Discriminative Angle Feature Learning for Open-Set Deep Fault Classification

Dr.Vinoth R
Assistant Professor, Dept. of Computer Science Engineering,
SRM Institute of Science and Technology,
Chennai, India,

M.L. Deepak
UG Scholar, Dept. Computer ScienceEngineering,
SRM Institute of Science and Technology,
Chennai, India,

D.Rajanesh
UG Scholar, Dept. Computer Science Engineering,
SRM Institute of Science and Technology,
Chennai, India,

Sharabu Yogananda
UG Scholar, Dept. Computer Science Engineering ,
SRM Institute of Science and Technology,
Chennai, India,

Abstract-

One of the most important parts of rotating machinery is the gearbox, which is also essential for fault diagnosis. This work overcomes the limitations of using limited features to diagnose gearbox faults by introducing a unique model of gearbox fault diagnosis that makes use of multi-model feature fusion. This is especially important in situations where different gearbox speeds mix complex, unimportant noise components with the vital signals in the vibration data. Therefore, before performing any analysis, it is crucial to successfully separate the vibration signal's relevant components from its noise. This work introduces a novel totally automatedfault classification techniqe for gearboxes that does not require specialized knowledge of the gearbox's operational load or design. Our technique separates the predicted error from the vibration data using an adaptive filter. In order to precisely categorize the gearbox's state, the standard deviation of these prediction errors is further examined using a support vector machine (SVM).

Keywords- fault classification,support vector machine

I. INTRODUCTION

Electrical generators, automobiles, and industrial machinery all depend on gearboxes as essential parts. They are prone to flaws since they are exposed to demanding and constant operating conditions. These flaws not only harm the gearbox directly but also have the potential to cause the mechanical system as a whole to fail, posing a serious risk to public safety and causing large financial losses. As a result, it's critical to keep an eye on gearbox health and identify any new problems as soon as possible.The most popular non-destructive technique for keeping an eye on gearbox conditions is vibration characteristic analysis, which includes fault-related component analysis. In order to detect gear problems, these vibrations usually exhibit complicated sideband frequencies surrounding the meshing frequency and its harmonics. In essence, a gearbox vibration signal is a phase- and amplitude-modulated signal with many frequency tones dispersed throughout the spectrum. Every set of these tones consists of a core meshing frequency and its harmonics, encircled by sideband frequencies that are tuned by particular oscillation frequencies or gears.

It is essential to separate these fundamental fault-related components for efficient gearbox fault classification. For this reason, signal analysis is commonly used, and accelerometers are frequently used over acoustic emission sensors because of their simpler installation. Nevertheless, the vibration signals emitted by gearboxes are non-linear and non-stationary, particularly when there is variation in rotational speed. These signals also contain noise from other sources, including electronic control systems, data collecting systems, mechanical components like shafts and gears that resonate, environmental influences.Background noise can mask important fault-related features in vibration signals, especially in more intricate gearbox types where noise components may appear at random. occur everywhere throughout the frequency spectrum, possibly concealing or warping the key meshing frequencies and their harmonics. Accurate diagnostics therefore depend critically on selecting the appropriate signal processing methods to reduce noise interference and extract useful components. Because of its lightweight, compact construction and changeable transmission ratios, planetary gear trains are essential components of rotating machinery and are used in wind turbines, helicopters, and other mechanical systems. However, the severe operating conditions of these gearboxes can lead to failures, thus the development of efficient diagnostic methods is required to avoid serious hazards to safety and the economy.

Comprising a planet carrier, sun gear, ring gear, and several planet gears that revolve both around and on their own axes, planetary gearboxes have intricate structural design. Vibration signals with strong amplitude, frequency, and phase modulations are produced by this movement, and these signals may be signs of possible problems. Usually, the diagnostic procedure entails examining these vibrations through techniques like thermography, acoustic emission testing, and oil analysis. As the primary indicator of gear problems since the 1980s, traditional vibration analysis has been the cornerstone, concentrating on the meshing frequency and its sidebands. However, noise from multiple sources is frequently present in the vibration signals, making fault diagnosis more difficult.

The accuracy of fault classification has been improved by the use of advanced signal processing techniques. These include the envelope analysis technique, which finds recurring shock amplitudes from damaged gear teeth, the Fourier transform for frequency analysis, and the wavelet transform for handling non-stationary data. In non-stationary situations, methods such as time-frequency analysis and the short-time Fourier transform (STFT) aid in capturing important events. Nevertheless, issues like signal noise and gearbox signal unpredictability demand more development. Entropy-based techniques have been applied in recent research to analyze non-stationary and non-linear data. Although multiscale entropy techniques might be computationally costly, they aid in the detection of dynamic changes in rotating machinery. Additionally, dimensionality reduction methods like PCA and t-SNE are used to control datacomplexityand enhance classifier performance. In general, gearbox failure detection is an important field that necessitates ongoing study to improve operational systems' safety and efficiency and adjust to the complexity of various machinery.

II. LITERATURE REVIEW

[1] In his analysis of small modular reactors (SMRs), Roose (2022) draws attention to the SMRs' portability, reduced size, and financial benefits over conventional nuclear reactors. The article gives a general review of SMR types, focusing on their structural design, uses, and effects on power systems. These types include light water reactors (LWRs), gas-cooled reactors (GCRs), liquid metal-cooled reactors (LMRs), and molten salt reactors (MSRs).

[2] Rombach et al. (2022) introduce latent diffusion models (LDMs) for high-resolution image synthesis. By breaking down the image formation process into denoising autoencoders and using cross-attention layers for conditioning inputs, they achieve state-of-the-art results that allow for effective convolutional synthesis.

[3] Pennycook and Rand (2021) investigate why people believe and spread false information online. They discover that political beliefs do not alone determine susceptibility; rather, poor truth discernment is linked to a lack of careful reasoning and a reliance on heuristics, with social media sharing frequently being motivated by inattention as opposed to deliberate disseminating of false information.

[4] Singh and Sharma (2022) present an effective multi-modal method that combines text analysis with a sentence transformer and visual analysis with EfficientNet to identify bogus photographs on microblogging sites. Their approach outperforms existing state-of-the-art frameworks on the Twitter and Weibo datasets, achieving high prediction accuracies.

[5]Bird et al. (2023) show how conditional Generative Adversarial Networks (GANs) and robotic arms can conduct false-acceptance attacks against signature verification systems. Their research emphasizes the necessity of optimizing systems using robotic forgeries in order to reduce the frequency of attacks.

[6] Khosravy et al. (2021) examine the viability of model inversion attacks (MIA) in a gray-box scenario on deep learning-based face recognition systems. They show how users' facial photos can be regenerate without revealing any personal information about them, which presents a significant privacy risk.

[7] Bonettini et al. (2021) suggest using machine learning techniques and Benford's law divergence values for intra-class classification of biometric fingerprint images. These methods yield high accuracy results of 100% with Decision Tree and Convolutional Neural Networks (CNN), and 90.54% and 95.95% with Naïve Bayes and Logistic Regression, respectively.

[8] Ramesh et al. (2021) described a simple technique that uses a transformer model that autoregressively models text and picture tokens to produce text-to-images in a single shot.Despite its simplicity, the method obtains competitive performance when compared to previous domain-specific models when evaluated in a zero-shot manner.

[9] Deb et al. (2020) present a method that creates adversarial face images that are exact replicas of source photos by using facial landmark recognition and superpixel segmentation to inform attack techniques. Their approach successfully carries out adversarial attacks against face recognition systems in the real world by projecting printouts of deliberately hostile images onto a camera to fool the recognition model.

[10] Saharia et al. (2022) provide Imagen, a text-to-image diffusion model that nachieves previously unheard-of photorealism and language understanding by fusing diffusion models with massive transformer language models. Imagen achieves a state-of-the-art FID score of 7.27 on the COCO dataset, outperforming recent approaches in sample quality and image-text alignment, and receiving preference from human raters.

[11] Chambon et al. (2022) provide the Medical VDM, which uses variational diffusion models to produce medical images with good quality while maintaining important features. With a reconstruction loss of 0.869, diffusion loss of 0.0008, and latent loss of 5.740068×10^{-5}, experimental results show its effectiveness and point to its uses in medical diagnosis, treatment planning, and teaching.

[12]Schneider et al. (2023) investigate the use of diffusion models in the production of music, introducing a cascading latent diffusion technique that can produce excellent stereo music in real-time from textual descriptions using a single consumer GPU. To aid in upcoming studies in the area, they offer libraries and music samples that are freely accessible.

[13]Schneider (2023) suggests text-conditional latent audio diffusion models with stacked 1D U-Nets in an effort to investigate the possibilities of diffusion models for audio creation. The project offers open-source libraries to support further study in the field and strives for real-time inference on consumer GPUs..

[14] Yi et al. (2021) address ethical concerns in AI-generated artworks by building an AI art model trained on works influenced by Vincent van Gogh. Their methodology uses computer vision models to achieve 98.14% accuracy in differentiating between artwork generated by humans and artificial intelligence (AI) and allows style transfer to underrepresented groups by leveraging context from a library of approximately 6 billion photos. [15] Guo et al. (2023) present ArtVerse, a paradigm for collaborative painting between humans and machines for the metaverse era, utilizing parallel theory to support innovation, exploration, and development. In order to create decentralized art groups and illustrate a new ecosystem of artistic creativity in the metaverse, their architecture includes essential technology.

[16] Sha et al. (2022) conduct the first thorough study on the validity of fictitious images generated using text-to-image diffusion models. Their work presents techniques for universal detection and source attribution, leveraging linguistic and visual modalities to distinguish false images and connect them to their model source. This provides insights into the underlying properties of these models and encourages the creation of countermeasures.

[17] Corvi et al. (2022) suggest improving computer vision-based AI-generated image recognition by creating a synthetic dataset that mimics CIFAR-10 with latent diffusion, allowing a CNN to classify real and AI-generated images as binary. With 92.98% accuracy, their method is interpretable by Gradient Class Activation Mapping, which highlights the model's attention to minute visual flaws in picture backdrops.

[18] In order to discern between phony and authentic video sequences, Amerini et al. (2019) provide a forensic technique that uses optical flow fields, which improves performance over single-frame methods. Using CNN classifiers, their method produces encouraging outcomes on the FaceForensics++ dataset.

[19] Güera and Delp (2018) examine the performance of pre-trained deepfake detection models on more recent datasets. They discover that the XceptionNet model from Rössler et al. (2019) is ineffective, with a 51.31% classification accuracy, and that it struggles in particular to detect deepfake videos (13.16% accuracy). This suggests that since deepfake technology is developing, detection methods need to be continuously tested. [20]Wang et al. (2022) use transformer-based architectures like DINO and CLIP, as well as supervised and self-supervised deep learning models, to study deepfake detection. Their investigation over a number of datasets shows that transformer models perform better than CNNs; the FaceForensics++ and DFDC datasets show superior generalization ability, and picture augmentations enhance performance.

III. EXISTING SYSTEM

For open-set fault classification in real-world applications—where unknown faults frequently occur—this paper presents a revolutionary normalized one-versus-all classification loss with center and contrastive regularization. Our approach, which is perfect for addressing the difficulties presented by a disproportionate number of unknown classes, improves intra-class compactness and inter-class divergence by directly optimizing deep characteristics. The technique shows notable improvements over conventional methods in defect diagnosis when tested with vibration signals from motor bearings and gears that were measured in the field. We provide a technique that uses cosine distances in angular feature space to enable efficient unseen defect recognition and classification. But there are drawbacks as well, like the requirement for a lightweight model for real-time applications and the training model's modification to allow for a larger test label space. Subsequent investigations will concentrate on enhancing invariant angle feature extraction across various domains to enhance model flexibility and minimize deployment expenses.

IV. PROPOSED SYSTEM

To identify structural problems and insights in a dataset and to determine whether additional data should be collected, cleaned, or reprocessed, effective exploratory data analysis (EDA) is essential. To avoid inaccurate conclusions and statistical misjudgments, EDA also detects any data-driven inaccuracies. Our approach for feature selection is ensemble-based and iterative, meaning that it starts with all features and refines them one at a time. By measuring each feature's significance based on how well it performs across a number of trustworthy classification models, this algorithm takes a greedy approach. Sequential removal of features that detract from accuracy is done. The procedure is stopped after 'k' successive drops in performance, returning to the best feature set previously used, to mitigate any potential negative effects of this greedy approach.

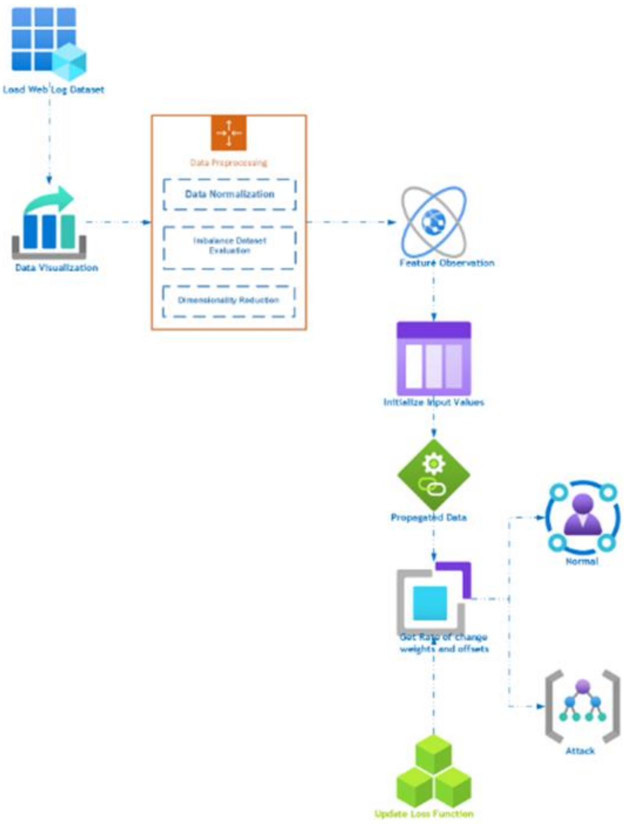


Figure 1: General Architecture

The architectural diagram provides a systematic representation of the process for GAN Generated Fake Face Detection using Facial Behavior Analysis here are the modules included :

- **Module 1** : One method used in Data Science to uncover key features and trends for machine learning and deep learning models is exploratory data analysis, or EDA. Using visuals and graphics to examine and evaluate a data set is known as exploratory data analysis, or EDA. Rather than validating statistical theories, the objective is to explore, investigate, and learn. Exploratory data analysis, or EDA, is the process of examining our dataset and determining possible correlations between variables using numerical summaries and visualizations. In the investigative process known as exploratory data analysis, we make use of graphical tools and summary statistics to learn more about our data and determine what insights they may provide.

- **Module 2:** The technique of finding the most pertinent features in a dataset by removing noisy, redundant, or irrelevant data is known as feature selection. By ensuring that only necessary features are used and preventing the model from learning from noise and unimportant patterns, this procedure is critical to maximizing model performance.

- Use strategies like regularization (L1 and L2), which decrease less significant feature coefficients to zero and add a penalty to the loss function in order to lessen overfitting.

Random Forest Importance: This approach makes use of tree-based techniques to evaluate the significance of features by evaluating their effect on impurity reduction and model accuracy. This aids in the identification of essential features.

- **Module 3:** SVM, or support vector machine Initially created for binary classification, SVM is a flexible statistical learning technique that finds the largest margin between two categories by identifying a

boundary. For nonlinear classification, SVM uses kernel functions to map input data into a higher-dimensional space, enhancing its ability to classify complex datasets. Different kernel choices can significantly influence the classification results. The boundaries of the classifier. In order to improve its capacity to classify complicated datasets, SVM employs kernel functions to map input data into a higher-dimensional space for nonlinear classification. The outcomes of the categorization can be strongly impacted by different kernel selections.

SVM is extended for multi-class settings using the one-against-all method. To do this, distinct SVM models must be built for every class and compared to all other classes. Every model successively isolates each class from the others until each is classified independently by treating one class as positive and the others as negative. This method effectively decomposes multi-class problems into multiple binary classification tasks, allowing SVM to handle broader applications like regression, pattern recognition, and more complex predictive tasks.

V. RESULTS AND DISCUSSION

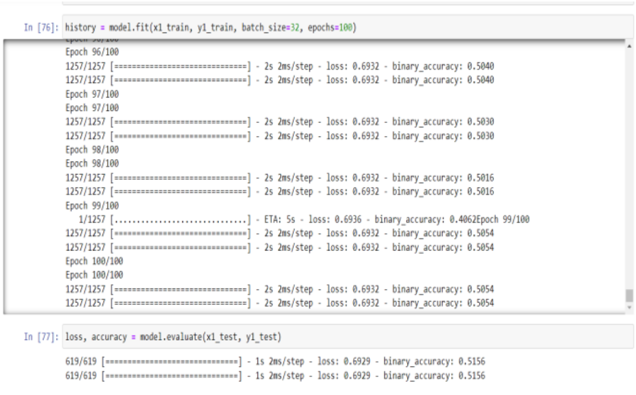
A. DETAILS OF THE DATASET

This dataset had four different forms of gear faults and four different types of bearing defects, as shown in Table 1. In this investigation, data that were gathered under operational settings with a rotating speed-load arrangement of 20 Hz–0 V were used.Germany's Paderborn University (PU) donated the bearing dataset [32], [33].The PU dataset was created by selecting real-world damaged bearing data, which were listed in Table 2 and included KA04, KA15, KA16, KA22, KA30, KB23, KB24, KB27, KI14, KI16, KI17, KI18, and KI22.The positions on the outer ring, the inner ring, and both the outer and inne r rings were damaged, according to KA, KB, and KI, respectively. The test rig had a radial force of and a load torque of 0.7 Nm when operating at 1,500 rpm.

Label	Fault Code	Fault Mode[1]	Fault Location[2]	Description[3]
0	KA04	SP+S+1	O	FP
1	KA15	SP+S+1	O	PDI
2	KA16	SP+R+2	O	FP
3	KA22	SP+S+1	O	FP
4	KA30	D+R+1	O	PDI
5	KB23	SP+M+2	OI	FP
6	KB24	D+M+3	OI	FP
7	KB27	D+M+1	OI	PDI
8	KI14	SP+M+1	I	FP
9	KI16	SP+S+3	I	FP
10	KI17	SP+R+1	I	FP
11	KI18	SP+S+2	I	FP
12	KI21	SP+S+1	I	FP

[1] For the first term, SP and D represent single-point and distributed damage, respectively. For the second term, S, R, and M denote single, repetitive, and multiple damage, respectively. The third term represents the damage level.
[2] O, I, and OI indicate that the damage is on the outer ring, inner ring, and both rings, respectively.
[3] FP represents damage caused by fatigue and pitting, and PDI represent damage caused by plastic deformation and indentation.

figure 1. . Detailed description gear dataset



```
In [76]: history = model.fit(x1_train, y1_train, batch_size=32, epochs=100)
Epoch 96/100
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5040
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5040
Epoch 97/100
Epoch 97/100
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5030
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5030
Epoch 98/100
Epoch 98/100
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5016
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5016
Epoch 99/100
   1/1257 [..............................] - ETA: 5s - loss: 0.6936 - binary_accuracy: 0.4062Epoch 99/100
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5054
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5054
Epoch 100/100
Epoch 100/100
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5054
1257/1257 [==============================] - 2s 2ms/step - loss: 0.6932 - binary_accuracy: 0.5054

In [77]: loss, accuracy = model.evaluate(x1_test, y1_test)
619/619 [==============================] - 1s 2ms/step - loss: 0.6929 - binary_accuracy: 0.5156
619/619 [==============================] - 1s 2ms/step - loss: 0.6929 - binary_accuracy: 0.5156
```

Figure.2.implementing

B. IMPLEMENTATION DETAILS AND FAULT DIAGNOSIS TASKS

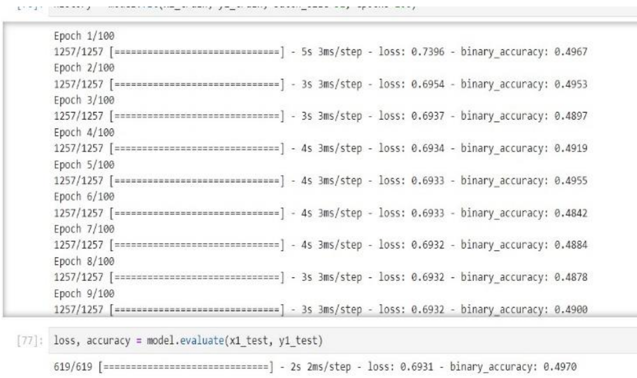
To confirm the efficacy of our suggested approach, several OSR fault diagnosis jobs were created for every dataset, as seen in figure 3. There were varying numbers of known and unknown classes in each job. Openness– $O = 1 - K/(K + U)$ was defined in [12] and used to indicate the level of difficulty of a given open-set recognition test. K and U represent the number of known and unknown classes, respectively, in this case. The degree of difficulty connected with the OSR work increases with the degree of openness O. The tasks that were set have a broad range of openness. On the PU dataset, for instance, the tasks' degree of openness ranged from 0.5196 to 0.0801. We separated the samples in a partially overlapping or non-overlapping way from the raw vibration signals.

Dataset	Task	Known Classes	Unknown Classes	Openness
SEU	S1	0,1,2	3,4,5,6,7,8	0.4226
	S2	0,5,6	1,2,3,4,7,8	0.4226
	S3	0,1,5	2,3,4,6,7,8	0.4226
	S4	0,1,2,3	4,5,6,7,8	0.3333
	S5	0,5,6,7	1,2,3,4,8	0.3333
	S6	0,1,2,3,4	5,6,7,8	0.2546
	S7	0,5,6,7,8	1,2,3,4	0.2546
	S8	0,1,2,3,4,5	6,7,8	0.1835
	S9	0,1,2,3,5,6,7	4,8	0.1181
	S10	0,1,2,3,4,5,6	7,8	0.1181
PU	P1	0,1,2	3,4,5,6,7,8,9,10,11,12	0.5196
	P2	5,6,7	0,1,2,3,4,8,9,10,11,12	0.5196
	P3	0,5,8	1,2,3,4,6,7,9,10,11,12	0.5196
	P4	0,1,2,3	4,5,6,7,8,9,10,11,12	0.4453
	P5	0,1,2,3,4	5,6,7,8,9,10,11,12	0.3798
	P6	0,1,5,6,8,9	2,3,4,7,10,11,12	0.3206
	P7	0,1,2,5,6,7,8,9,10	3,4,11,12	0.1679
	P8	0,1,2,3,5,6,7,8,9,10,11	4,12	0.0801

figure 3.

figure 4 displays the SEU dataset's open-set fault classification results. Across all SEU dataset tasks, our technique produced the greatest UDA. The proposed method has an average UDA of 84.16% for all tasks, which is 23.27% higher than the next best method. The UDA of the suggested technique OSDAF is still 23.27% and 29.37% greater than the UDAs of the previous methods, respectively, despite the fact that the face recognition methods CosFace and ArcFace likewise use discriminative angle feature learning. This is because the suggested strategy explicitly optimizes the cosine distances between and within classes of the depth angle features.After resizing, data is standardized by dividing each RGB value by 255.0, speeding up CNN convergence to the global minimum loss. Labels are then reassigned: '1' for tampered images, '0' for authentic ones. Finally, the dataset is split, with 80% for training and 20% for validation.

	precision	recall	f1-score	support
0.0	0.85	0.71	0.77	10022
1.0	0.74	0.88	0.80	9778
accuracy			0.79	19800
macro avg	0.80	0.79	0.79	19800
weighted avg	0.80	0.79	0.79	19800



```
Epoch 1/100
1257/1257 [==============================] - 5s 3ms/step - loss: 0.7396 - binary_accuracy: 0.4967
Epoch 2/100
1257/1257 [==============================] - 3s 3ms/step - loss: 0.6954 - binary_accuracy: 0.4953
Epoch 3/100
1257/1257 [==============================] - 3s 3ms/step - loss: 0.6937 - binary_accuracy: 0.4897
Epoch 4/100
1257/1257 [==============================] - 4s 3ms/step - loss: 0.6934 - binary_accuracy: 0.4919
Epoch 5/100
1257/1257 [==============================] - 4s 3ms/step - loss: 0.6933 - binary_accuracy: 0.4955
Epoch 6/100
1257/1257 [==============================] - 4s 3ms/step - loss: 0.6933 - binary_accuracy: 0.4842
Epoch 7/100
1257/1257 [==============================] - 4s 3ms/step - loss: 0.6932 - binary_accuracy: 0.4884
Epoch 8/100
1257/1257 [==============================] - 3s 3ms/step - loss: 0.6932 - binary_accuracy: 0.4878
Epoch 9/100
1257/1257 [==============================] - 3s 3ms/step - loss: 0.6932 - binary_accuracy: 0.4900

[77]: loss, accuracy = model.evaluate(x1_test, y1_test)
619/619 [==============================] - 2s 2ms/step - loss: 0.6931 - binary_accuracy: 0.4970
```

Figure.4

For the purpose of classifying gearbox faults, a linear classifier is used, which presents a straightforward but efficient method for identifying complex mechanical systems. This strategy enables maintenance teams to prioritize work based on fault likelihood by adopting a probabilistic model that enables detailed risk evaluations. Scalability is an essential component that makes it possible to apply it in real-time across multiple gearboxes, which Is essential for reducing downtime and averting malfunctions. Workforce training and compatibility requirements are just two of the major obstacles to integration Into current systems. Additionally, the maintenance culture must change from routine to condition-based techniques in order to implement this data-driven approach. To further increase diagnostic accuracy and dependability, future developments might concentrate on incorporating more complex data inputs and investigating cutting-edge machine learning strategies.

IX. CONCLUSION

Our work presents a dependable approach for diagnosing faults in gearbox systems operating at different speeds. It combines machine learning classification to identify the gearbox failure states with adaptive noise management to drastically reduce noise. Firstly, we constructed a collection of Gaussian reference signals as a function of rotation speed. These signals include a variety of noise components, including band and white noise, which are independent of the inherent informative components and associated to the parasitic noise in the vibration signals. This work proposes and validates a multi-model feature fusion model, which forms the basis of the gearbox defect diagnosis approach. An accelerometer was used to collect raw vibration data from the experimental gearbox malfunction diagnosis platform.

X. REFERENCES

[1] S. Tang, S. Yuan, and Y. Zhu, "Intelligent fault diagnosis techniques based on deep learning applied to rotating machinery," IEEE Access, vol. 8, pp. 9335–9346, 2019.
[2] M. T. Pham, J.-M. Kim, and C. H. Kim, "Efficient fault diagnosis of rolling bearings using neural network architecture search and sharing weights," IEEE Access, vol. 9, pp. 98 800–98 811, 2021.
[3] L. Wen, X. Li, L. Gao, Y. Zhang, "A novel data-driven fault diagnosis approach utilizing convolutional neural networks," IEEE Transactions on Industrial Electronics, vol. 65, no. 7, pp. 5990–5998, 2017.
[4] Q. Lv, X. Yu, H. Ma, J. Ye, W. Wu, and X. Wang, "Applications of machine learning to reciprocating compressor fault diagnosis: A review," Processes, vol. 9, no. 6, p. 909, 2021. [5] R. Huang, Y. Liao, S. Zhang, and W. Li, “Deep decoupling convolutional neural network for intelligent compound fault diagnosis,” IEEE Access, vol. 7, pp. 1848–1858, 2018.
[6] H. Chen, B. Jiang, S. X. Ding, and B. Huang, “Data-driven fault diagnosis for traction systems in high-speed trains: A survey, challenges, and perspectives,” IEEE Transactions on Intelligent Transportation Systems, 2020.
[7] H. Wang, J. Xu, R. Yan, C. Sun, and X. Chen, “Intelligent bearing fault diagnosis using multi-head attention-based cnn,” Procedia Manufacturing, vol. 49, pp. 112–118, 2020, proceedings of the 8th International Conference on Through-Life Engineering Services – TESConf 2019.
[8] Y. Ding, M. Jia, Q. Miao, and Y. Cao, “A novel time– frequency transformer based on self–attention mechanism and its application in fault diagnosis of rolling bearings,” Mechanical Systems and Signal Processing, vol. 168, p. 108616, 2022.
[9] Abeer M. Mahmoud , Maha M. A. Lashin , Fadwa Alrowais and Hanen Karamti “A Dual Soft-Computing Based on Genetic Algorithm and Fuzzy Logic Defect Recognition for Gearbox and Motors: Attempts Toward Optimal Performance” 2022.
[10] Yun Kong , Tianyang Wang , Zhaoye Qin and Fulei Chu “Sparse Representation Classification With Structured Dictionary Design Strategy for Rotating Machinery Fault Diagnosis” 2021
[11] Jong Moon Ha and Byeng D. Youn “A Health Data Map-Based Ensemble of Deep Domain Adaptation Under Inhomogeneous Operating Conditions for Fault Diagnosis of a Planetary Gearbox “2021
[12] Dongying Han , Xiaoci Guo and Peiming Shi” An Intelligent Fault Diagnosis Method of Variable Condition Gearbox Based on Improved DBN Combined With WPEE and MPE “2020
[13] Shengnan Tang , Shouqi Yuan and Yong Zhu “Deep Learning-Based Intelligent Fault Diagnosis Methods Toward Rotating Machinery” 2020
[14]Ran Wang , Fengkai Liu , Xiong Hu and Jin Chen “Unsupervised Mechanical Fault Feature Learning Based on Consistency Inference-Constrained Sparse Filtering” 2020
[15] Ying Tao , Xiaodan Wang , Ren-Vinicio Snchez , Shuai Yang and Yun Bai” Spur Gear Fault Diagnosis Using a Multilayer Gated Recurrent Unit Approach With Vibration Signal” 2019
[16] Yu Wang , Shuai Yang and Ren Vinicio Snchez” Gearbox Fault Diagnosis Based on a Novel Hybrid Feature Reduction Method” 2018
[17] Weiwei Qian , Shunming Li and Jinrui Wang” A New Transfer Learning Method and its Application on Rotating Machine Fault Diagnosis Under Variant Working Conditions” 2018