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Acoustic condition prediction of electrical engine

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ABSTRACT

Nowadays, modern industry relies heavily on condition-based maintenance (CBM) and fault diagnosis (FD) for rotating equipment (RM). In addition, monitoring and timely repair of machinery require knowledge of its remaining useful life (RUL). Furthermore, high-efficiency electric transportation systems are based on electric motors. The increasing demand for efficiency, availability, and reliability has led to extensive research in this field. In particular, the analysis of electric motor sound data using artificial intelligence (AI) has emerged as a significant advancement. This paper presents the mel-frequency cepstral coefficients (MFCC) features of the array of a recurrent machine learning (ML) model that can learn and classify a wide variety of electric motor voice signals with robust performance. Moreover, new electric motor diagnostic tools are more accurate and efficient thanks to rotor signals from Kaggle's IDMT-ISA-ELECTRIC-ENGINE dataset and AI defect detection methods that enhancing their flexibility and efficiency. In this study, MFCC demonstrates strong performance in identifying operating modes, even in the presence of background noise. Additionally, recurrent models improve performances by increasing the robustness and reduce the time complexity associated with monitoring low-level motors. The proposed MFCC-based deep recurrent neural network (DRNN) model on the test dataset, achieving an exceptional overall accuracy of 99.83%.

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1. INTRODUCTION

In contemporary industrial applications, the increasing desire for automation, performance degradation prediction, and ensuring reliability and dependability in electric machines necessitates significant improvements in electric motor technology. These electric motors are considered the cornerstone of the modern industrial revolution that enables automation, transportation, power generation, and manufacturing across different applications [1]. Multiple applications need flexible motor performance, which is offered by induction motors, synchronous motors, and direct current (DC) motors. Synchronous motors are used for accurate speed control in robotic manipulator systems, whereas induction motors are used to operate reliably under harsh environments. Problematically, though, these machines are not infallible; many mechanical problems may occur and they are also susceptible to overheating or undesirable electrical imbalances that

might lead to degraded performance [2], [3]. Electrical machines of different kinds are still one of the most important components in modern technology. Traditionally, several diagnostic techniques such as vibration analysis, thermal scanning, acoustic monitoring, and current signature analysis were employed for diagnosing the motor performance in operation. Yet, these conventional methods are limited by their inability to distinguish between mechanical faults, overheating, and electrical unbalance conditions. Fault localization has been knowledge and labor-intensive. The major causes of diagnostics underperformance include noise, human error, and system limitations [4], [5].

The work in this paper has been done using a special type of DC motor (2ACT motor brushless DC 42BLF01) with very good specifications and features as shown in Figure 1. It contains high-quality bearings with a low friction coefficient, long life, & smooth operation. The most important electrical specifications are condensed in Table 1. These characteristics make it suitable for numerous applications in robotics, e-mobility, and automation, all of which require compact, efficient, and low-maintenance solutions.



Figure 1. Brushless DC motor (2ACT motor brushless DC 42BLF01)

Table 1. Detectable electrical specifications of the brushless DC motor

Specification	Value	Specification	Value
Model	42BLF01	Peak torque	0.18 N·m
Number of poles	8	Peak current	5.7 A
Number of phases	3	Torque constant	0.035 N·m/A
Rated voltage	24 VDC	Back EMF	3.7 V/kRPM
Rated speed	4000 RPM	Rotor inertia	24 g·cm
Rated torque	0.063 N·m	Body length	47 mm
Rated current	1.9 A	Mass	0.33 kg
Output power	26 W		

AI in combination with artificial neural networks (ANNs) has enabled the electric motor industry to advance in numerous fields through improved pattern recognition for defect detection and other purposes. The approach shows promising results for improving predictive maintenance in motor systems. The desired results were very accurate and impressive, showing the motor's condition more effectively and reliably. The MATLAB software was essential for the above endeavor.

Some academics have utilized AI to classify and identify electrical engine acoustic condition predictions. A number of methods have also been used in prior research, such as: Qassab *et al.* [6] presented a novel model integrating a noise-based Hilbert-Huang Transform (HHT) with a support vector machine (SVM) has been developed for the diagnosis of engine faults. This approach showcases effectiveness, as evidenced by comprehensive cross-validation results. Wang *et al.* [7] showed various machine learning (ML) algorithms for identifying induction motor faults under various power supply and loading conditions. Palácios *et al.* [8] presented a method for automatically identifying diesel engine defects from anomalous acoustic data, using the dislocation superimposed method (DSM), which uses random decrement, differential function, and correlation analysis for position searching. Dayong *et al.* [9] suggested using acoustic signal analysis to find problems with the stator in single-phase electrical motors. They focus on three motor states: healthy, shorted auxiliary winding coils, and a mix of the two.

Glowacz and [10] demonstrated data from adaptive kernel spectral clustering (AKSC) and long short-term memory (LSTM) recurrent neural network (RNN) to monitor machine health, with a deep learning (DL) model predicting machine failure using the Euclidean distance method. This method detects deterioration indicators in signals and recovers features, achieving high efficiency and effectiveness comparable to recognized methods. Cheng *et al.* [11] presented deep autoencoders used to diagnose electric

motor issues unsupervised, using accelerometers to record vibration signals. All auto encoder-based methods perform better than the OC-SVM algorithm, with multi-layer perceptron (MLP) achieving the best results. Evaluation examines three autoencoder designs: recurrent LSTM, MLP, and convolutional neural network (CNN) [11]. Principi *et al.* [12] proposed a cascade-CNN (C-CNN) with progressive optimization for motor fault diagnostics. The approach effectively mitigates information loss and eliminates the constraints of a fixed kernel size, thereby facilitating the extraction of features from nonstationary vibration signals. Diagnostic performance increases with constant or variable rotation speed.

Wang *et al.* [13] discussed effective methods for identifying faults in an induction motor, including vibration-based techniques and motor current signature analysis. However, identifying faults without signal processing presents challenges. Advancements in signal processing and AI offer opportunities for improved reliability, efficiency, robustness, and real-time diagnostics. Kumar *et al.* [14] showed that faults in a three-phase induction motor were detected using DL and signal processing techniques. The analysis of the motor current signature reveals the single phase, the stator windings, and the defects. The authors use the motor current signature analysis (MCSA) simulation for both single-phase and mixed conditions. DL models MLP, One-Dimensional CNN (1D-CNN), and LSTM were developed and evaluated for fault classification. Hussain *et al.* [15] proposed the use of ML to monitor and evaluate a three-phase induction motor, utilizing the CRNN algorithm to identify abnormal conditions. It measures THD (%), accuracy, and dependability by tracking fault current patterns and retrieving important characteristics.

Saxena *et al.* [16] the implemented system demonstrated its effectiveness and practical application in various industries based on significant findings. It enhanced defect detection, predictive maintenance, real-time monitoring, cost savings, and efficiency. The system's internet of things (IoT) and sophisticated analytics increased motor dependability, downtime, maintenance schedules, and cost savings. The system accurately identified vibration, temperature, speed, three-phase currents, and voltage anomalies [16]. Although techniques of deep recurrent neural networks (DRNN) and analysis of electric motor sound data were used separately before, as far as we know, no prior study has recommended combining the DRNN method with the mel-frequency cepstral coefficients (MFCC) technique. As in our work, this combination rapidly and accurately analyzes or diagnoses various acoustic conditions affecting electric motor health, resulting in impressive or unique results that are highly accurate and precise.

2. METHOD

2.1. Proposed method

First of all, effective control of an electric motor relies on monitoring anomalies using various acoustic signals and sound data sourced from Kaggle. Acoustic prediction is more effective in the determination of loss. Past studies established that DRNNs combined with MFCC are good at extracting features and carrying out predictions, which provide important information on the mechanical conditions to be considered [17]. This paper will deal with brushless DC (BLDC) motors, which have better performance characteristics and specifications. In motor systems, feature extraction is important in the prediction of acoustic behaviors. Multiple acoustic signals, such as unprocessed audio data, present valuable information on motor performance and mechanical health. Signal processing methodology includes both time-domain and frequency-domain analysis to produce averaged spectral data, and waveform properties can be used to reduce noise and make signal analysis in spectrograms possible. MFCC is the key technique in motor sound recognition and acoustic analysis with the help of progressive spectral processing and mathematical transformations [18].

Model validation is an important component of the training process, since it offers simultaneous assessment of acoustic data. Concurrent evaluation is necessary to reduce the risk of overfitting and increase the model's generalizability and reliability in various operating conditions. DRNNs possess both short-term and LSTM capabilities, enabling them to learn temporal sequences and continuously update hidden states. Consequently, the main benefit of applying DRNNs to fault detection and classification in electric motors is their ability to model and encode the time-varying trends of sequence data patterns. DRNNs are able to deal with large quantities of motor sounds by processing acoustic signals and sound data [19]. This allows the network to distinguish between normal operational noise and abnormal signs, which is more reliable in predictive maintenance of electric engines. Furthermore, the DRNN is a deep learning network, so it has the capability to automatically analyze the input data and potentially provide suitable filtering for it. Figure 2 presents the basic steps of the offered approach.

The proposed method has economical and practical impacts. Specifically, regarding the maintenance efficiency, it can report improvements compared to other analyses of vibration or current. That is, maintenance can be considered for each electric engine function immediately after classifying its operation. Examples of these are: removing the plenty load if the heavy load is identified, cutting off the electricity when the broken (faulty) case is recognized, and allowing the motor to continue working as long as it is classified for the good operation.

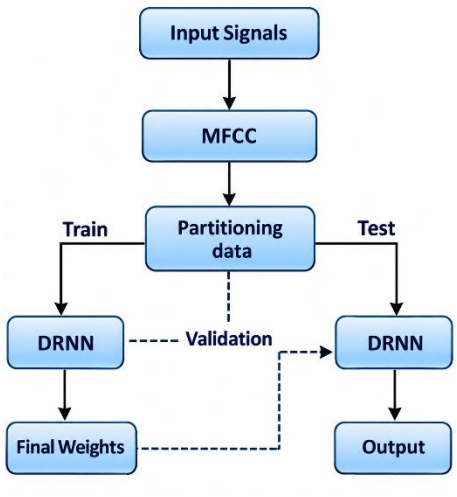

Figure 2. The general block diagram of the proposed method

2.2. Mel-frequency cepstral coefficient (MFCC)

The first milestone in the automated analysis of acoustic signals is the extraction of features from the voice signal to improve the performance of the computation and the classification process. This paper focuses on MFCC, as it extracts key features of an acoustic signal in a more effective way than classical digital signal processing techniques. MFCC has been proven to be effective in several domains of voice processing and analysis, such as speech recognition and speaker identification. Moreover, it has also been applied successfully to the study of the acoustics of high-power mechanical systems such as welders, electric motors, pumps and fans, and also used in biomedical applications, including cardiac pump diagnostics. The MFCC feature extraction process includes windowing, FFT, Mel-scaled discrete filter banks, magnitude logarithm, and discrete cosine transform (DCT) applied in this order. When combined, these processes form a systematic manner of projecting the time-domain signal to the frequency domain while keeping the perceptually important information of the acoustic signal. Conventional features such as power spectral density are not as successful as MFCC in differentiating different failure types, as these features do not capture acoustically nonlinear features and lack spectral resolution for lower-order coefficients [20]. However, while customary time-frequency features can provide valuable insights, they may lack the discriminative power required for precise classification and prediction tasks. Recent research has concentrated on ensemble-based feature selection and on wrapper-based feature selection in fault detection systems, where multiple feature detectors are used to improve classification. Real-time implementation of these approaches is difficult due to their computational requirements and the number of dimensions involved. Finally, the computational problems intrinsic to these algorithms must be solved. To overcome these challenges, the accuracy of these algorithms with regard to the fault detection problem is important for many applications and can be addressed by dimensional reduction and computationally efficient algorithms. Future work on more efficient computation structures, or also on improved dimensionality reduction, would extend the applicability of the techniques and make stronger predictive maintenance solutions acceptable in practice with reduced disruptive effects [21].

2.3. Deep recurrent neural network (DRNN)

Over the past two decades, AI and DL technologies have significantly advanced speech and audio signal processing. The main reason for this is that DL models can learn and extract appropriate features from large datasets automatically, without any prior feature definitions [22]. As sound signals are intrinsically sequential, recurrent neural networks (RNNs) were created specifically for modelling such data from the ground up. Their capacity to capture long- and short-term memory enables them to model long temporal dependencies using successive changes to the hidden state at each time step [23], [24]. This is useful in applications such as diagnosis of electrical faults by acoustic emission analysis on machinery. RNN architectures have also been shown to detect small deviations and anomalies in the motor sound signature that are representative of mechanical problems. This is due to RNNs' intrinsic advantage of being able to capture long-term dependencies for pattern recognition in time series data [25], [26]. These promising results have been extended to AI-based diagnostic techniques in industrial electrical machines, allowing predictive maintenance and improvement of machine performance by detecting faults before they lead to unplanned downtime [27].

3. RESULTS AND DISCUSSION

The employed dataset in this study is called the IDMT-ISA-ELECTRIC-ENGINE. It contains records for the DC motor which is of type (2ACT motor brushless DC 42BLF01). Its data are acquired at the Fraunhofer Institute for Digital Media Technology in 2017. Different supplied voltages and mechanical loads are considered. It can be used for acoustic diagnosis where it has signals of three different conditions (good, heavy load and broken) and three identical units. The dataset involves sounds records of the electric motor but with the inference of the various background noise types such as people talks, white noise of outside speakers, factory atmospheric sounds (high, medium and low loudness) with using speakers, and stress of simulating manipulations for the people knocking and setup. In addition to pure records of no more background noises. The records are also considered with a pre-cut where 3 seconds long segments are utilized for short time periods evaluation and easy shuffling [28].

An audio sample classified as "good class" input signals is presented here, along with its amplitude variations over approximately 140 thousand instances. The signal has exhibits typical audio features, with an amplitude modulation varying from -1 to +1 as is typically the case in audio normalization. Across time (0 to 8×10^4), some regions of lower activity can be discerned. However, two separate high-energy intervals develop at approximately 9×10^4 and 11×10^4 times with broad-band spectra, higher amplitudes and enhanced variability. These segments likely represent the most energetic acoustical events in the dataset.

The analysis results indicate that the audio signal is very complex in both frequency content and energy distribution. Therefore, from those signals we will extract the MFCC features to capture its spectro-temporal characteristics before classification with a DRNN model. Lastly, Figure 3 illustrates the waveform representation of a 'good class' input signal, highlighting its temporal amplitude fluctuations.

Figure 4 represents an MFCC feature representation of a good class audio sample that depicts the transformed spectral characteristics across about 300 MFCC features. The plot illustrates distinct amplitude patterns represented by the yellow and blue lines at the top, displaying larger amplitude values ranging from approximately 2 to 5. These values correspond to lower-order MFCC coefficients, which effectively capture crucial information regarding the spectral envelope. This MFCC transformation has successfully decoded the raw time-domain audio to a slimmed-down frequency spectrum that captures perceptually salient spectral information and can be used as an input for our DRNN classifier. The fixed and organized pattern of these MFCC coefficients reflects the steady spectral feature in the "good class" audio samples, so the neural network is able to learn discriminative features for performing precise classification. This figure reviews good class Audio MFCC features. Eventually, Figure 4 illustrates spectral characteristics of 'good class' audio in MFCC representation.

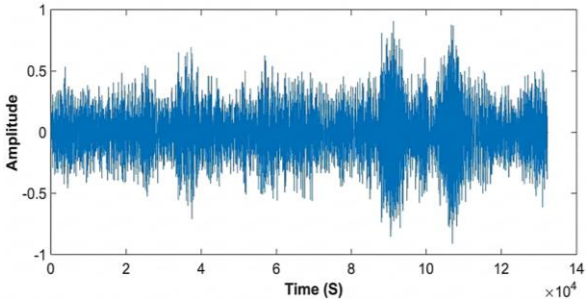

Figure 3. Time-domain representation of 'good class' audio signal

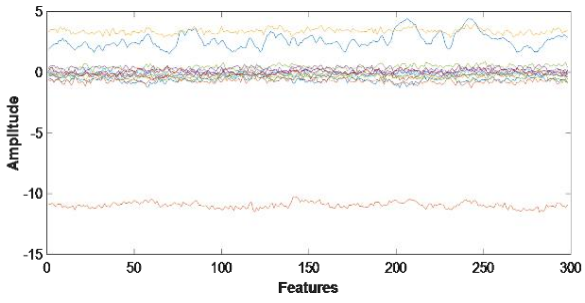

Figure 4. MFCC features of a 'good class' audio sample

An audio waveform sample of the broken or faulty class input signal is illustrated in Figure 5. This waveform represents a 140,000-time sample of a 'broken class' audio example, generated by distorting the amplitude of the signal toward chaotic and irregular patterns. Consequently, its sound profile differs significantly from the original audio signal. It begins following an avalanche of near-maximal activity, with spikes of energy occurring at 1×10^4, 5×10^4, 1.1×10^5, and 1.3×10^5 time steps. It also includes chaotic amplitude patterns in the range of -1 to +1 perhaps showing anomalies or defects. The noisy class pattern has high amounts of noise, as well as many amplitude excursions to -1 or +1. This results in the typical temporal patterns that are effectively separated from satisfactory class pattern samples. The separated distinctive cues are then used for MFCC extraction and passed through the DRNN classifier to precisely recognize broken audio conditions.

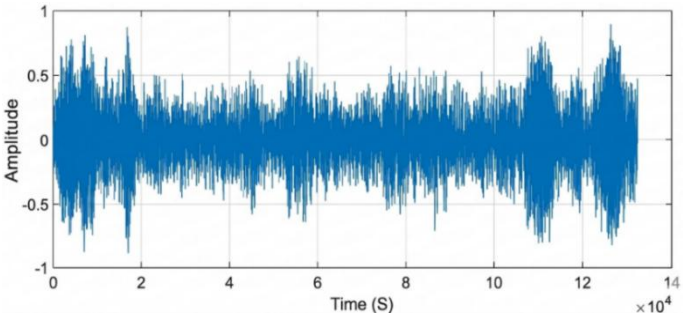

Figure 5. 'Broken class' audio signal with repetitive high-amplitude events and chaotic amplitude variations

For example, the MFCC representation of the "broken class" audio sample as shown in Figure 6. The 300 coefficients exhibit irregular spectral patterns, marked by significant amplitude fluctuations and erratic temporal dynamics that clearly differentiate them from normal audio signals. The upper coefficients fluctuate inconsistently with amplitudes between 1 and 5, while the middle coefficients oscillate more intensely around zero. Conversely, the lower coefficients remain relatively stable near −10. These distinctive and non-uniform MFCC characteristics effectively capture the spectral anomalies and degradation inherent in faulty audio, providing robust distinguishing attributes for fault classification through deep recurrent neural networks (DRNNs). Because the DRNN classifier models long-term temporal dependencies and nonlinear time-varying dynamics, it is better suited for the complex structure of these audio feature vectors than other classifiers that do not utilize localized dynamic information in their decisions.

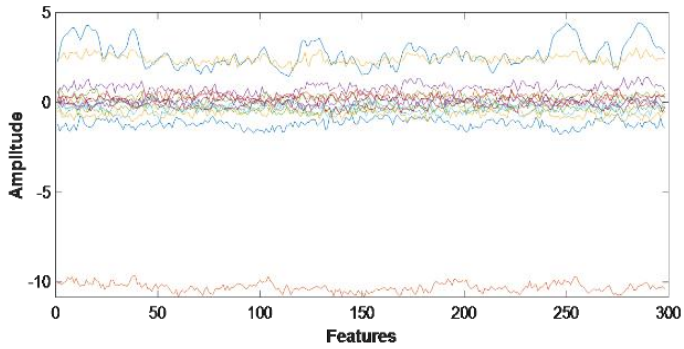

Figure 6. MFCC-based spectral characterization of defective audio samples for anomaly classification

To illustrate the characteristics of the heavy load condition, Figure 7 demonstrates an example audio signal with a length of approximately 140,000-time samples. A bimodal scenario is clearly represented by this waveform, exhibiting two distinct phases. The first part (0-9.0×10⁴ samples) has a moderate amplitude and its values oscillate between -0.8 and +0.8. During the second part (9.0×10⁴-14.0×10⁴ samples), the amplitude is high and the signal oscillates between the regions of maximum amplitude. This temporal transition indicates the sound characteristics of devices under most severe operational loading conditions, when mechanical loading increases vibration and noise levels, higher electrical pressure and impedance ratios create modulations of the audio signal, build up electrical energy, increase the amplitude, and include additional frequencies into the oscillation. The mechanical friction generates noise causing further fluctuations. The amplitude and energy density suggest that the operating conditions under high load or intensive usage differ greatly from those under normal operating conditions. These features can resolve heavy load samples in both good class (normal operation) and broken class (broken). The time history of the structural response and the energy distribution over time are good separating features. These characteristic patterns can be represented in details by MFCC feature extraction and can be identified and classified without error using the DRNN-based identification and classification model.

The MFCC of a heavy load class sample subsequent representation exhibits unique spectrum like properties over 300 features which distinguishes it from the good and broken class samples. Firstly, the first 200 features show stationary pattern where their upper coefficients maintain relatively consistent amplitudes

of around 3-4 and middle coefficients are concentrated on zero. A transition occurs however at the feature 200, where the upper coefficients start oscillations late apart considerably up to an amplitude of six (the bottom coefficient displays also important negative excursions down to -12.0). In addition, this transition is a convenient way to represent the bimodal behavior observed in the input time-domain signal induced by the change from moderate to heavy load. Therefore, our dynamic MFCC patterns are capable of giving discriminating features for the DRNN to identify heavy load from normal and faulty status. The temporal progression of these coefficients shows that the model captures not only steady-state, but also transient spectral features required for accurate classification. Finally, Figure 8 shows transition and classification bimodal MFCC patterns for heavy load class audio signal. Thus, the temporal variation of these coefficients reflects model-based steady-state and transient spectral features required for correct discrimination.

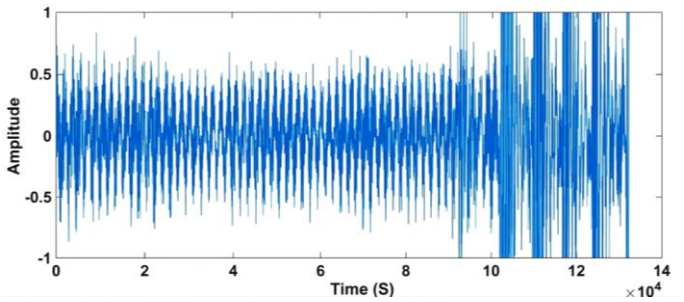

Figure 7. Bimodal amplitude and energy distribution of 'heavy load class' audio signal

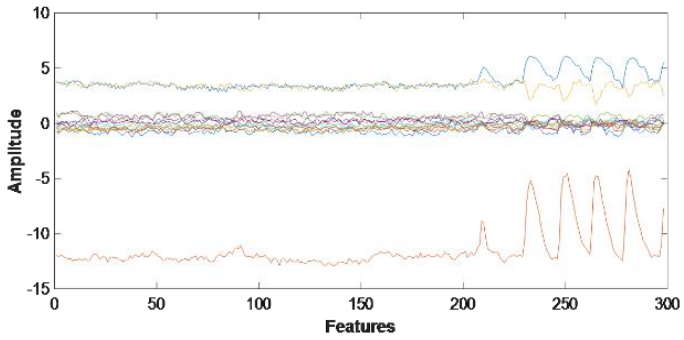

Figure 8. Discriminative spectral features in MFCC representation of heavy load audio for DRNN classification

In this study a DRNN structure with MFCC input features was examined for audio processing applications. The model is trained for 5 epochs, at the learning rate of 0.001 with 440 iterations per epoch, and it took around 13.77 seconds to converge completely. Both training and validation accuracies converged swiftly, achieving ~99.33% with corresponding decreases in loss functions. The validation loss was also plateaued appropriately, demonstrating the avoidance of overfitting and high generalization ability. Experimental results showed that the proposed model could achieve efficient inference with response time of 0.31 second, indicating its good suitability for real-time scenarios. The experiments validate that our DRNN is effective in learning the temporal patterns from MFCCs with less computation cost. In practical audio processing tasks such as speech recognition, audio classification and speaker identification systems, this approach is easily practical. Finally, Figure 9 shows training and validation metrics for DRNN architecture with MFCC input features.

The training and validation performance of the DRNN without MFCC is presented in Figure 10. For this model, the training interface illustrates the deep network performance over 8 epochs and 170 completed iterations. From the performance curves, we can see that the training accuracy (blue curve) has a fast convergence, which increases from 40% to around 100% in two epochs and then stabilizes. Meanwhile, validation accuracy (black dashed curve) continually increases and approaches 69% throughout the training process. Both loss curves show that learning is effective with a quick stabilization of the training (orange line) to nearly zero and validation loss which decreases from 1.5 to 0.8 before saturating after the first epoch. Our relevant statistics are training time of 296.09 seconds (about 4min and 47 seconds), a test time 1.73 seconds, and an outstanding final test accuracy of 99.83%. The model had a fixed learning rate of 0.001,

and was validated every 10 iterations on one CPU. Notably, the very high overall final test accuracy values (99.83%) with an intermediate validation accuracy 69.19% support the claim that our model achieved sufficient generalization capabilities and learned the essential features for classification efficiently. Figure 10 presents the performance of DRNN without MFCC. Statistically, the training required 296.09 seconds (approximately 4 minutes and 47 seconds), with a testing time of 1.73 seconds and an outstanding final test accuracy of 99.83%. The model was trained using a fixed learning rate of 0.001 and validated every 10 iterations on a single CPU. Notably, achieving a very high final test accuracy (99.83%) alongside an intermediate validation accuracy of 69.19% demonstrates that the model achieved strong generalization capabilities and efficiently learned the essential features for classification.

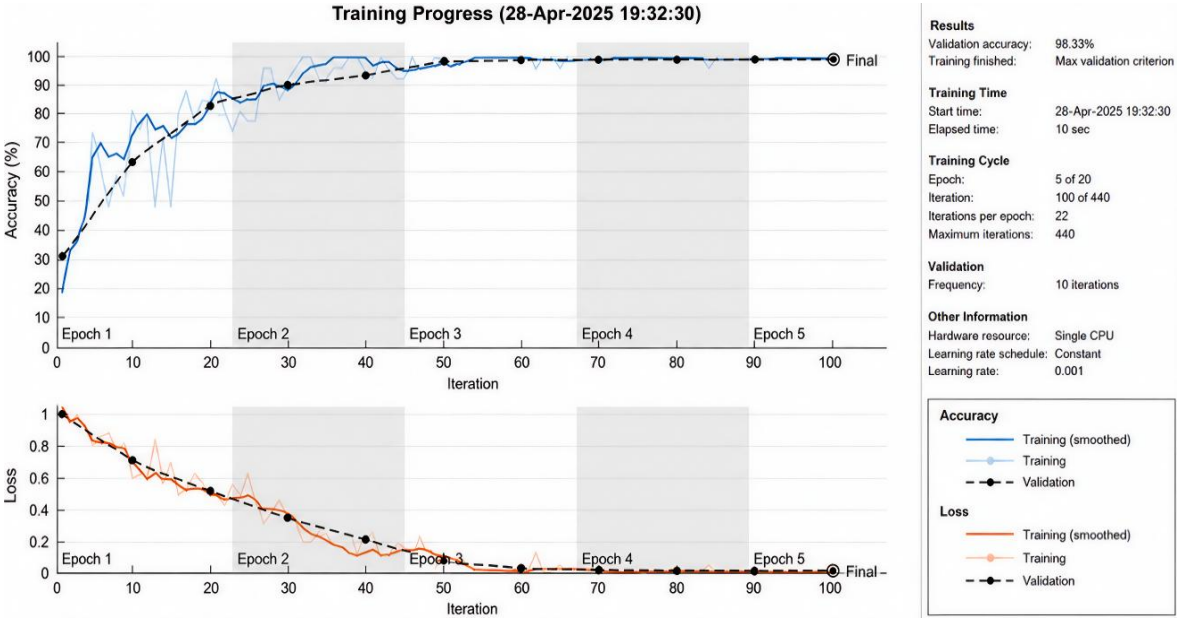

Figure 9. Training and validation metrics for DRNN architecture with MFCC input features

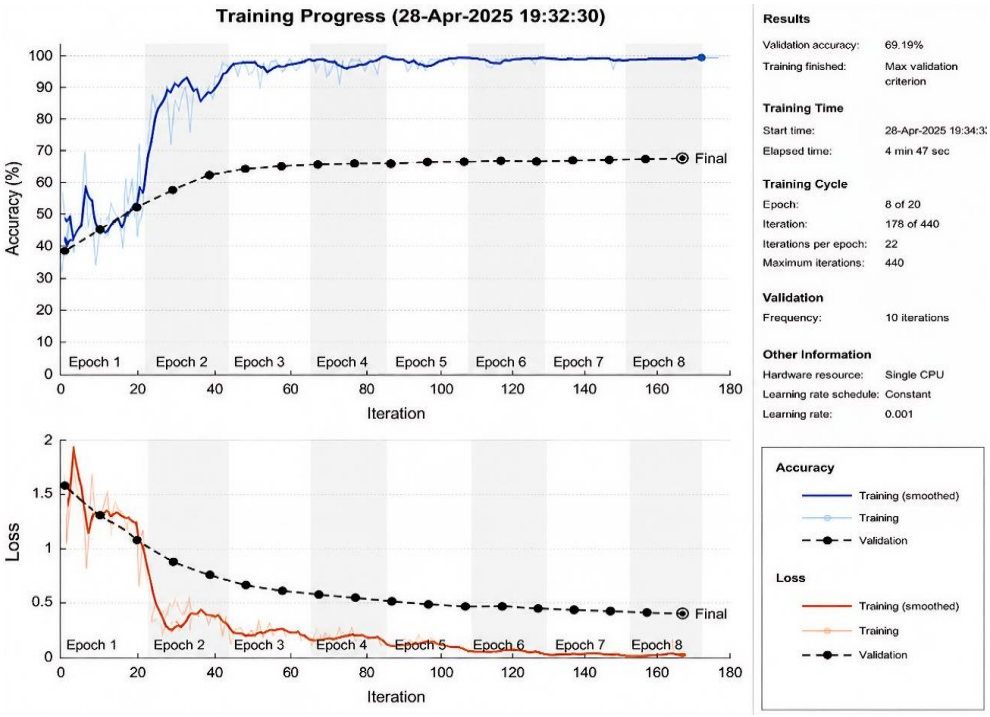

Figure 10. Illustrates DRNN training and validation without MFCC

The confusion matrix of the DRNN model evaluated on the test dataset is presented in Figure 11, demonstrating a remarkably high overall accuracy of 99.8319%. The model exhibits near-perfect sensitivity across all target categories. Specifically, Class 0 achieves a 100% precision rate, while Class 2 also demonstrates ideal classification performance, correctly identifying 152 and 205 samples, respectively. Category 1 had an accuracy of 99.3% (157 labelled cases among the total of 158), and one sample from Category 1 was misclassified as Category 0. The confusion matrix shows that the misclassification rate is very small with only one misclassification over all testing examples. The balanced distribution of the samples in the categories (152,158 and 205 examples) ensures a fair evaluation regardless of any category. Moreover, the accuracy rates were uniformly high, ranging from 99.3% to 100%, indicating the model's strong discriminative power as well as excellent generalization capacity. These experimental results further confirm the strong performance of the MFCC-based DRNN model in the audio categorization task, and also show that the error rate approach zero (0.1681%), indicating this model can be applied directly to practical services. Finally, the confusion matrix provides a comprehensive summary of testing results. This exposes the patterns for accuracy and inaccuracy classifications and offers reference points for assessing the model's performance. The figure illustrates a confusion matrix analysis based on the DRNN structure, demonstrating its effectiveness in achieving high-accuracy audio classification.

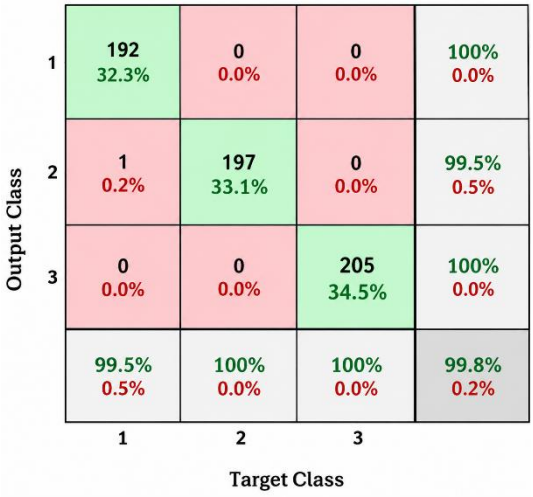

Figure 11. Confusion matrix and analysis, DRNN test data performance

It is worth mentioning that translating the acoustic classification into the classes of good, broken, and heavy load has predictive maintenance benefits. That is, actionable maintenance can be scheduled for each electric engine class. For the heavy load operation, removing the plenty load is required. For the broken operation, cutting off the electricity is required. For the broken operation, cutting off the electricity is required. For the good operation, leaving the motor to continue works, however, turning it off after appropriate period of time is required in order to prevent it from being excessive strain.

For the purpose of comparisons, other signal processing techniques are taken into accounts. These are the discrete wavelet transform (WT), short-time fourier transform (STFT) and power spectral density (PSD). Each one of these compared methods is utilized instead of the MFCC. Table 2 shows results of the testing accuracies of using the MFCC and other compared signal processing techniques.

Table 2. Results of the testing accuracies of using the MFCC and other compared signal processing techniques

Signal processing technique	Testing accuracy
PSD	67.34%
WT	94.95%
STFT	95.12%
MFCC	99.83%

From this table it can be seen that the worse testing accuracy of 67.34% is recorded for the PSD. Close accuracies of 94.95% and 95.12% are reported for the WT and STFT, respectively. Such performances are due to the algorithms of these compared methods, where each one of them could not effectively obtain the most useful features that lead to attain the highest accuracies. Noticeably, the employed MFCC in this study has proven its effectiveness in acquiring the most valuable features which lead to the highest accuracy of 99.83%.

For time comparisons, other models of a CNN and SVM are considered instead of the DRNN. A CNN is obtained the training elapsed time of 7 min and 35 seconds and the testing elapsed time of 0.94 seconds. On the other hand, an SVM shows faster implementations where it is attained the training elapsed time of 3.33 seconds and the testing elapsed time of 0.84 seconds. Although, the SVM was so fast in its training, it has failed in well predicting the conditions of electrical engine as it shows a very testing accuracy of 34.18%. Whilst, the applied CNN achieved a slightly less testing accuracy to our DRNN. Our employed DRNN reaches the training elapsed time of about 4 min. and 47 s, a testing elapsed time of 1.73 seconds, and a superior testing accuracy of 99.83%. It can be noticed that all testing times for all compared models are too short and this is valuable for embedded motor monitoring. Furthermore, the DL models are much efficient in classifying the acoustic conditions of electrical engine than the traditional model of SVM. Finally, the employed DRNN can surpass other ML models in its overall efficiency in terms of analyzing motor acoustic signals.

The outcomes of this paper can be considered as promising results for the case of scalability to larger induction or synchronous machines. Examples of such machines are that they are used in electric vehicles (EVs), renewable systems and industrial drives. Principally, our AI study of predicting electrical engine operations based on acoustic conditions can be applied and evaluated for larger machines. This can be so valuable, where normal and faulty operations would be recognized by the power of ML without the need of humans' monitoring. This further reduces personal efforts and times, and even may decrease electrical controlling costs.

4. CONCLUSION

In this study, MFCC-based features integrated with DRNN are used to predict the acoustic conditions and the fault states of various types of electric motors such as BLDC. The MFCC feature is used for the extraction of the spectral features of the acoustic signature. It allows distinguish between normal, fault, and overloaded conditions. Additionally, DRNN architecture addresses temporal dependencies, which allows it to model sequential components, and helps detect early-stage degradation and mechanical faults that can otherwise be missed by conventional diagnostic approaches. Additionally, as the DRNN can handle time series data while preserving the context of the data, as well as the context within the layer, this positively impacts the performance of the detection. The DRNN architecture developed also achieved a validation accuracy of 99.33%, showing its potential as a smart predictive maintenance model for industrial environments. Therefore, operational downtime is minimized while system reliability is substantially improved.

This model was computational efficient and runtime of testing and training were only 0.31 seconds and 13.77 seconds respectively. Fast processing validates real-time application and is a key asset for those industries that apply predictive maintenance. By combining MFCC with MDC for inclusion into the DRNN, a significant enhancement of malfunction identification approaches can be achieved in addition to practical solutions for preventive maintenance. Thus, a platform for potential improvements that includes the optimization of variable selection, dimensionality reduction and online monitoring systems is created. Such advances will likely help broaden the industrial relevance of this technology.

For future work, predicting other BLDC motor acoustic conditions related to electrical performance, such as torque ripple, efficiency and current imbalance, can be considered. Also, acoustic features to motor drive characteristics will be provided and explicit. More suggestions for future work, investigating other BLDC motor acoustic conditions of actual electrical and mechanical faults, as bearing wear, stator imbalance and rotor eccentricity, can be taken into account. This requires acquiring a dataset for such faults, then, considering a new class for each fault.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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