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Acoustic Signal Processing and Deep Learning Nexus for Brushless Direct Current Motor Status Classification

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Abstract: Brushless Direct Current (BLDC) motors are ubiquitously deployed in various industries that underline the present industrial revolution. Owing to their versatility and relevance in the manufacturing industry, predictive maintenance of these motors calls for critical concern, over implications such as operational downtime and maintenance cost. This paper presents the development of a BLDC motor classification framework leveraging acoustic signal processing and deep learning. The IDMT-ISA-ELECTRIC-ENGINE dataset for the 42BLF01 Brushless Direct Current (BLDC) motor classification under artificially induced states, was imported for model development. This audio dataset contains three classes, namely, 'engine1_good', 'engine2_broken' and 'engine3_heavyload'. Audio processing was carried out on the dataset, to convert the audio signals into mel spectrograms, via the Short-time Fast Fourier and Normalization techniques. Three recurrent deep learning models (Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM) and an LSTM-GRU hybrid), three transformer models with positional encodings (pe) (rotational_pe, sinusodal_pe and relative_pe) and a convolutional neural network (CNN) model (cnn2d_model) were implemented to fit the processed data. Model training, validation and inference were carried out and it was discovered that although all the models performed excellently, the best performing models were sinusodal_pe and relative_pe on the basis of Loss score. Furthermore, a BLDC motor status classifier application was developed using Streamlit. Developed recurrent models along with an ensemble of the models were deployed in the application and could classify BLDC motor operational status excellently.

Key words: Brushless Direct Current, Motor, Operational Status, Deep Learning, Classification

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1. INTRODUCTION

A brushless DC (BLDC) motor is a highly preferred manufacturing choice owing to qualities such as exceptional efficiency, high power density, low noise levels, among others. BLDC motors are therefore extensively employed in cutting-edge manufacturing and industrial control sectors such as robotics and automotive systems, due to their reliability and compactness (Yaşa, 2022; Mohanraj et al., 2022). Furthermore, the durability and capacity demonstrated by BLDC motors while operating smoothly under diverse conditions have further resulted in their accelerated adoption for advanced manufacturing processes. BLDC motors are typically powered by electronically commutated motor drives which manage the electrical input, while each phase is regulated via a closed-loop control system. The closed-loop controller delivers precise current pulses to the motor windings, so as to ensure effective control over motor speed and torque (Albadr et al., 2025). These motors therefore require highly complex control circuits, leading to higher cost. BLDC motors also depend on positional data for accurate operation (Cira, Arkan and Gumus, 2016). Since precise speed as well as position determination are critical in BLDC operations, early fault detection becomes imperative so as to mitigate degradation in motor performance as well as sensitivity.

BLDC motors are highly susceptible to various mechanical and electrical faults, such as shaft misalignment, bearing wear, excessive load conditions, rotor imbalance, among others. These faults could in turn result in severe failures, such as unexpected downtimes and elevated maintenance costs, thus affecting productivity. Early diagnosis and classification of motor operational status is thus crucial for sustaining optimal production and minimizing repair costs (Zhang and Lin, 2019). Traditional scheduled fault detection methods are often limited in handling real time issues, resulting in slow interventions or potential industrial component damages. Machine learning has already gained traction as a highly effective method for intelligent classification and identification of motor status (Hsiao and Htet, 2024; Bozovic et al., 2024; Gouveia et al., 2023). Whereas machine learning interventions are promising, the shallow learning methods have certain limitations in that they cannot fully and automatically explore the deep features of training data. This limitation further affects their fault diagnosis and classification accuracy (Lin, 2018). Deep learning on the other hand, not only increases model capacity by deepening the network, it exhibits the characteristics of universal approximator, capable of feature learning on complex datasets. Deep learning algorithms can thus be used to develop highly efficient predictive models for BLDC motor fault diagnosis and classification. In machine diagnostics, the acoustic signal has emerged as one of the most promising, although it demands significant compute and high sampling rates for signal processing (Kozłowski et al., 2020).

Various researchers have employed machine learning (ML) for motor operating status diagnosis and classification. Suawa et al. (2022) employed microphone and accelerometer sensory data for predicting the BLDC engine states. The data was used to develop three models, namely Deep Convolutional Neural Network (DCNN), Long Short Term Memory (LSTM) and a hybrid (CNN-LSTM). The models achieved respective accuracies of 98.8%, 73.6% and 93.5%. Chen, Wang and Zhang (2024) introduced a novel machine learning-based technique for predicting and diagnosing brushless motor faults. They

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employed sensor data and ML algorithms such as Support Vector Machine (SVM), Random Forest (RF) and Neural Networks (NN). SVM yielded 95 percent accuracy, NN yielded 97 percent accuracy, while RF yielded 92 percent accuracy in real-time monitoring. In Glowacz and Glowacz (2016), the K-nearest Neighbours (KNN) classifier was implemented for induction motor fault diagnosis. An accuracy score of 88 percent was attained by the model. Uzel et al. (2025) employed the IDMT-ISA-ELECTRIC-ENGINE dataset for motor operational status classification. In order to prevent data leakage, the study employed file-level splitting, session separation, 5-fold cross-validation, and repeated trials. The raw audio signals were transformed into Mel spectrograms and processed through a CNN architecture. The proposed model achieved a test accuracy of 99.7%, outperforming other approaches such as ResNet-18, a convolutional-recurrent architecture and transformer classifiers.

The diagnostic results obtained in studies above could be improved upon, furthermore other novel approaches can be employed for BLDC motor status classification, hence this study.

2. Methodology

The entire pipeline for developing the BLDC status classifier leveraging acoustic signal processing and deep learning techniques is illustrated in Figure 1.

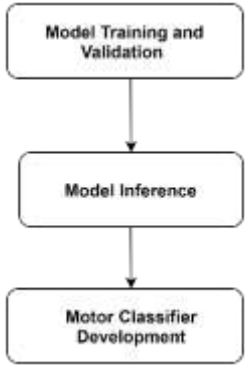

Figure 1: BLDC Motor Classifier Development Pipeline

2.1 Model Training and Validation

2.1.1 Importation of Dataset

The IDMT-ISA-ELECTRIC-ENGINE dataset was imported from Kaggle.com. It contains distinct acoustic signals obtained from three similar units of the 2ACT Motor Brushless DC 42BLF01, 4000 RPM, 24VDC. In each of three data files, the activity of a single motor is simulated. The rationale is that a motor can only have one of the three considered operational states (“good”, “heavy load” and “broken”). Three operational states

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were simulated by changing motor supply voltage and loading weight thus resulting in sound changes. The first motor was operated with sixty percent of supply voltage to represent "good" operational state. In the case of the second motor, supply voltage was altered every 18 milliseconds between fifteen percent and seventy-five percent of original value to simulate the "broken" unit. For the third motor, an additional weight was applied while it was powered by sixty percent of supply voltage, to represent "heavy load". The dataset properties are described below:

File duration: 42.32 minutes
Number of Samples for Operational State "good": 774
Number of Samples for Operational State "broken": 789
Number of Samples for Operational State "heavy load": 815
Total Number of WAV Files: 2378
Sampling rate: 44.1KHz
Resolution: 32-bit
Mono audio (Sascha et al., 2019).

2.1.2 Dataset Encoding and Audio Signal Processing

Label encoding was used to convert the three classes to numerical representations as follows: 0 for 'engine1_good', 1 for 'engine2_broken' and two for 'engine3_heavyload'. The train_test_split function from the sklearn library was then employed to split the data into 90 percent training and 10 percent validation respectively. Data split was carried out at the file/recording level using GroupShuffleSplit, so every segment from a given recording is entirely on one side of the split (i.e., training OR testing) to prevent leakage.

Audio signal processing was carried out using the Short Time Fourier Transform (STFT) method. The audio data form was thus converted into mel spectrogram via the following parameters: n_fft=1024, hop_length=1024//2, n_mels=80 and sampling_rate=16_000.

In other words, the STFT window size was 1024, the number of mel bins produced was 80 and the sampling rate was 16kHz.

2.1.3 Development of Deep Learning Classifiers

Three recurrent deep learning models (Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM) and an LSTM-GRU hybrid), three transformer models (rotational_pe, sinusodal_pe and relative_pe) and a convolutional neural network model (cnn2d_model) were implemented to fit the processed data. Similar hyperparameters tuned for the recurrent deep learning models include:

n_class = 3
batch_size = 32
input_size = 80
n_layers = 2
hidden_size = 512

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In addition, similar hyperparameters tuned for the transformer models include:
in_channel = 1
embed_dim = 1024
patch_size = 16
num_head = 16
n_blocks = 12
max_seq_len = 2048

While hyperparameters tuned for cnn2d_model (three progressive convolutional blocks followed by a pooling stage) include:

- **Layer 1 (Conv2d)**:

Output channels (Filters): 32
Kernel size: 3 × 3
Padding: 1
Stride: 1 (default PyTorch behavior)

- **Max Pooling 1 (MaxPool2d)**:

Kernel size: 2 × 2
Stride: 2

- **Layer 2 (Conv2d)**:

Input channels: 32
Output channels (Filters): 64
Kernel size: 3 × 3
Padding: 1
Stride: 1

- **Max Pooling 2 (MaxPool2d)**:

Kernel size: 2 × 2
Stride: 2

- **Layer 3 (Conv2d)**:

Input channels: 64
Output channels (Filters): 128
Kernel size: 3 × 3
Padding: 1
Stride: 1

- **Global Pooling (AdaptiveAvgPool2d)**:

Output size: 1 × 1 (in order to flatten the spatial height and width dimensions to 1)
Dropout = 0.3
Activation Function = ReLU

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A 100 epoch run was implemented for training all models. The Adam optimizer (Kingma and Ba, 2014) with a learning rate of 0.001 and the cross-entropy loss function were also implemented. The Gaussian Error Linear Unit (GeLU) activation function was implemented for all model layers (excluding CNN with ReLU). For final layer in the models, softmax function was implemented owing to the multiclass objective. Early stopping was also introduced into the training pipeline to mitigate overfitting of the models. All model developments were carried out via the Pytorch framework. After training, the models were thereafter validated using the held out ten percent of the original data.

2.1.4 Motor Status Classifier Application Development

A BLDC operational status classifier application was further developed using the Streamlit framework. The recurrent models were deployed both on individual basis and as an ensemble. The motor acoustic under consideration was test data for 'engine1_good' class which included background noise simulating atmospheric sounds from a factory environment at high loudness level.The study was conducted among married women in Emure Local Government Area of Ekiti State, Nigeria. Descriptive research design of the survey type was used for the study. A sample of 220 married women was selected using multi stage sampling technique. The headquarter was purposively being the only urban town in the Local Government Area (LGA) and three villages were selected through simple random sampling. Respondents were selected using convenience sampling technique. Data were collected using a pre-tested close-ended questionnaire designed from related studies. The content validity was determined by experts while Cronbach Alpha with a coefficient of 0.68 was used to establish the reliability of the questionnaire. A total of 220 copies of questionnaire were administered by the researcher with the aid of three research assistants who were trained both on the content and the modalities of administering the questionnaire. The instrument was administered to the participantsin their residences, offices or in the hospitals during post natal clinics after obtaining verbal consent.

3. Results and Discussion

3.1 Results

3.1.1 Results for Training and Validation

The results for training and validation of all models considered are illustrated in Figures 2 to 22. Performance metrics include Accuracy, F1-Score and Loss.

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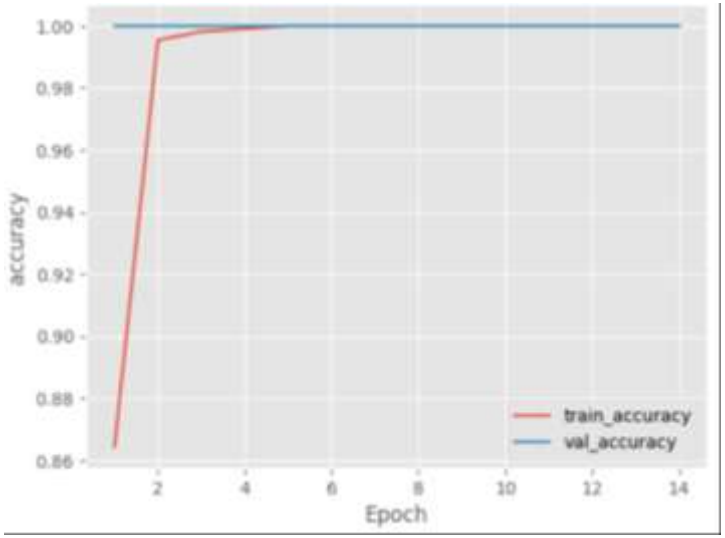

Figure 2: GRU Accuracy

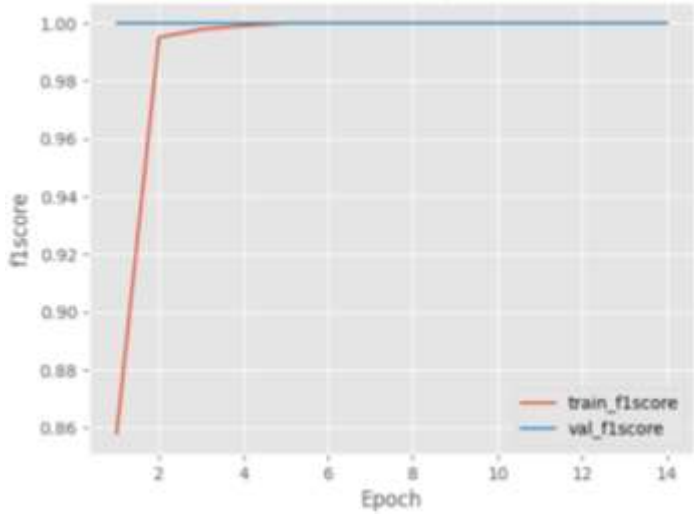

Figure 3: GRU F1-Score

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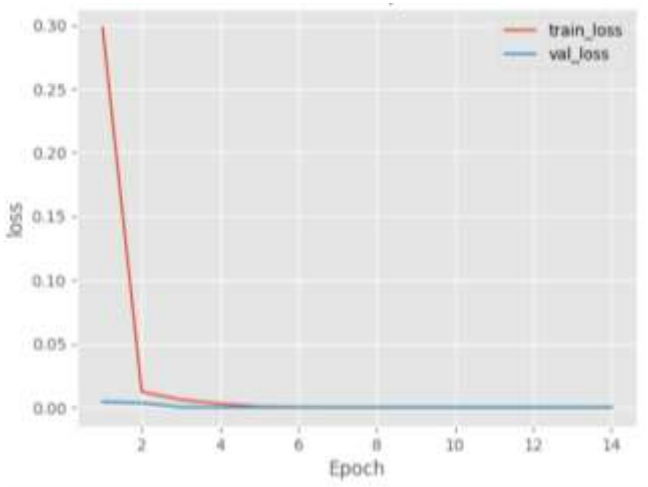

Figure 4: GRU Loss

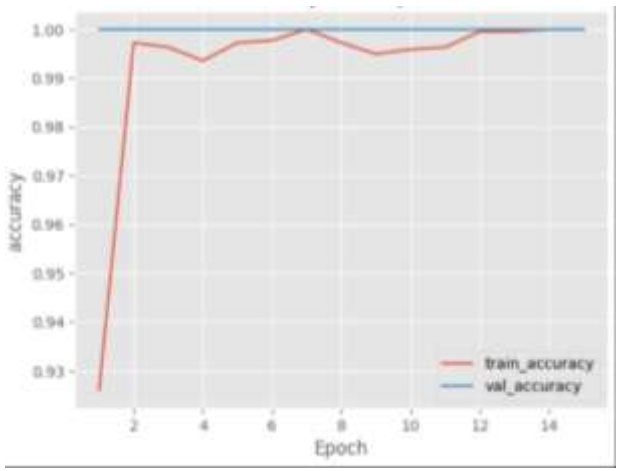

Figure 5: LSTM Accuracy

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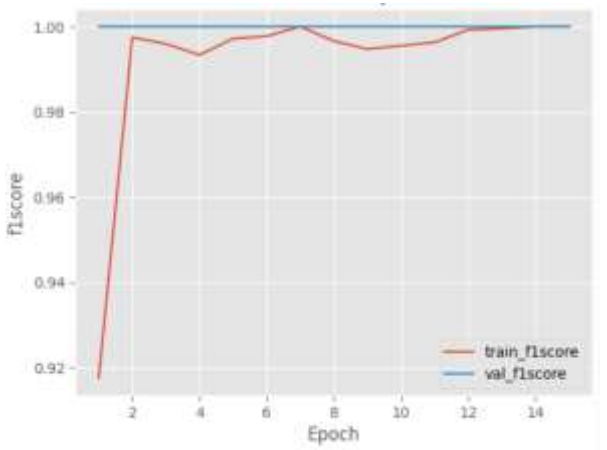

Figure 6: LSTM F1-Score

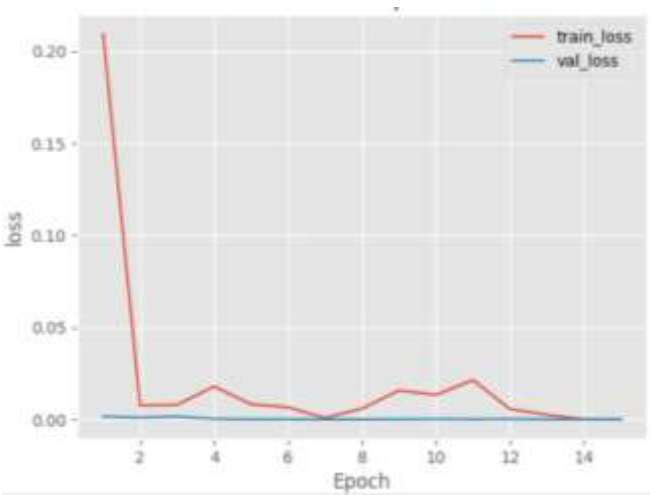

Figure 7: LSTM Loss

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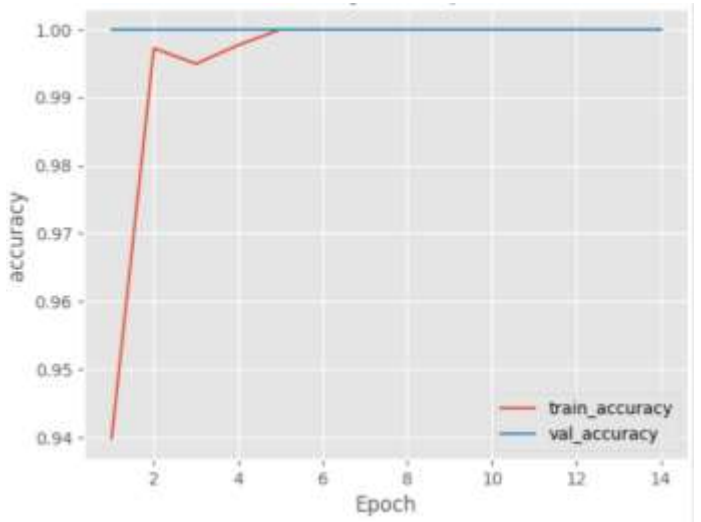

Figure 8: LSTM-GRU Accuracy

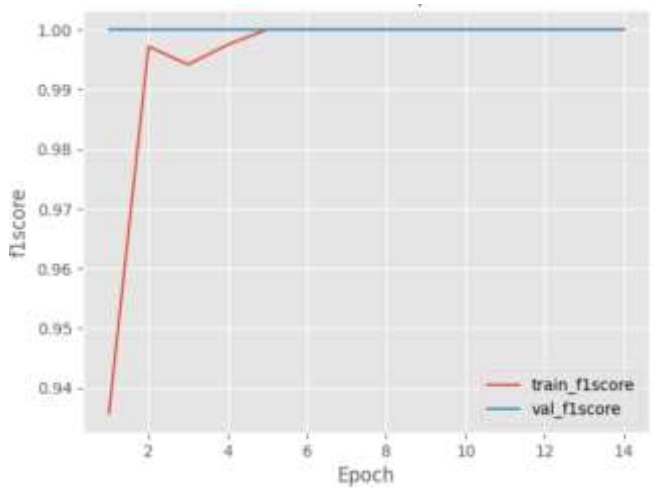

Figure 9: LSTM-GRU F1-Score

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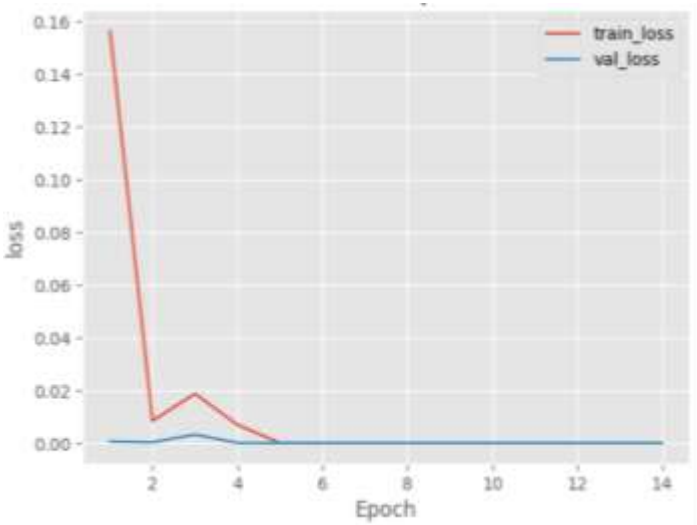

Figure 10: LSTM-GRU Loss

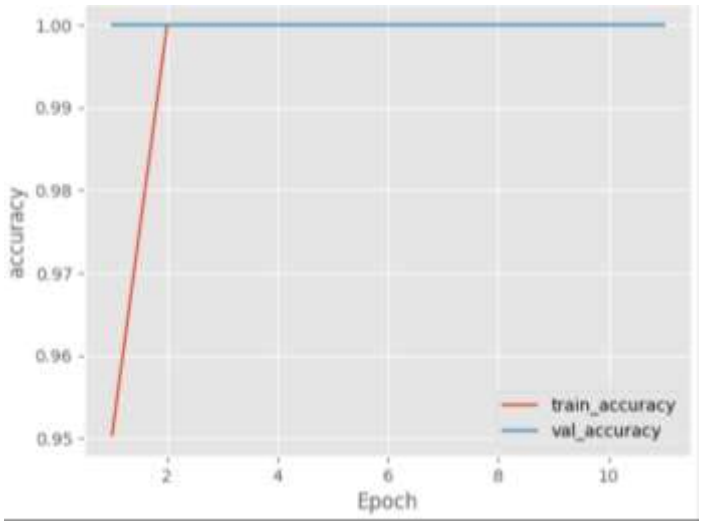

Figure 11: Rotational_pe Accuracy

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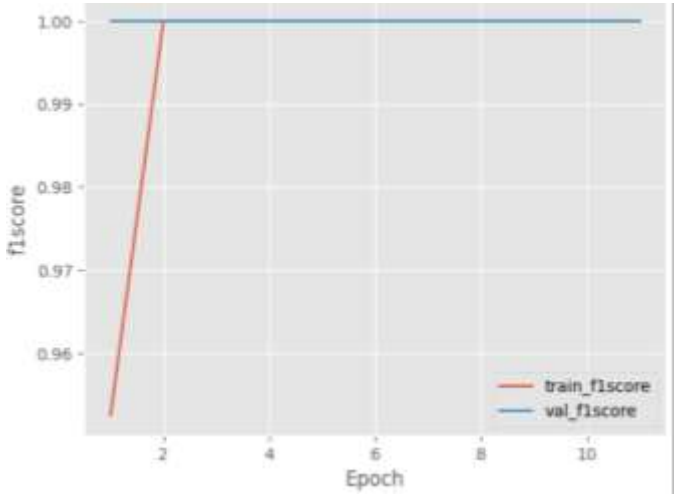

Figure 12: Rotational_pe F1-Score

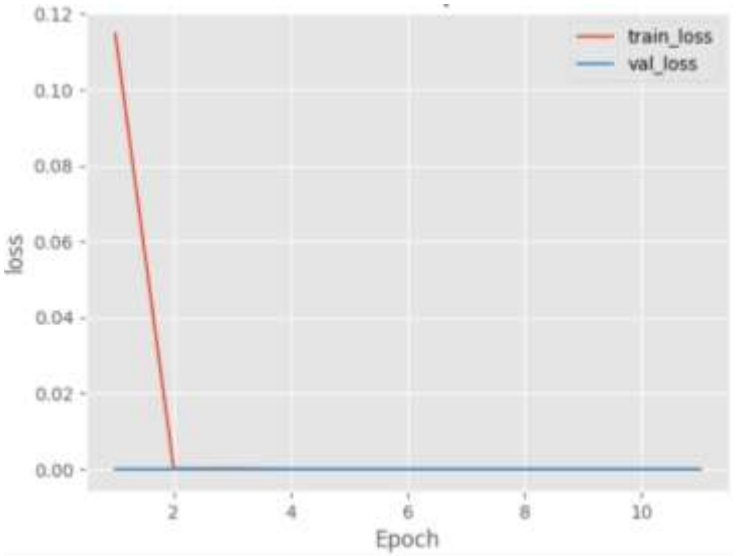

Figure 13: Rotational_pe Loss

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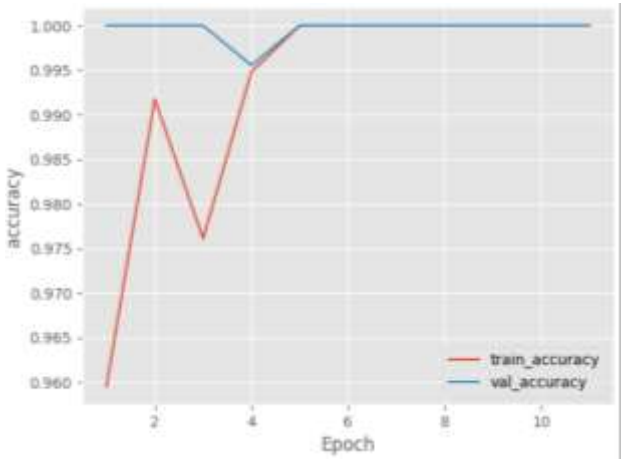

Figure 14: Sinusoidal_pe Accuracy

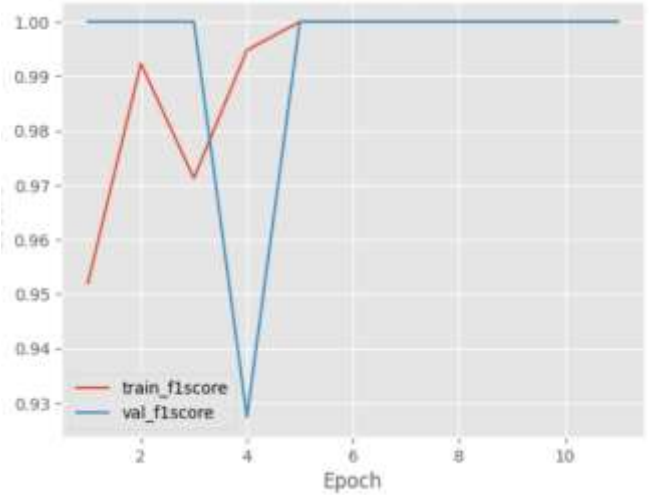

Figure 15: Sinusoidal_pe F1-Score

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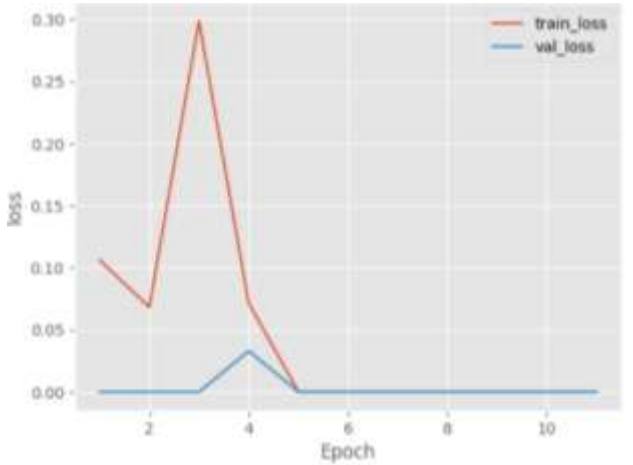

Figure 16: Sinusoidal_pe Loss

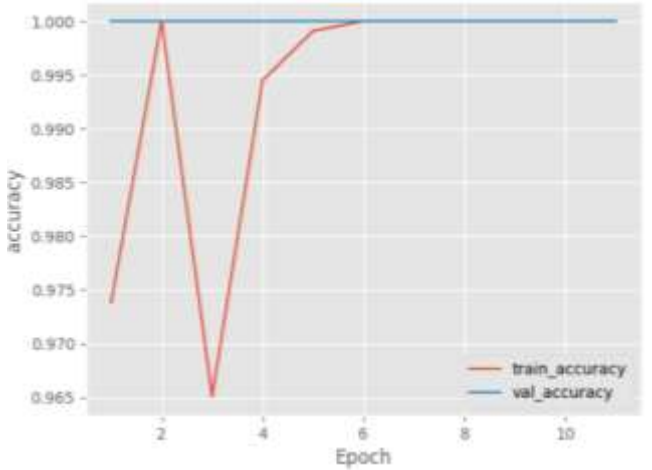

Figure 17: Relative_pe Accuracy

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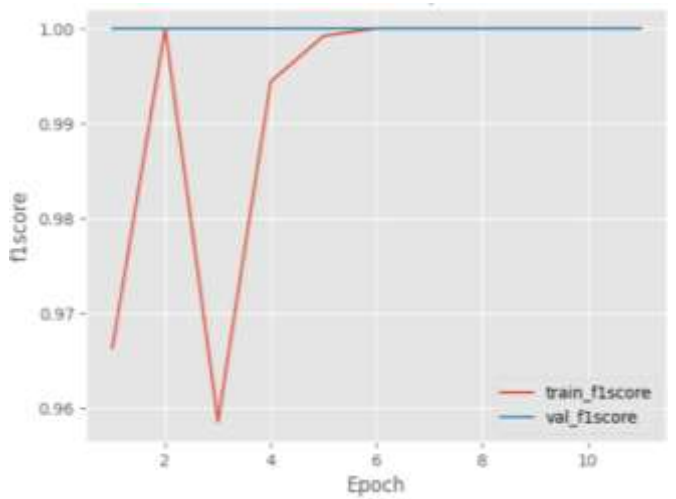

Figure 18: Relative_pe F1-Score

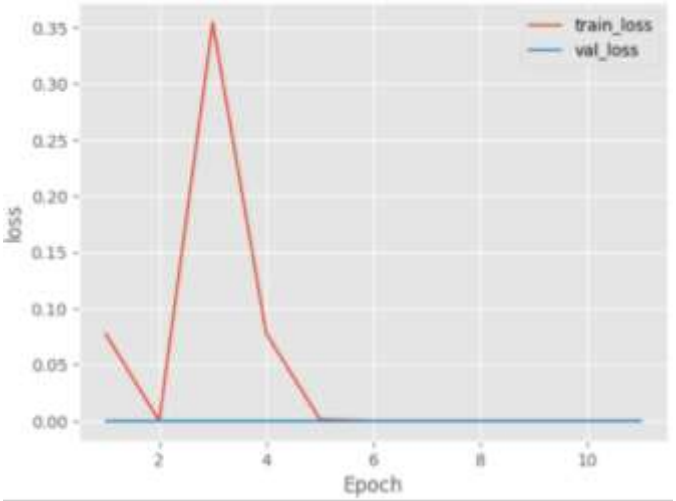

Figure 19: Relative_pe Loss

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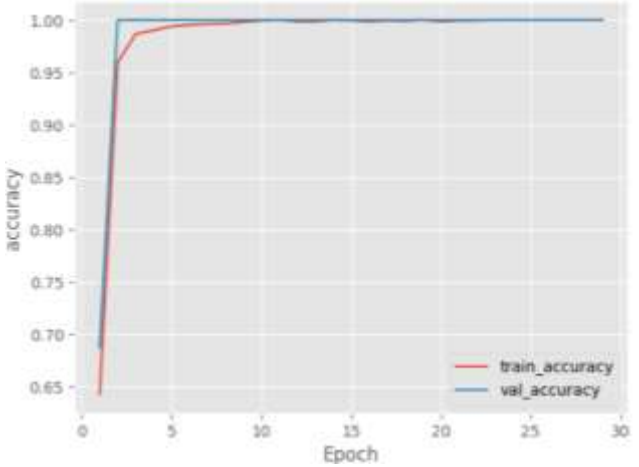

Figure 20: cnn2d_model Accuracy

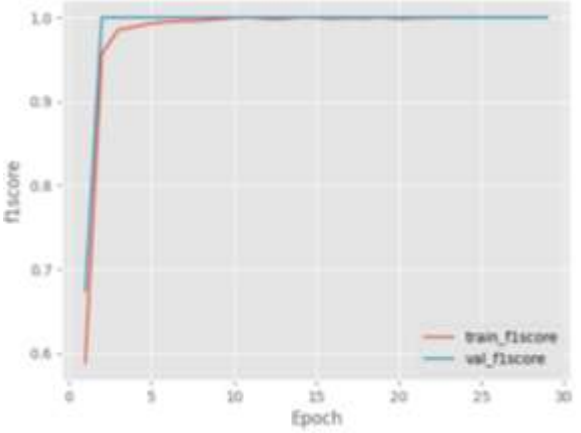

Figure 21: cnn2d_model F1-Score

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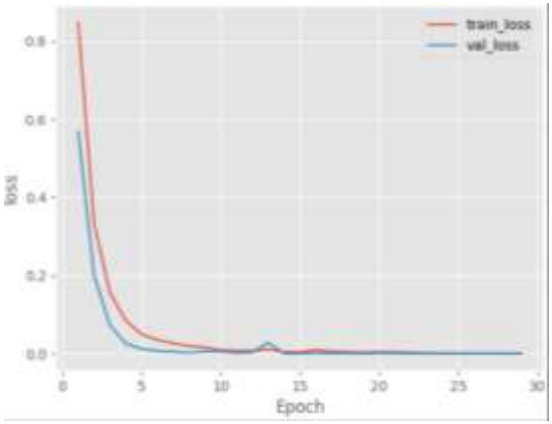

Figure 22: cnn2d_model Loss

Table 1: Performance Comparism of Classifier Models

Model	Accuracy	F1-Score	Precision	Recall	Loss
GRU	1.0000	1.0000	1.0000	1.0000	5.4177e-06
LSTM	1.0000	1.0000	1.0000	1.0000	1.4210e-05
LSTM-GRU	1.0000	1.0000	1.0000	1.0000	2.2151e-06
Rotational_pe	1.0000	1.0000	1.0000	1.0000	1.0644e-09
Sinusoidal_pe	1.0000	1.0000	1.0000	1.0000	0.0000e+00
Relative_pe	1.0000	1.0000	1.0000	1.0000	0.0000e+00
cnn2d	1.0000	1.0000	1.0000	1.0000	1.8170e-05

3.1.2 Results for Model Inference

The three panel representation of the audio data used for inference is described in Figure 23. The top panel represents the raw waveform with amplitude envelope shading, the middle panel represents the linear-frequency STFT spectrogram, while the bottom panel represents the normalised log-mel spectrogram (in mel-bin scale).

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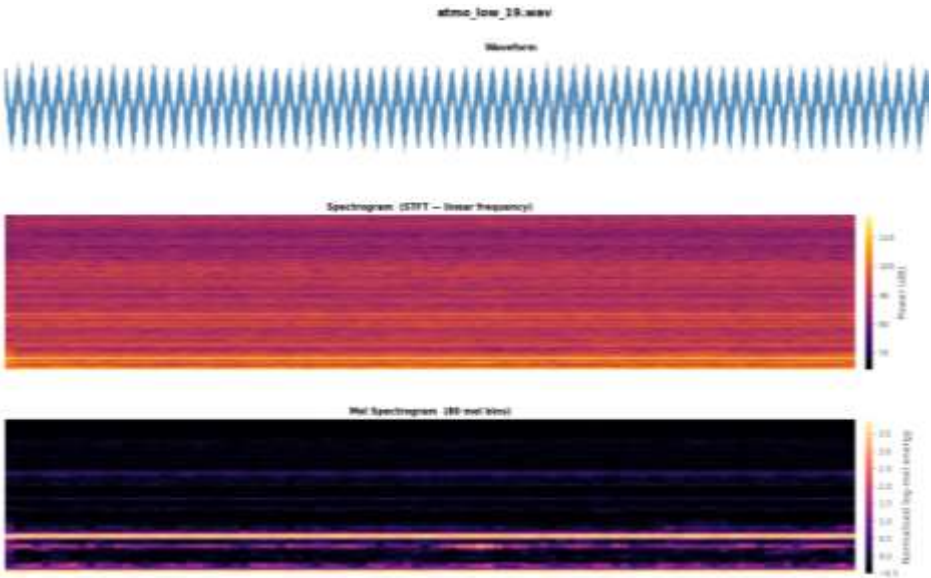

Figure 23: Visualization of Inference Audio Data Processing

3.1.3 Result for Motor Classifier Application

Audio data visualization by the motor classifier application is illustrated in Figure 24.

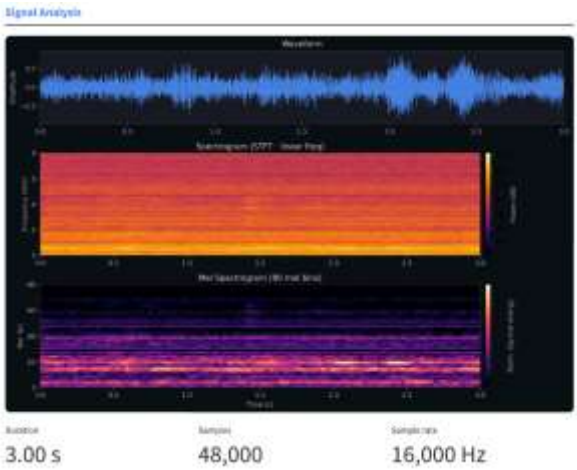

Figure 24: Audio Data Visualization by Motor Classifier Application

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The classifier performances of an ensemble as well as individual recurrent model deployments are described in Figures 25.

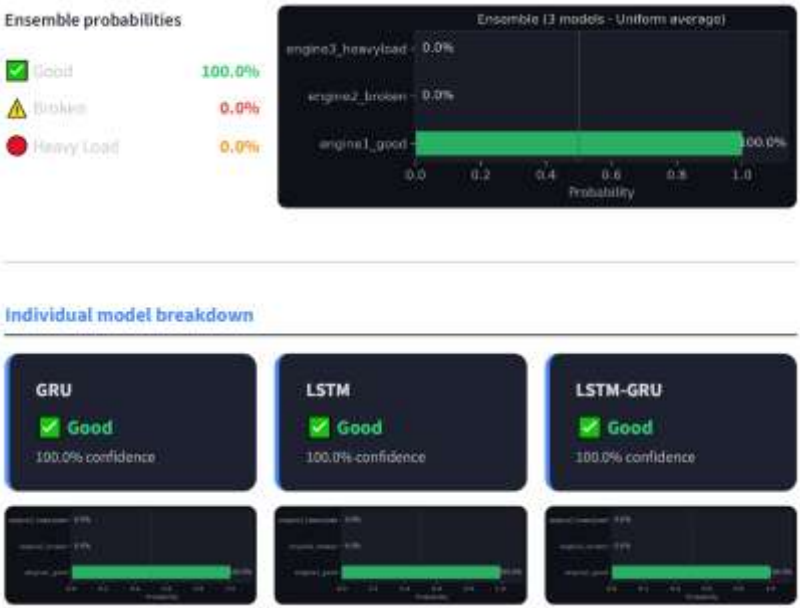

Figure 25: Recurrent Model Performances

3.2 Discussion of Results

Early stopping was triggered at epoch 13 for the GRU model, as can be seen from Figures 2 to 4 and Table 1, the respective optimal validation scores were 1.0000, 1.0000 and 5.417671e-06, for accuracy, F1 and loss respectively. Early stopping was triggered at epoch 15 for the LSTM model, as can be seen from Figures 5 to 7 and Table 1, the respective optimal validation scores were 1.0000, 1.0000 and 1.420986e-05, for accuracy, F1 and loss respectively. Early stopping was triggered at epoch 13 for the LSTM-GRU, as can be seen from Figures 8 to 10 and Table 1, the respective optimal validation scores were 1.0000, 1.0000 and 2.215067e-06, for accuracy, F1 and loss respectively. Early stopping was triggered at epoch 11 for the rotational_pe, as can be seen from Figures 11 to 13 and Table 1, the respective optimal validation scores were 1.0000, 1.0000 and 1.064369e-09, for accuracy, F1 and loss respectively. Early stopping was triggered at epoch 11 for the sinusoidal_pe, as can be seen from Figures 14 to 16 and Table 1, the respective optimal validation scores were 1.0000, 1.0000 and 0.000000e+00, for accuracy, F1 and loss respectively. Early stopping was triggered at epoch 11 for the relative_pe, as can be seen from Figures 17 to 19 and Table 1, the respective optimal validation scores were 1.0000,

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1.0000 and 0.000000e+00, for accuracy, F1 and loss respectively. For the cnn2d_model, as can be seen from Figures 20 to 22 and Table 1, the respective optimal validation scores were 1.0000, 1.0000 and 1.816952e-05, for accuracy, F1 and loss respectively. The results on the overall represented excellent performing models.

As presented in Table 1, performance comparism of the developed models shows that the best performing models were sinusodal_pe and relative_pe on the basis of Loss score.

Figure 24 shows that the developed classifier application can visualize external audio data inputs in accordance with the three panel representation configured during training. Figure 25 shows that the respective models could be deployed on both ensemble and standalone bases in applications for classifying BLDC operational status by acoustic signals.

Conclusion

This study involved the development of an acoustic signal processing and deep learning nexus for BLDC motor status classification. The IDMT-ISA-ELECTRIC-ENGINE dataset was imported from Kaggle.com for model development. This dataset contains three classes, namely, 'engine1_good', 'engine2_broken' and 'engine3_heavyload'. Audio processing was carried out on the dataset, to convert the mono audio into mel spectrograms, via the Short Time Fast Fourier technique. Seven deep learning models were implemented to fit the processed data, they include GRU, LSTM, LSTM-GRU hybrid, three transformer models with positional encodings (pe) (rotational_pe, sinusodal_pe and relative_pe) and a convolutional neural network model (cnn2d_model). Model training, validation and inference were carried out and it was discovered that though all models performed excellently, the best performing models on the basis of loss score were sinusodal_pe and relative_pe. Furthermore, a BLDC operational status classification application was developed in the Streamlit environment. This study is however limited, in that it involves operating-condition classification under artificially induced states on a small set of motors, not actual general-purpose fault diagnosis. A real-world fault diagnosis problem would require validation on a dataset with actual motor faults to show that the developed approach in this study transfers beyond the three specific units considered.

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