing- Original Draft Preparation:** Raied Qaied Ajmi, Layth Saleem Kamal and Ali Jasim Atiyah; **Visualization:** Layth Saleem Kamal and Ali Jasim Atiyah; **Investigation:** Raied Qaied Ajmi and Layth Saleem Kamal; **Supervision:** Layth Saleem Kamal and Ali Jasim Atiyah; **Validation:** Raied Qaied Ajmi and Layth Saleem Kamal; **Writing- Reviewing and Editing:** Raied Qaied Ajmi, Layth Saleem Kamal and Ali Jasim Atiyah; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

References

- [1]. S. Suryawanshi, S. Gavali, V. Darwai, S. Patil, A. Wankhede, and A. Borse, "Gearbox Fault Diagnosis: A Comparative Study of Machine Learning and Deep Learning Approaches," *Inventive Communication and Computational Technologies*, pp. 335–349, 2024, doi: 10.1007/978-981-97-7710-5_25.
- [2]. N. S. K. S. K. Ramalinge Gowda, Rayappa Shrinivas Mahale, and A. Patil, "A Review on Gearbox Condition Monitoring and Signal Analysis Techniques," *Scientific Hypotheses*, vol. 1, pp. 36–46, Apr. 2024, doi: 10.69530/15vwy749.
- [3]. Y. Guo, S. Jiang, Y. Yang, X. Jin, and Y. Wei, "Gearbox Fault Diagnosis Based on Improved Variational Mode Extraction," *Sensors*, vol. 22, no. 5, p. 1779, Feb. 2022, doi: 10.3390/s22051779.
- [4]. W. Wen, Y. Bai, and W. Cheng, "Generative Adversarial Learning Enhanced Fault Diagnosis for Planetary Gearbox under Varying Working Conditions," *Sensors*, vol. 20, no. 6, p. 1685, Mar. 2020, doi: 10.3390/s20061685.
- [5]. Q. Xu, H. Jiang, X. Zhang, J. Li, and L. Chen, "Multiscale Convolutional Neural Network Based on Channel Space Attention for Gearbox Compound Fault Diagnosis," *Sensors*, vol. 23, no. 8, p. 3827, Apr. 2023, doi: 10.3390/s23083827.
- [6]. S. Chen, Z. Liu, X. He, D. Zou, and D. Zhou, "Multi-mode fault diagnosis datasets of gearbox under variable working conditions," *Data in Brief*, vol. 54, p. 110453, Jun. 2024, doi: 10.1016/j.dib.2024.110453.
- [7]. X. Wang, Y. Du, and X. Ji, "Gearbox Fault Diagnosis Based on Adaptive Variational Mode Decomposition–Stationary Wavelet Transform and Ensemble Refined Composite Multiscale Fluctuation Dispersion Entropy," *Sensors*, vol. 24, no. 22, p. 7129, Nov. 2024, doi: 10.3390/s24227129.
- [8]. J.-D. Wu, W.-J. Luo, and K.-C. Yao, "Electric Motor Vibration Signal Classification Using Wigner–Ville Distribution for Fault Diagnosis," *Sensors*, vol. 25, no. 4, p. 1196, Feb. 2025, doi: 10.3390/s25041196.
- [9]. D. Aiordăchioaie, "A comparative analysis of fault detection and process diagnosis methods based on a signal processing paradigm," *Discover Applied Sciences*, vol. 7, no. 1, Dec. 2024, doi: 10.1007/s42452-024-06390-3.
- [10]. M. Bessaoudi, H. Habbouche, T. Benkedjouh, and A. Mesloub, "A hybrid approach for gearbox fault diagnosis based on deep learning techniques," *The International Journal of Advanced Manufacturing Technology*, vol. 133, no. 5–6, pp. 2861–2874, Jun. 2024, doi: 10.1007/s00170-024-13873-5.
- [11]. I. Lupea and M. Lupea, "Continuous Wavelet Transform and CNN for Fault Detection in a Helical Gearbox," *Applied Sciences*, vol. 15, no. 2, p. 950, Jan. 2025, doi: 10.3390/app15020950.
- [12]. Afia A, Gougam F, Rahmoune C, Touzout W, Ouelmokhtar H, Benazzouz D. Gearbox fault diagnosis using remd, eo and machine learning classifiers. *J Vib Eng Technol*. 2024;12(3):4673-97. DOI: 10.1007/s42417-023-00613-4
- [13]. H. Song, Y. Sun, H. Gao, L. Guo, and Y. Chen, "Multibranch Time-Frequency Spectrum Segmentation Approach for Gearbox Fault Diagnosis," *IEEE Sensors Journal*, vol. 24, no. 22, pp. 38155–38164, Nov. 2024, doi: 10.1109/jsen.2024.3457878.

- [14]. L. Wang, Z. Zhang, H. Long, J. Xu, and R. Liu, “Wind Turbine Gearbox Failure Identification With Deep Neural Networks,” *IEEE Transactions on Industrial Informatics*, vol. 13, no. 3, pp. 1360–1368, Jun. 2017, doi: 10.1109/tii.2016.2607179.
- [15]. Z. Yuan, M. Qiao, and C. Xu, “Gear Fault Diagnosis Using the WSET-CNN-BKA-LSSVM Method,” *2024 5th International Conference on Electronic Communication and Artificial Intelligence (ICECAI)*, pp. 282–286, May 2024, doi: 10.1109/icecai62591.2024.10675198.
- [16]. Y. Dong, H. Jiang, X. Wang, M. Mu, and W. Jiang, “An interpretable multiscale lifting wavelet contrast network for planetary gearbox fault diagnosis with small samples,” *Reliability Engineering & System Safety*, vol. 251, p. 110404, Nov. 2024, doi: 10.1016/j.ress.2024.110404.
- [17]. X. Zheng, R. Hao, H. Sun, B. Yao, T. Shang, and T. Wang, “Gearbox Fault Diagnosis Based on MTF-ECA-ResNeXt,” *2024 IEEE International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)*, vol. 37, pp. 295–300, Jul. 2024, doi: 10.1109/sdpc62810.2024.10707726.
- [18]. H. Gong, X. Nie, and G. Xie, “Research on Gearbox Fault Diagnosis Method Based on ECA Improved VGG16,” *2024 43rd Chinese Control Conference (CCC)*, pp. 4996–5001, Jul. 2024, doi: 10.23919/ccc63176.2024.10662349.
- [19]. I. Ahmed, M. Ahmad, A. Chehri, and G. Jeon, “A Smart-Anomaly-Detection System for Industrial Machines Based on Feature Autoencoder and Deep Learning,” *Micromachines*, vol. 14, no. 1, p. 154, Jan. 2023, doi: 10.3390/mi14010154.
- [20]. S. Arshad Mayo, S. Rehman, and Z. Cai, “High-accuracy gearbox fault detection using deep learning on vibrational data,” *Journal of Physics: Conference Series*, vol. 2853, no. 1, p. 012066, Oct. 2024, doi: 10.1088/1742-6596/2853/1/012066.
- [21]. J. van den Hoogen, D. Hudson, S. Bloemheuvel, and M. Atzmueller, “Hyperparameter analysis of wide-kernel CNN architectures in industrial fault detection: an exploratory study,” *International Journal of Data Science and Analytics*, vol. 18, no. 4, pp. 423–444, Sep. 2023, doi: 10.1007/s41060-023-00440-6.
- [22]. Y. Byun, D. Maeng, and J.-G. Baek, “Unsupervised fault detection using frequency-wise angular filtering in contaminated vibration signals,” *International Journal of Production Research*, vol. 63, no. 10, pp. 3733–3759, Nov. 2024, doi: 10.1080/00207543.2024.2427895.
- [23]. Z. Hazim Obaid, B. Mirzaei, and A. Darroudi, “An efficient automatic modulation recognition using time–frequency information based on hybrid deep learning and bagging approach,” *Knowledge and Information Systems*, vol. 66, no. 4, pp. 2607–2624, Jan. 2024, doi: 10.1007/s10115-023-02041-y.

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