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Diagnostic Sonance: Sound-Based Approach to Assess Engine Ball Bearing Health in Automobiles

***Abstract**. Induction motors have been extensively used in the automobile industry. This paper introduces an innovative sound-based Engine Classification method to identify the defects in engine ball-bearing. We employ sound-based sound component extraction techniques to identify recurring patterns over time. Our research uses the NASA-bearing dataset and proposes enhancements to Resnet and Hybrid CNN Models. We gain invaluable insights into the method's performance with good accuracy rates.*

Streszczenie**. Silniki indukcyjne są szeroko stosowane w przemyśle samochodowym. W artykule przedstawiono innowacyjną metodę klasyfikacji silników opartą na dźwięku, pozwalającą na identyfikację uszkodzeń łożysk kulkowych silnika. Stosujemy techniki ekstrakcji komponentów dźwięku w oparciu o dźwięk, aby zidentyfikować powtarzające się wzorce w czasie. W naszych badaniach wykorzystujemy zbiór danych NASA i proponujemy ulepszenia modeli Resnet i hybrydowych CNN. Uzyskujemy bezcenne informacje na temat wydajności metody przy dobrych wskaźnikach dokładności.* (Sonance diagnostyczne: podejście oparte na dźwięku do oceny stanu łożysk kulkowych silnika w samochodach***)

Keywords: Sound Based Audio Classification, Health, Engine Ball Bearing, Automobiles.
Słowa kluczowe: Klasyfikacja dźwięku oparta na dźwięku, zdrowie, łożysko kulkowe silnika, samochody

Introduction

The most prevalent type of rotating machinery in contemporary industry is three-phase induction motors (TIM). The Stator and rotor abandons are the primary drivers of TIM failures [1]. Ball Bearings, a crucial component of rotors, are the source of the majority of TIM failures in industrial environments and are therefore the subject of extensive research [2]. Recent works present a variety of approaches for bearing fault prognostics. The majority of these approaches use characteristics of vibration or current signal to identify defect signatures [3- 5]. Notwithstanding transient and consistent state dissected current signs, thermograph information is likewise used to survey the engine condition subjectively [6]. Audio Data (AD) methods have recently been used to find TIM faults [7,8]. There is evidence to suggest that the frequency components of AD signals exhibit the same bearing defect signatures [9]. As a result, instead of current or vibration signals, Audio signals, that are captured through microphones as well as processed online or offline, can be utilised in defect detection. Audio feature extraction is used to create a system that uses bearing and stator short circuit faults to diagnose issues with single-phase motors [10]. A specific bearing defect prognostic system is proposed [11], to discuss the fault frequency signatures. This system employs an extensive band AD sensor that works between 125 kHz and 1 MHz and is attached directly to the bearing housing. Though This method classified all of the situations under investigation based on entropy values, the diagnostic accuracy needs to be addressed.

The challenge of identifying faulty bearings in railway cars was addressed by Kreuzer et al. [12] through the analysis of audio data collected during normal operations. They developed a multi-layer perceptron classifier using input features with Mel frequency Cepstral Coefficients (MFCCs). The Fast Fourier Transform (FFT) technique was employed by Karyatanti et al. [13] to recognize and mitigate the damage caused by induction motor audio data to ball bearings. Lucena-Junior et al. [14] utilized engine noise signals to describe failures in rigid ball bearings within a 3-phase induction motor. They employed signal analysis with chaos using a density maximum technique. However, the accuracy is not improved This method uses a low-cost sensor and algorithm to identify the potential peaks in engine sound in real-time with a short acquisition window of 0.28 seconds.

Singh et al. [15] extracted acoustic data from machinery using statistical coefficients such as mean and correlation coefficients. Among the existing research works, much interest has been focused on attaining better fault detection and work has been done on providing better accuracy. Grounded on this motivation this paper proposes a sound-based Engine Classification using Improved Resnet and Hybrid CNN. The experimental results show the performance of the proposed model with relatively better accuracy when compared to existing methods.

The contributions of this study are:

1. We propose an original technique for Sound-Based Engine Classification (SEC) in view of Audio Data (AD) signals produced via car machines. The essential point of this technique is to dissect the strength of a Ball Bearing blames and concentrate straightforward highlights.
2. Using a pair of condenser microphones, capture the AE signals and extract frequency and time patterns using sound-based audio feature extraction to identify working and malfunctioning machines.
3. NASA-bearing dataset is used for training and testing
4. Improved ResNet and Hybrid CNN are proposed by using a combination of two deep neural network architectures, an improved ResNet and a hybrid CNN, for the task of sound-based audio classification to analyze the health of an engine ball bearing in automobiles.
5. By examining specific peaks within the spectra, discuss the main variations between the acoustic signals in terms of fault frequency signatures.

Background

Fault Bearings

This section goes into detail about the vibration behaviour of TIMs in bearing failures or unbalanced voltage supplies. Additionally, the time-frequency characteristics-based fault classification features are provided. This paper looks into defects in bearing outer races. The frequency peak in the vibration signal spectra caused by such faults is referred to as the Ball Pass Outer Raceway Frequency (BPOF).

(1) $$f_{BPOF} = \frac{N_B}{2} f_r \left(1 - \frac{D_B}{D_C}\cos\theta\right)$$

In equation (1), D_B as well as D_C have the ball and cage diameters, respectively, N_B represents the number of balls in the bearing, and f_r denotes rotor frequency or motor speed. Fig.1. depicts a schematic of an eight-ball bearing and its constituent parts.

Voltage Unbalance of Power Supply

Due to the power supply's voltage imbalance of TIM, the machine spins erratically. Because of the irregularities, the engine's mechanical parts occasionally vibrate, causing sound waves to travel through the air. According to a hypothesis of 2f vibration [16], engines operating with voltage imbalance produce an air hole mutilation as a result of poor electromagnetic equilibrium. The square of a machine's power repeat is comparable to a 2f vibration. An imbalanced attractive power will cause vibrations in the air hole, which can be addressed by a Fourier series. The harmonic resonance of the vibration gets stronger as the eccentricity goes up [17].

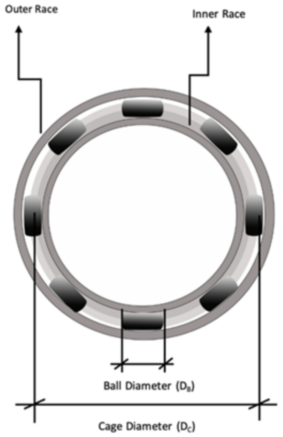

Fig.1. 8- Ball Bearing with Elements

An imbalanced attractive power will cause vibrations in the air hole, which can be addressed by a Fourier series. The harmonic resonance of the vibration gets stronger as the eccentricity goes up [17]. It is anticipated that AE signals will also contain this feature. Voltage unbalance also contributes to errors in TIM fault diagnosis.[18]

Features of Audio Data

Features must be extracted from the AD signals to perform fault detection and classification. The AD signals for bearing fault detection in the TIM shaft with varying coupled load values and balanced and unbalanced power supplies are examined. Time and frequency characteristics of the signals are discussed here, as they are used to describe the motor state. In the case of electrical machines, AD signals exhibit periodicity. The classifiers used both frequency characteristics and time-domain patterns as features in this manner. Numerous flaws change the magnitudes of the spectra of vibration signals at the supply frequency, which was 60 Hz in the experiments done in the current analysis. Bearing deficiencies were considered the source of vibrations in TIM, an additional feature was also derived from the spectral peak close to 30 Hz. These characteristics, labelled f1 through f4 for ECM 1(Electret Condenser Mic), and f5 through f8 for ECM 2 , were determined by analysing the spectra of the respective signals. f1 and f5 represent 30 Hz neighbourhood not normalized peaks, f2 and f6 denotes 60 Hz neighbourhood not normalized peaks. f3and f7:120 Hz neighbourhood not normalized peaks. f4 and f8, Modulated bearing fault neighbourhood not normalized peaks [19]. When a TIM bearing fails, it always produces the same modulated high-frequency peak in the spectrum, typically above 2.4 kHz. Cross-correlation between ECM signals was used to extract the temporal properties, on the other hand. Eqn (2) represents the cross-correlation of two signals x_1 and x_2 with length N, where m=0, 1..., N−1and $x_1(n)$and $x_2(n)$ are the signal value at n sample.

(2) $R\_ECM1ECM2(\tau) = \Sigma\,[ECM\ 1(t + \tau) * ECM\ 2(t)]$

where: R_ECM1ECM2(τ) represents the cross-correlation between signals ECM 1(t) and ECM 2(t) at lag "τ." Σ (summation) denotes the summation operation over all time points. t is the time index variable. ECM 1(t + τ) denotes the value of signal ECM 1 at time t + τ, which is shifted by the lag τ. ECM 2(t) denotes the value of signal ECM 2 at time t.
f9: Linking Microphone Cross-Correlation Peak, f10: Linking microphone sample-delay, f11 and f12: Autocorrelations Each ECM signal's autocorrelation peak is the third and fourth characteristic. These values grow larger as the periodicity of the signals increases. These features identify patterns and similarities in ECM signals, which help to mitigate the impact of extraneous noise and interference.

Pattern Classifiers

Bearing failure detection pattern classifiers have been used frequently to verify the efficacy of feature extraction techniques [20,21]. In this investigation, the Audio Data signal provides features in the preceding section and is employed as inputs for these methods. This paper investigates the performance of Improved Resnet and Hybrid CNN for better classification. Both Hybrid classifiers are within the umbrella of supervised learning. Using randomly selected features from the experimental data set, these systems establish a training group that must encompass the entire data domain. To assess the exhibition of every classifier, the k-overlap cross-approval strategy [22-23] is utilized. This strategy includes testing 10 unique geographies for every classifier. The optimum classifying setup for the test population was chosen.

Proposed Methods

In this section, we describe a unique technique for Sound-based Engine Classification (SEC) that examines the status of ball-bearing problems using Audio Data (AD) signals generated by automobile machines. We have used a pair of condenser microphones with omnidirectional microphone patterns to collect the frequency-based audio data and then the sound-based sound component extraction algorithms to discover differential frequency and temporal patterns that distinguish between operating and defective bearings.

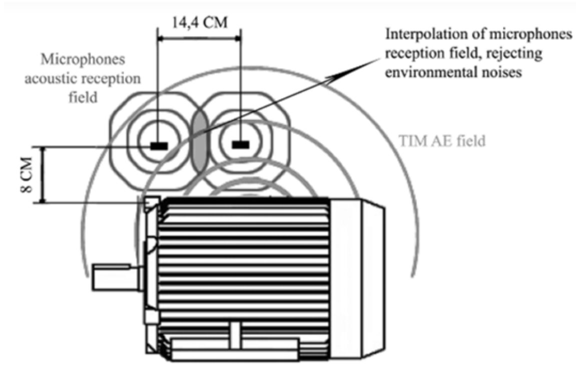

Fig.2. Test Setup and Location of Two ECMs with the TIM

A novel approach to Sound-based Engine Classification (SEC) that analyzes the health of a ball-bearing fault using Audio Data (AD) signals produced by automobile machines is experimented. We utilize a couple of condenser receivers to record these signals and utilize sound-based and sound component extraction to recognize distinct frequency and time patterns that differentiate between operational and faulty machinery. The sound information securing is dealt with by a Focusrite Scarlett 2i2, and the Acoustic Emission sensors are 2 Behringer ECM8000 omnidirectional receiver condensers. We find that placing the microphones at 8 cm from the motor is optimal. As seen in Fig 2, ECM 1 is installed upside down on the machine's shaft, and ECM 2 is positioned 14.4 centimetres backwards, pointing towards the motor fan.

The AD signals are collected in a laboratory for electrical machines, which is also used for other tests, as opposed to an industrial setting. As a result, the experiments are accompanied by a variety of other random sources of sound, including the noise of people, machines, and air conditioners. In the end, these challenges help prove that the methodology is robust enough to withstand interference from sounds that are not produced by the TIM being evaluated. Then, it is sampled at 96 kHz, and we record 30 seconds of AD signals for each setup. By replacing good motor parts with bad ones and tinkering with the voltage levels, we introduce faults. The abrasive paste-coated bearing outer race corrosion also reproduces the referred faults. Voltage unbalance in the power supply is brought about by a 2% reduction in stage A voltage, a 2% ascent in gradually work B voltage, and a 4% drop in stage C voltage, as well as a 4% drop in ease A voltage, a 4% ascent in work B voltage, and a 4% drop in stage C voltage.

Table 1 Experimental Test Bench Configuration

Aspect	Description
Sound Information Acquisition	Focusrite Scarlett 2i2
Acoustic Emission Sensors	2 Behringer ECM8000 omni-directional receiver condensers
Feature Measurement & Categorization	Utilizing data acquisition (DAQ) and computer communication
Microphone Placement	8 cm from the motor (optimal distance)
AE Signal Distortion	Increased with decreased sensor-to-machine distance
Sensor Configuration	ECM 1 installed upside down on the machine's shaft; ECM 2 installed backwards pointing towards the motor fan
AE Signal Origin Zeroing	Sensors arranged to focus on the expected AE origin; ECM reception fields interpolated to dampen unwanted signals
AE Signal Collection	Conducted in a laboratory for electrical machines, accompanied by various random sounds
Sampling Rate	96 kHz
AE Signal Recording Time	30 seconds for each setup
Fault Introductions	Good motor parts replaced with bad ones; voltage levels tinkered with to introduce faults
Reproduction of Faults	Abrasive paste-coated bearing outer race corrosion used to reproduce referred faults
Voltage Unbalance	2% reduction in stage A voltage; 2% ascent in gradually work B voltage; 4% drop in stage C voltage; 4% drop in ease A voltage; 4% ascent in work B voltage; 4% drop in stage C voltage

NASA Bearing Dataset

This is a dataset of vibration and acoustic signals collected from a set of ball bearings operating under different conditions, including normal operation and various types of faults. The dataset is publicly available. [24]

In Fig 3, the phases of the proposed strategy are recorded. The two microphones were placed on top of the motor along the shaft axis, and 30 seconds of AD signals were recorded first. Next, 45 windows of 3-second length with 50% overlap were created for each signal in the training set. Every window had the twelve times and recurrence highlights (f1 to f12) removed from it in the way recently depicted.

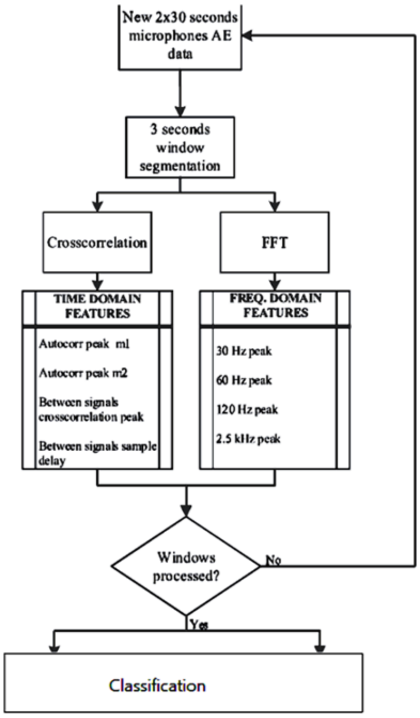

Fig.3. Flowchart of proposed technique with steps of extracting frequency & time features

Feature Extraction using Resnet

The following are the steps followed to extract features using Resnet.

1. Apply a convolutional layer with a kernel size of 7x7 and a stride of 2 to the input spectrogram.

(4) $C_{1,i,j} = \sum_{m=0}^{6}\sum_{k=1}^{K} W_{1,m,n,k}X_{i+m,j+n,k} + B_1$

where Xi,j,k is the input spectrogram at position (i,j) and channel k, W1,m,n,k is the weight of the convolutional kernel at position (m,n) and channel k, K is the number of input channels, B1 is the bias term

2. Apply batch normalization and ReLU activation function

(5) $Z_{1,i,j,k} = \frac{C_{1,i,j,k}-\mu_k}{\sigma_k}$

(6) $H_{1,i,j,k} = \frac{c_{1,i,j,k}-\mu_k}{\sigma_k}$

Where μ_k and σ_k are the mean and standard deviation of the batch for channel k.

3. Apply a residual block

(7) $C_{2,i,j,k} = \sum_{m=0}^{2}\sum_{n=0}^{2}\sum_{l=1}^{L} W_{2,m,n,l,k}\, H_{1,i+m,j+n,l}$

whereW_2,m,n,l,k is the weight of the convolutional kernel at position (m,n) and channel l in layer 2, and L is the number of output channels in layer 1.

4. Add the input of the residual block to the output

(8) $Z_{2,i,j,k} = C_{2,i,j,k} + H_{1,i,j,k}$

5. Apply batch normalization and ReLU activation function

(9) $H_{2,i,j,k} = max\left(0, \frac{Z_{2,i,j,k}-\mu_k}{\sigma_k}\right)$

6. Repeat steps 3-5 for multiple residual blocks.

7. Apply average pooling to reduce the spatial dimension

(10) $P_k = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W} H_{L,i,j,k}$

8. Flatten the pooled features and apply a fully connected layer

(11) $F = flatten(P)$

$$Y = softmax(FW_{out} + B_{out})$$

where W_{out} and B_{out} are the weight and bias of the output layer, respectively, and Y is the predicted class probabilities The above steps can be used for sound-based audio classification using ResNet, which can be applied to analyze the health of an engine ball bearing in automobiles.

The ResNet model can extract meaningful spectral features from the Mel Spectrograms, while the Hybrid CNN can learn temporal features and capture the dynamics of the audio data. The data is split into training, validation and test sets. The Hybrid CNN architecture takes the extracted ResNet features as input and learns temporal and spectral features from the audio data. Libraries like TensorFlow or PyTorch are used to define the model architecture.

The loss function measures how well the predicted labels match the true labels in the training data. For classification tasks, a common loss function is categorical cross-entropy. The Hybrid CNN is trained using a suitable loss function, such as categorical cross-entropy, and an Adam optimizer, is Used. ISFO is used as a learning rate scheduler to improve the training process. ISFO is a stochastic optimisation approach that dynamically modifies the learning rate in response to the model's performance. It calculates the ideal learning rate using a frequency-based method. Adam optimizer can be used with a suitable loss function such as categorical cross-entropy or mean squared error. These loss functions can be used to compute the difference between the predicted and actual health status of the ball bearing based on the audio signals

The combination of ResNet and the Hybrid CNN can extract meaningful spectral and temporal features from the audio data, while ISFO can dynamically adjust the learning rate and speed up the convergence of the model.

Results & Discussions

This section shows findings from audio classification analysis of TIM bearings. At first, the statistical measures are shown that can be used to evaluate the extracted features. The amplitude of the features was standardised to lie between -1 and 1. The proposed architecture uses two classifiers working in parallel. The ResNet classifier can tell if the motor is working fine or if there is a problem with the bearings. The second method, Hybrid CNN is used to detect the imbalances in power supplies. The behaviour of various classes to the extracted features is the subject of the first type of analysis. Then the audio data signals are classified into four groups, normal, defective, Balanced and unbalanced voltages. In Fig 4, the Healthy and defective cases with altered voltage supplies and their standardized mean with the standard deviation are displayed.

The proposed work (Improved ResNet+ISFO+deepCNN) is compared with five different classifiers, Power normalized cepstral coefficients (PNCC) [25], Mel frequency cepstral coefficient (MFCC) [26,27], Linear predictive coefficient (LPC) [28], Perceptual linear prediction (PLP) [29], Relative spectral perceptual linear prediction (RASTA-PLP) [30]. To analyze the abilities of these classification strategies, Table 2 looks at the presentation of various classifiers in comparison of precision and accuracy. The proposed model excels in different classifiers regarding both precision and accuracy, due to the analysis of the motor speed, supply frequency, and their harmonics. The method is dependent on the frequency of the power supply. The PNCC and LPC classifiers had the most minimal precision and accuracy, while the MFCC, PLP, and RASTA-PLP classifiers performed generally well.

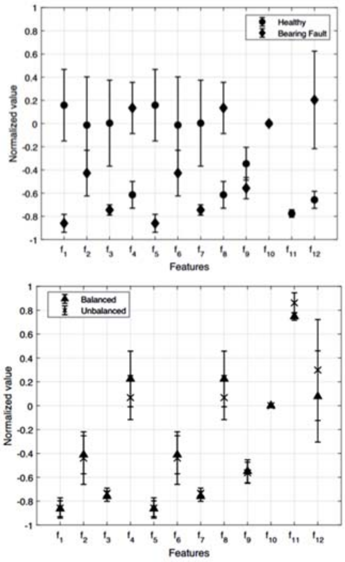

Fig.4. Mean & SD values of features for healthy & faulty cases with balanced and unbalanced power supply voltages.

Table 2 Comparative analysis on existing classifiers

Classifiers	Accuracy (%)	Precision (%)
PNCC	75	76
MFCC	83	85
LPC	68	70
PLP	79	80
RASTA-PLP	81	82
Proposed Hybrid CNN (Improved ResNet+ISFO+deepCNN)	91	92

These findings emphasize the significance of leveraging state-of-the-art techniques to achieve superior performance in classification tasks. The proposed Improved ResNet+ISFO+deepCNN hybrid model's outstanding results suggest its potential for advanced applications requiring accuracy and precision predictions.

Conclusion

To assess the strength of automotive ball bearings, the Audio Data (AD) signals were analyzed using hybrid classifiers that applied an innovative Sound Engine Classification (SEC) technique. Using time and frequency features that can be deduced from the signals and their spectra using AD signals to find TIM-bearing faults. The tests considered realistic scenarios found in real-world industrial settings, like power supply voltage imbalance and a change in the torque of the coupled load.

According to the findings, bearing faults in line-connected TIMs can be detected using the proposed method under a variety of coupled load conditions. Because the features are based on particular peaks in the AD signal spectra that correspond to motor speed, supply frequency, and their harmonics, the method is dependent on the frequency of the power supply. In any case, the stockpile recurrence must be known before the method can be used with inverter machines.

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REFERENCES

[1] Fu C., Jean JS., Weidong Z., Kuan L., and Yongfeng Y. A state-of-the-art review on uncertainty analysis of rotor systems. *Mechanical Systems and Signal Processing* 183 (2023): 109619.

[2] Akpudo, Ugochukwu E., and Jang WH., Towards bearing failure prognostics: A practical comparison between data-driven methods for industrial applications. *Journal of Mechanical Science and Technology* 34 (2020), 4161-4172.

[3] Bermeo A., Miguel A., Vincent C., Carlos OM., and Javier., Remaining useful life estimation of ball-bearings based on motor current signature analysis. *Reliability Engineering & System Safety* 235 (2023), 109-209.

[4] ADAMCZYK M, ORŁOWSKA-KOWALSKA T. Bezpośrednie polowo-zorientowane sterowanie silnikiem indukcyjnym tolerujące uszkodzenia czujników prądu z wykorzystaniem podwójnego zmodyfikowanego obserwatora Luenbergera. *Przeglad Elektrotechniczny*. 2023 Apr 1;99(4)..

[5] Ródenas.P., M.J., Combination of noninvasive approaches for general assessment of induction motors. *IEEE Trans. Ind. Applicat*. 51(3), 2172–2180 (2015)

[6] Huang, D.,Novel adaptive search method for bearing fault frequency using stochastic resonance quantified by amplitude-domain index. IEEE Trans. Instrum. Meas. 69(1), 109–121 (2020)

[7] Glowacz A., Acoustic-based fault diagnosis of three-phase induction motor. *Applied Acoustics* 137, 82–89 (2018)

[8] Delgado-Arredondo, P.A., Methodology for fault detection in induction motors A sound and vibration signals. *Mech. Syst. Signal Process.* 83, 568–589 (2017)

[9] Santos, Herman, Scalassara P., Endo W., Goedtel A., Guedes J., and Gentil M., Non-invasive sound-based classifier of bearing faults in electric induction motors. *IET Science, Measurement & Technology* 15, no. 5 (2021): 434-445.

[10] Encalada-Dávila, Ángel, Puruncajas B., Tutivén C., and Vidal Y., "Wind turbine main bearing fault prognosis based solely on scada data." *Sensors 21*, no. 6 (2021): 2228.

[11] Liu, Zepeng, Wang X., and Zhang L., Fault diagnosis of industrial wind turbine blade bearing using acoustic emission analysis. *IEEE Transactions on Instrumentation and Measurement 69*, no. 9 (2020): 6630-6639.

[12] Kreuzer., Matthias., Schmidt D., Wokusch S., and Kellermann W., Airborne-Sound Analysis for the Detection of Bearing Faults in Railway Vehicles with Real-World Data. *arXiv preprint* arXiv:2304.07307 (2023).

[13] Karyatanti, Prahmana I.D., Zulkifli R.S.,Noersena A., Purnomo. F.R, Dewantara B.Y., and Wijayanto A. Identification of Ball Bearing Damage On Induction Motors Through Sound Signal Analysis. *Journal of Electrical and Electronics Engineering* 15, no. 1 (2022): 33-38.

[14] Lucena-Junior, Anselmo J., Lima T.L.V, Bruno G.P., Alisson V. Brito, Ramos. J.G, Belo. F.A., and Lima-Filho A.C., Chaos theory using density of maxima applied to the diagnosis of three-phase induction motor bearings failure by sound analysis. *Computers in Industry* 123 (2020): 103304

[15] Singh, Mahesh K., Kumar S., and Nandan D., Faulty Voice Diagnosis of Automotive Gearbox Based on Acoustic Feature Extraction and Classification Technique. *Journal of Engineering Research* (2023): 100051

[16] Santos, Herman, Scalassara P., Endo W., Guedes A.G.J, and Murillo Gentil. Non-invasive sound-based classifier of bearing faults in electric induction motors. *IET Science, Measurement & Technology* 15, no. 5 (2021): 434-445.

[17] Pang, Liang, Yang Q., Shen H., Qin H, and ZhaoC. Research on vibration and noise of magnetic pole eccentricity tangential magnetizing parallel structure hybrid excitation synchronous motor. *Energy Reports* 8 (2022): 233-240.

[18] Balakrishna P., and Khan U., An autonomous electrical signature analysis-based method for faults monitoring in industrial motors. *IEEE Transactions on Instrumentation and Measurement* 70 (2021), 1-8.

[19] Yang, Cheng, and Jia M., Hierarchical multiscale permutation entropy-based feature extraction and fuzzy support tensor machine with pinball loss for bearing fault identification. *Mechanical Systems and Signal Processing* 149 (2021), 107-182.

[20] Cui, Mingliang, Wang Y., Lin X., and Zhong M., Fault diagnosis of rolling bearings based on an improved stack autoencoder and support vector machine. *IEEE Sensors Journal 21*, no. 4 (2020): 4927-4937.

[21] Bai., Ruxue., Xu Q., Meng Z., Cao L., Xing K., and Fan F., Rolling bearing fault diagnosis based on multi-channel convolution neural network and multi-scale clipping fusion data augmentation. *Measurement* 184 (2021): 109885.

[22] Serra, Angela, Fratello M., Cattelani L, Liampa I., Melagraki G., Kohonen P., Nymark P., Transcriptomics in toxicogenomics, part III: data modelling for risk assessment. *Nanomaterials 10*, no. 4 (2020): 708.

[23] SZYMAŃSKI, S., GÓRSKI, K., & GRZESIAK, J. (2023). System detekcji i pozycjonowania bezzałogowych statków powietrznych. Przeglad Elektrotechniczny, 2023(9).

[24] https://www.kaggle.com/datasets/vinayak123tyagi/bearing-dataset

[25] Tamazin., Mohamed., Gouda A., and Khedr M., Enhanced automatic speech recognition system based on enhancing power-normalized cepstral coefficients. *Applied Sciences* 9, no. 10 (2019): 2166

[26] Xie, Suchao, Liu R., Du L., and Tan H., Anomaly detection in rolling bearings based on the Mel-frequency cepstrum coefficient and masked autoencoder for distribution estimation. *Structural Control and Health Monitoring* 29, no. 11 (2022): e3096.

[27] D. S. A, S. Juliet, K. Ezra, M. Palmer and B. A. Flora J, "Frequency based Audio Classification for Preventive Maintenance in Automobile Engines," 2023 First International Conference on Advances in Electrical, Electronics and Computational Intelligence (ICAEECI), Tiruchengode, India, 2023, pp. 1-6

[28] Akdeniz, Fulya, and Becerikli Y., Linear Prediction Coefficients based Copy-Move Forgery Detection in Audio Signal. In 2022 *International Symposium on Multidisciplinary Studies and Innovative Technologies* (ISMSIT), pp. 770-773. IEEE, 2022.

[29] Kadiri, Reddy S., and Alku P., Analysis and detection of pathological voice using glottal source features. *IEEE Journal of Selected Topics in Signal Processing* 14, no. 2 (2019): 367-379.

[30] Saldanha, Jennifer C., and Suvarna M., Perceptual linear prediction feature as an indicator of dysphonia. *In Advances in Control Instrumentation Systems* Select Proceedings of CISCON 2019, pp. 51-64.