FAULT DETECTION IN DIESEL ENGINES USING ARTIFICIAL NEURAL NETWORKS AND CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

This research aims to create a deep learning model utilizing Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) to detect and classify damage or faults in diesel engines effectively. The main contribution of this study entails the creation of a classification model aimed at problem identification in diesel engines. The study used the DEFault dataset, which has 3,500 rows of data classified into four distinct labels. The DEFault dataset comprises four discrete noise levels, namely 0dB, 15dB, 30dB, and 60 dB. The findings indicate that both models have demonstrated satisfactory outcomes regarding model assessment. The model performance is most ideal when trained on the DEFault dataset with 60dB white noise, whereas the dataset with 0dB white noise leads to the least favourable model performance. The results suggest that artificial neural networks (ANN) perform better than convolutional neural networks (CNN) in datasets with higher levels of white noise. Conversely, CNN demonstrates superior performance in datasets with lower levels of white noise. An additional investigation could prove advantageous in implementing the deep learning model on a device that can identify diesel engine faults in real-time.

Keywords: *Diesel Engine, Fault Detection, Deep Learning, Artificial Neural Network (ANN), Convolutional Neural Network (CNN)*

1. INTRODUCTION

Diesel engines show extensive application in several sectors such as machinery construction, heavy-duty trucks, electric power generation, petrochemical industries, and military equipment [1]. In practical application, after obtaining information regarding the malfunction status of the diesel engine, production and maintenance activities can be more effectively organized [2], [3]. The reduction of unscheduled shutdowns can be efficiently achieved, and the implementation of more efficient maintenance practices can be facilitated by utilizing status information. This, in turn, leads to a further decrease in maintenance costs [2], [4], [5]. Therefore, it is vital to acquire knowledge regarding the fault diagnosis technologies of diesel engines in order to assure the secure running of those engines. The direct characterization of engine faults using raw vibration signals is not possible. Therefore, it is necessary to process these signals in order to extract features from various domains. These features can be obtained through dimensionality reduction techniques or by directly inputting them into machine learning or deep learning algorithms for the purpose of classification [4], [6].

Machine learning techniques have been employed in the identification of engine malfunctions, yielding significant outcomes [7], [8]. However, their ability to analyze complex flaws with limited prior knowledge remains consistently inadequate [9], [10]. Furthermore, their ability to describe complex functions is hindered by subpar performance and limited generalization capacity [11]. These empirical findings highlight the constraints of shallow neural networks and motivate researchers to investigate methods for extracting features and representing intricate functions using deep neural networks.

The academic discipline of machine learning contains a subfield called "deep learning," which is dedicated to the development and implementation of techniques that enable neural networks to acquire knowledge from and provide predictions for large and complex datasets. Deep learning involves the interconnection of multiple layers of nodes, sometimes referred to as neurons [12]. Subsequently, these layers are utilized for the purpose of feature acquisition, analysis, and pattern categorization [13]. One notable benefit of deep learning lies in its capacity to extract meaningful information from raw data by employing numerous layers of non-linear transformations and approximating intricate non-linear functions [11]. The pressing demand for utilizing deep learning in fault diagnosis and prognostics arises from the necessity to precisely assess the condition of the equipment in order to make informed decisions regarding maintenance requirements.

The deep learning method draws inspiration from the complex structure of the human brain, wherein interconnected neural layers transmit and process information [14]. The neural networks in question engage in the processing of input data to autonomously extract and acquire knowledge pertaining to various aspects. This phenomenon represents the cognitive process of the human brain, wherein upon acquiring novel information, the brain endeavors to evaluate and interpret it considering preexisting knowledge [15]. Deep learning models have demonstrated outstanding performance across a range of tasks, encompassing natural language processing, game playing, as well as image and audio recognition. Deep learning is distinguished by its capacity to effectively comprehend intricate representations and patterns derived from unprocessed data [16].

Deep learning, a prominent area of study in computer science research, has witnessed significant advancements and diversification, resulting in the emergence of several types such as Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and others [15]. Because of that, no wonder deep learning algorithms have been employed to detect faults in diesel engines, enabling the network to effectively identify specific engine problems by leveraging the available dataset. To attain elevated success rates in engine failure identification, the network parameters acquired from one network can be transferred and utilized in other analogous networks. As a result, several research have employed deep learning techniques to identify engine malfunctions [16]–[18].

The objective of this study is to develop a model capable of detecting and identifying damage or fault in diesel engines. In order to achieve this objective, we employ deep learning methodologies, specifically Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), as classification models for the purpose of detecting faults in diesel engines. The primary contribution of this study involves the development of a classification model for the purpose of problem identification in diesel engines. In this study, an evaluation is conducted to assess the performance of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) in the classification of diesel engine fault detection.

2. RELATED WORKS

Engine fault detection studies have been conducted numerous times in the past few years. With the increasing technology development, machine learning and deep learning is a favorite for detecting faults in engine. One of the engine fault detection studies that have been conducted is detecting faults on diesel engine.

In the study [19] authors proposed a machine learning-based approach for diagnosing wear faults in marine diesel engines. This method combines several data-driven models to increase fault diagnosis accuracy. Three data-driven models, comprising an artificial neural network (ANN) model, a belief Rule-Based Inference (BRB) model, and an Evidence Reasoning (ER) rule model, produce evidence that is fused at the decision level. The fusion system defines reliability and importance weight of every single model respectively. A new approach is presented to determine the reliability of performance by considering the accuracy and stability of every single model. The important weight is optimized improve the performance of the fusion system.

The research [6] introduced a method based on Variational Mode Decomposition (VMD) and Convolutional Neural Network (CNN) for diagnosing faults in diesel engines. The method optimizes VMD and improves CNN to enhance the effectiveness of fault diagnosis. The authentic vibration sign is first decomposed by using the

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(VMD) algorithm, then the greatest range of decomposition layers is decided by using scattering entropy and the useful components are preferentially chosen for reconstruction. The continuous wavelet transforms (CWT) records preprocessing method is then delivered to radically change the noise-reduced vibration sign into a time-frequency map, which is fed into the CNN for model coaching and extraction of fault features.

Another novel diesel engine fault detection and diagnostic method by combining rule-based algorithm and Bayesian networks (BNs) or Back Propagation neural networks (BPNNs) was proposed by [20]. The authors processed the signals by wavelet threshold denoising and ensemble empirical mode decomposition and extracted signal-sensitive feature values from the decomposed intrinsic mode function. They identified seven faults using a rule-based algorithm and BNs or BPNNs.

3. METHOD

The methodology employed in this study encompasses several key steps. The first step is the data gathering phase, where we utilized a publicly available dataset, the details of which will be discussed in the next section. Once the data was collected, we partitioned the dataset into three distinct sets: training, validation, and testing data, employing the K-Fold technique. The training and validation data were used for model training, while the testing data was reserved for evaluation purposes. Figure 1 displays the schematic representation of the research workflow.

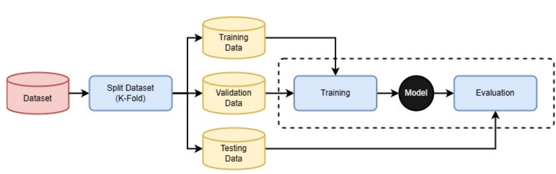

Figure 1: Research Workflow

2.1 Dataset

The Diesel Engine Faults Features Dataset (DEFault), as published by [4], [21] is utilized in this work. The dataset consists of 3500 rows of data that are categorized into four distinct labels, namely: normal, intake manifold pressure reduction, cylinder compression ratio reduction, and reduction of fuel injection into the cylinders. All labels except normal is a label showing fault condition of diesel engine. The data distribution shown in Table 1.

Table 1: Dataset Label Distribution

Label	Total Data
Normal	250
Pressure reduction in the intake manifold	250
Compression ratio reduction in the cylinders	1500
Reduction of amount of fuel injected into the cylinders	1500

Table 1 shows the dataset has four distinct sorts of dataset categories, namely datasets with noise levels of 0dB, 15dB, 30dB, and 60dB. The term 0dB, 15dB, etc. refers to the decibel level of white noise that has been introduced to the dataset. The addition of white noise to the original dataset is achieved through the utilization of additive Gaussian white noise (AWGN) [4], [9]. The dataset comprises a comprehensive set of 84 features. These features encompass the maximum values of pressure curves for each of the six cylinders, the mean values derived from the cylinders' pressure curves, and the spectral analysis results. The spectral analysis provides information on the frequency, amplitude, and phase for the first 24 harmonics. Specifically, it includes the first 24 half-order frequencies [4], [22]. Given a pre-existing dataset in the format of a feature vector, the author omits the step of feature extraction and moves directly to the tasks of data splitting and training.

2.2 K-Fold Cross Validation

K-fold cross-validation is a widely used technique in machine learning and deep learning for evaluating the performance of a model. This method involves partitioning the dataset into 'k' subsets or samples, the algorithm is then evaluated on each of these samples, and the average accuracy across all samples is computed to provide an overall assessment of the model's performance [23]–[25]. In essence, this approach involves partitioning the document into k segments, where one segment is designated as the test data and the remaining k-1 segments are utilized as the training data [26]. In this study, we employed a value of k=5 for the cross-validation procedure. The process of dividing a dataset using the K-Fold Cross Validation technique with a value of k=5 can be visualized in Figure 2.

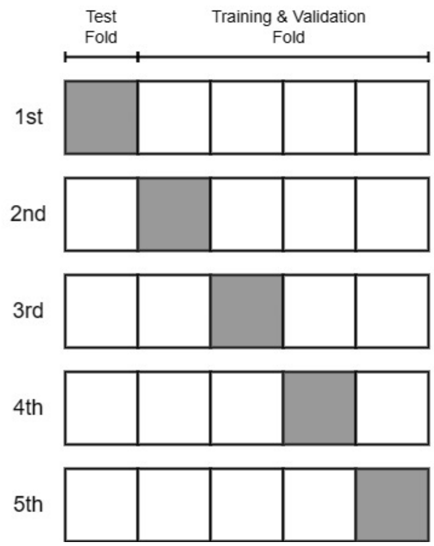

Figure 2: K-Fold Cross Validation with k=5

When the value of k is set to 5, the dataset is partitioned into five subsets. One of these subsets is designated as the test data, indicated by the color grey, while the remaining four subsets are allocated for training and validation purposes, denoted by the color white. K-fold cross validation, with a value of k set to 5, generates five separate datasets. Each dataset is divided into test data, as well as training and validation data, as depicted in Figure 2.

2.3 Artificial Neural Network (ANN)

Artificial neural network (ANN) are computational models that are commonly employed to simulate and replicate the problem-solving capabilities of the human brain [19], [27], [28]. Both structures consist of a diverse array of neurons, alongside interconnected processing units that possess changeable biases and weights [29] ANN presents mathematical calculations that are modeled in order to generate the output. ANN have demonstrated their efficiency in various applications and can be efficiently implemented through algorithmic representation [27]. The utilization of ANN can serve as a viable alternative approach in the process of decision making. A simple ANN illustration is shown in Figure 3.

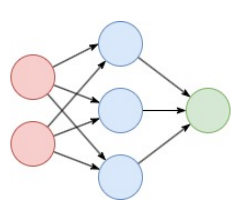

Figure 3: Simple ANN Illustration

The circle and arrow in Figure 3 represents neurons and connection. The neuron here is an artificial neuron which is a basic of artificial neural network. It takes an input, applies a function, and pass the ouput to the next neuron. In each neuron there is a connection, which is like synapses in a biological brain, it functions to transmit a signal from one neuron to another neuron.

2.4 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is a type of deep learning model specifically developed to handle input data that displays a grid-like arrangement, such as images. The present model takes inspiration from the complex architectural patterns observed in the visual cortex of several animal species. CNN typically exhibits a tripartite architecture, with three different layers: convolutional layers, pooling layers, and fully connected layers. This architecture consists of two primary components: the feature extraction component and the classification component [30]. The feature extraction component of a CNN model is responsible for acquiring knowledge pertaining to spatial hierarchies of features, which involves the progression from lower-level to higher-level patterns. Afterwards, the classification component employs the obtained features to make predictions about the output class [31].

In this study, we use one-dimensional CNN for detecting fault in diesel engines. We chose this type of CNN because our dataset is form of one-dimensional data and the one-dimensional CNN is specifically engineered to process and analyze data that is structured in a single dimension [32]. Just like the conventional two-dimensional CNN, the one-dimensional CNN likewise comprises of one-dimensional convolution layers, pooling layers, dropout layers, and activation functions for processing one-dimensional input [32].

2.5 Experiment Model Architecture

We used Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) to categorize data consisting of 84 features into four distinct classes. The ANN architecture we used consists of the combination of dense and dropout layer. While the CNN athitecture are consisted of the combination of conv1d, maxpool1d, flatten, dense, and droput layer. The model architecture for the classification of diesel engine defects is depicted in Figure 4 and Figure 5.

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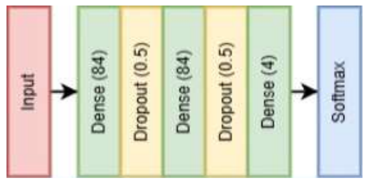

Figure 4: ANN Experiment Model Architecture

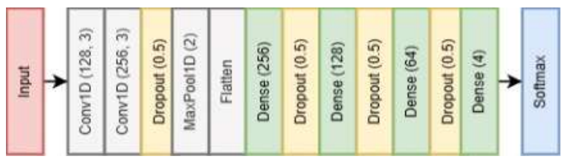

Figure 5: CNN Experiment Model Architecture

The architecture of the ANN model, as depicted in Figure 3 starts by receiving an input of size 84, corresponding to the 84 features present in the dataset. Next, the input is fed into a dense layer, consisting of 84 units. Subsequently, a dropout operation is applied with a dropout ratio of 0.5. Afterwards, the data is reintroduced into the dense layer of 84 units, followed by a dropout operation with a dropout rate of 0.5. Finally, the data is reintroduced into the dense layer, which consists of four units, in accordance with the designated class and activated using the SoftMax activation function.

Figure 4 presents the illustration of the CNN model architecture, which accepts an input identical in size of 84 to that of the ANN model. This input is then fed into a Convolutional 1D layer with a filter of 128 and a kernel size of 3. Subsequently, it is further processed by another Convolutional 1D layer with a filter of 256 and a kernel size of 3. Dropout regularization is applied with a ratio of 0.5, and max pooling 1D is performed with a pooling size of 2. In addition, the result of the maxpool 1D operation will be transformed into a flattened structure and afterwards fed through a mix of dense layers and dropout regularization. And finally, will be activated with softmax activation function.

2.6 Evaluation

The evaluation of the trained model is conducted by employing the accuracy metric in conjunction with K-Fold cross validation. The model's performance is determined by calculating the average accuracy throughout each fold. The metric of accuracy quantifies the proportion of accurate predictions relative to the total number of predictions made. The formula for accuracy is presented in Equation 1.

$$\text{Accuracy} = (TP+TN) / (TP+FN+FP+TN) \qquad (1)$$

The term "True Positive" (TP) denotes the count of positive samples that the models correctly forecasted as positive. While "True Negative" (TN) signifies the count of negative samples that the models accurately anticipated as negative. The term "False Positive" (FP) is used to describe instances in which the models incorrectly classify negative samples as positive. Conversely, "False Negative" (FN) refers to cases in which the models incorrectly classify positive samples as negative.

3. RESULTS AND DISCUSSION

The five datasets generated by K-Fold Cross Validation were utilized to train and assess the performance of the model. The datasets were partitioned using K-Fold Cross Validation in a random manner, with precautions taken to ensure that no data was present in both the test and training sets simultaneously within a single dataset. Additionally, the ratio between classes in each part of the dataset was maintained according to the original dataset. The model's performance is evaluated using K-Fold Cross Validation with a value of k=5. The average accuracy of the five K-Fold Cross Validation datasets is used as the measure of the model's performance.

The utilization of training and validation datasets is crucial to the process of training a model. Test data is utilized for the purpose of assessing the performance of a model. During the training phase, the model is trained using training data, while the evaluation and monitoring of the training process to minimize overfitting is carried out using validation data. This research employs the early stopping technique as a means to mitigate the issue of overfitting, which arises from excessive training [33]. The training procedure will terminate automatically by the implementation of early stopping if there is a lack of substantial progress. The training procedure includes an evaluation at the end of each epoch using validation data. If there is no substantial improvement in validation loss for 25 consecutive epochs, the training process is automatically terminated. In the training procedure, the learning rate was chosen at 5e-5 or 0.00005, the mini-batch size was set to 128, and the maximum number of epochs was limited to 10000. The training method is iteratively conducted using four initial datasets, specifically the 0dB, 15dB, 30dB,

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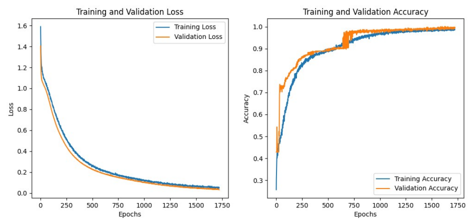
and 60dB datasets. Additionally, Cross Validation is performed on each of these datasets. The training graphs are illustrated in Figure 6 until Figure 9 for ANN, while Figure 10 through Figure 13 for CNN.



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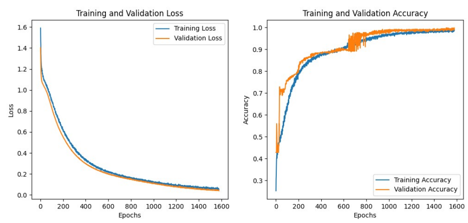

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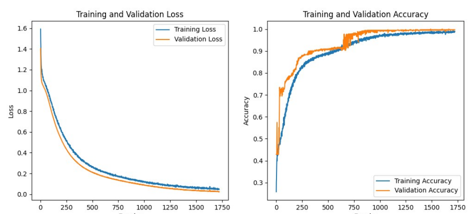

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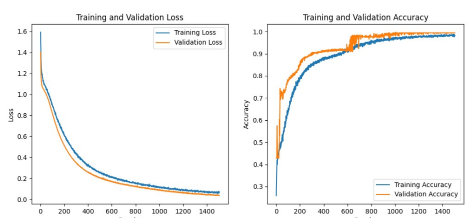

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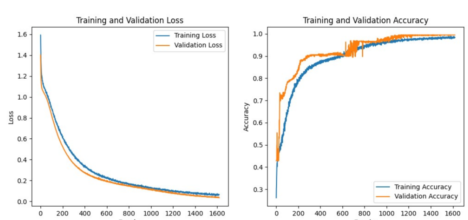
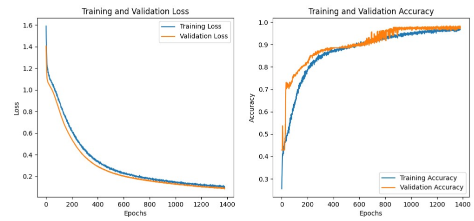


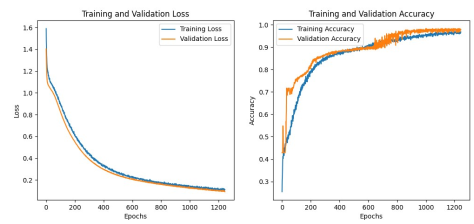
(e)

Figure 6: ANN Training Graph (60dB Dataset), (a) Fold 1, (b) Fold 2, (c) Fold 2, (d) Fold 4, (e) Fold 5

The Figure 6 shows the training graph of ANN model on 60dB Dataset. (a) – (e) are the fold 1 – 5 of cross validation. We can see that all loss graph are progressing to lower loss the higher the epoch, each of them are similar with only slight differences. As for the accuracy it increases along with the epoch, with slight differences between each fold.



(a)



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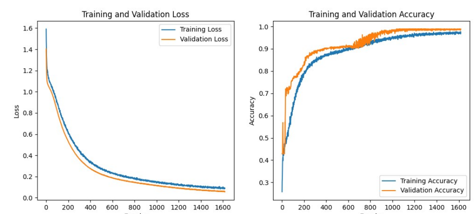

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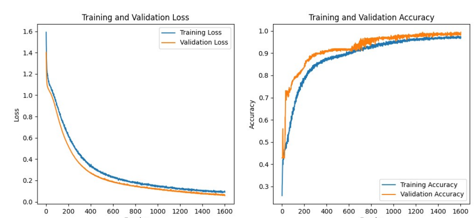

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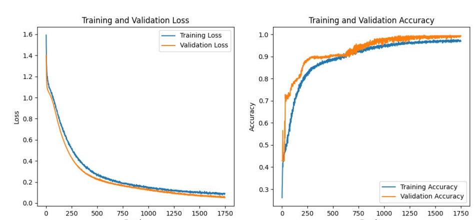
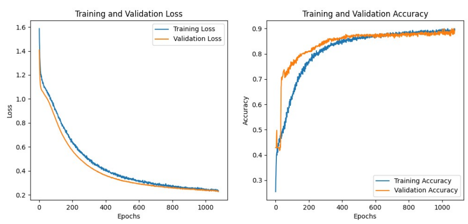


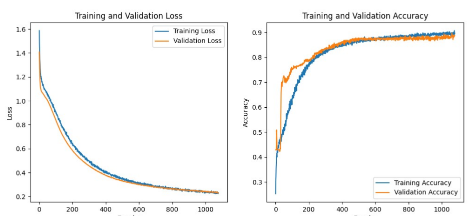
(e)

Figure 7: ANN Training Graph (30dB Dataset), (a) Fold 1, (b) Fold 2, (c) Fold 2, (d) Fold 4, (e) Fold 5

The Figure 7 depicted the training graph of ANN model on 30dB Dataset. (a) – (e) are the fold 1 – 5 of cross validation. Similar with previous figure that all loss graph are progressing to lower loss value the higher the epoch, each of them are similar with only slight differences. The accuracy also pretty similar with previous figure, it increases along with the epoch, with slight differences between each fold.



(a)



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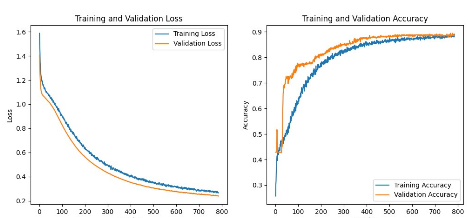

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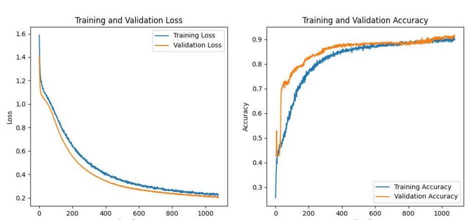

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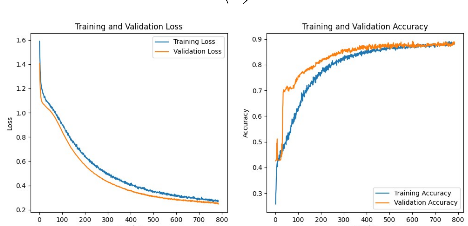
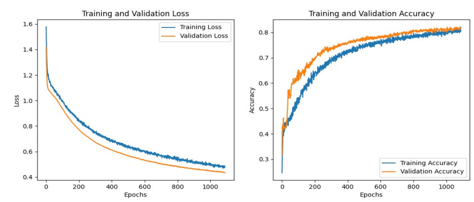


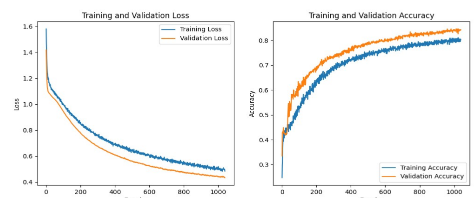
(e)

Figure 8: ANN Training Graph (15dB Dataset), (a) Fold 1, (b) Fold 2, (c) Fold 2, (d) Fold 4, (e) Fold 5

The Figure 8 illustrate the training graph of ANN model on 15dB Dataset. (a) – (e) are the fold 1 – 5 of cross validation. Similar with previous figure that all loss graph are progressing to lower loss value the higher the epoch, but all of them never reach below 0.2, and each of them are similar with only slight differences. The accuracy also pretty similar with previous figure, it increases along with the epoch, with slight differences between each fold, and it also never reach above 0.9 accuracy score.



(a)



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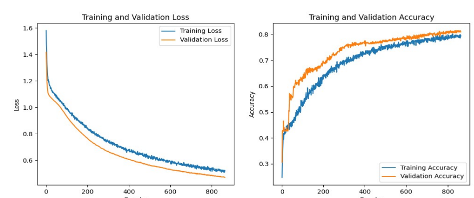

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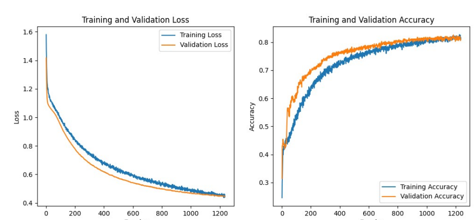

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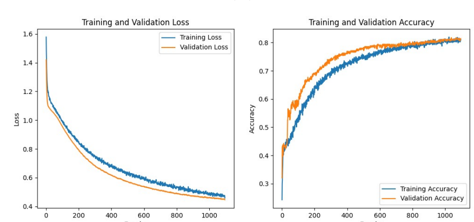

(e)

Figure 9: ANN Training Graph (0dB Dataset), (a) Fold 1, (b) Fold 2, (c) Fold 2, (d) Fold 4, (e) Fold 5

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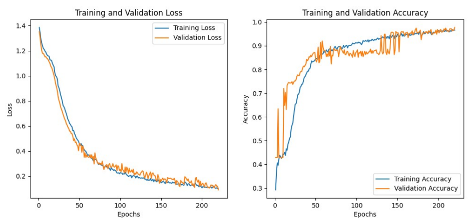
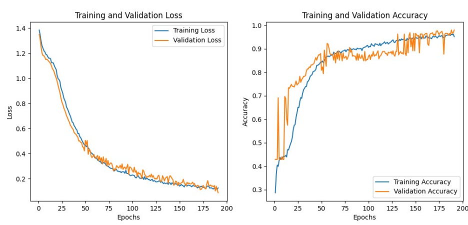
The Figure 9 demonstrate the training graph of ANN model on 0dB Dataset. (a) – (e) are the fold 1 – 5 of cross validation. Similar with previous figure that all loss graph are progressing to lower loss value the higher the epoch, but all of them never reach below 0.4, and each of them are similar with only slight differences. The accuracy also pretty similar with previous figure, it increases along with the epoch, with slight differences between each fold, and it also never reach above 0.8 accuracy score.



(a)



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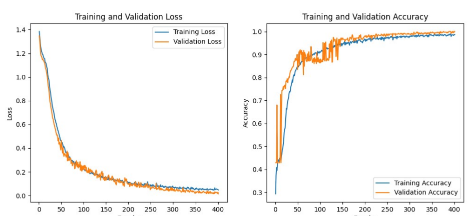

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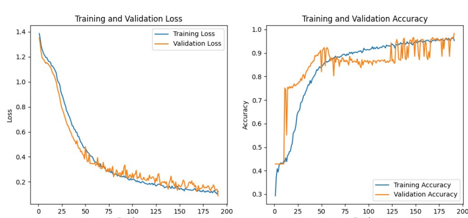

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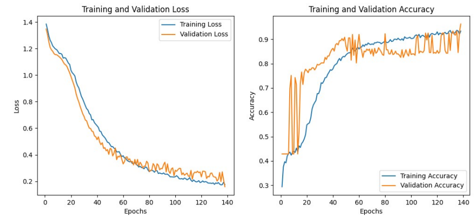
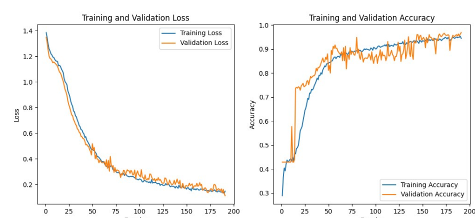


(e)

Figure 10: CNN Training Graph (60dB Dataset), (a) Fold 1, (b) Fold 2, (c) Fold 2, (d) Fold 4, (e) Fold 5

The Figure 10 shows the training graph of CNN model on 60dB Dataset. (a) – (e) are the fold 1 – 5 of cross validation. We can see that all loss graph are progressing to lower loss the higher the epoch, each of them are similar with only slight differences. As for the accuracy it increases along with the epoch, with slight differences between each fold.

(a)



(b)

(c)

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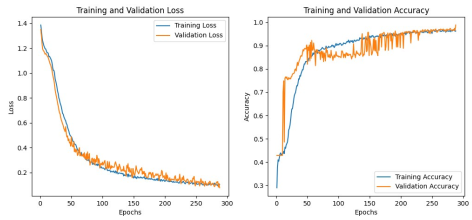
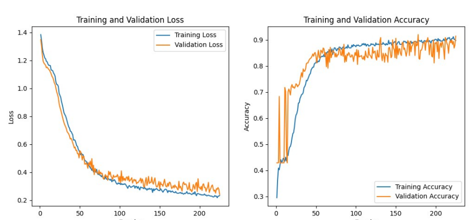


(d)

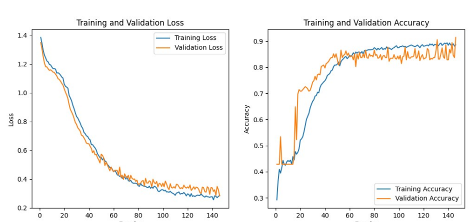
(e)

Figure 11: CNN Training Graph (30dB Dataset), (a) Fold 1, (b) Fold 2, (c) Fold 2, (d) Fold 4, (e) Fold 5

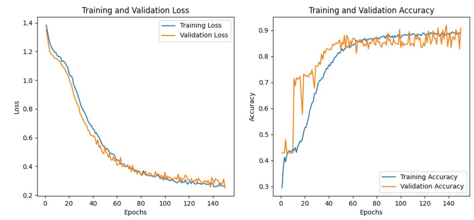
The Figure 11 depicted the training graph of CNN model on 30dB Dataset. (a) – (e) are the fold 1 – 5 of cross validation. Similar with previous figure that all loss graph are progressing to lower loss value the higher the epoch, each of them are similar with only slight differences. The accuracy also pretty similar with previous figure, it increases along with the epoch, with slight differences between each fold.



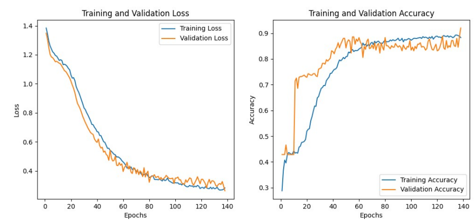
(a)



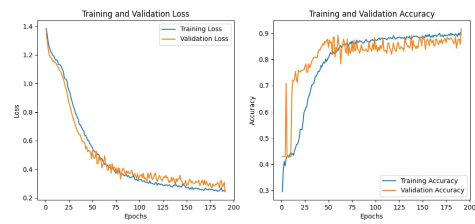
(b)



(c)



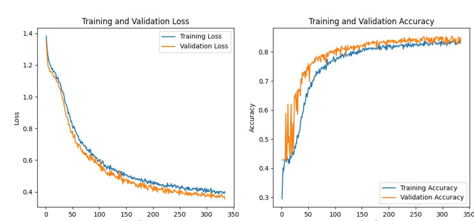
(d)



(e)

Figure 12: CNN Training Graph (15dB Dataset), (a) Fold 1, (b) Fold 2, (c) Fold 2, (d) Fold 4, (e) Fold 5

The Figure 12 illustrate the training graph of CNN model on 15dB Dataset. (a) – (e) are the fold 1 – 5 of cross validation. Similar with previous figure that all loss graph are progressing to lower loss value the higher the epoch, but all of them never reach below 0.2, and each of them are similar with only slight differences. The accuracy also pretty similar with previous figure, it increases along with the epoch, with slight differences between each fold, and it also never reach above 0.9 accuracy score.



(a)

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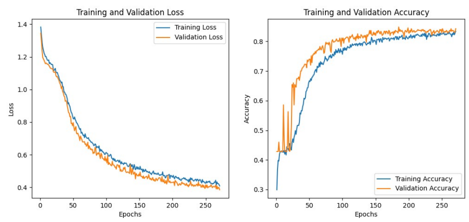
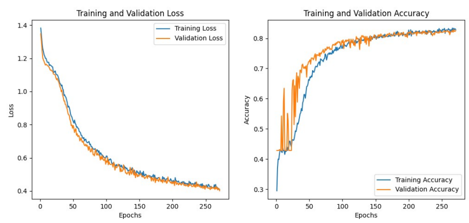
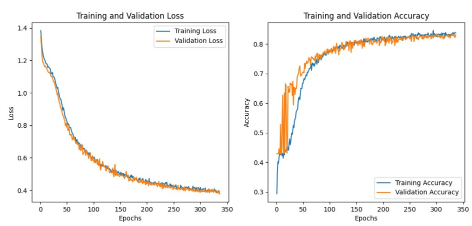


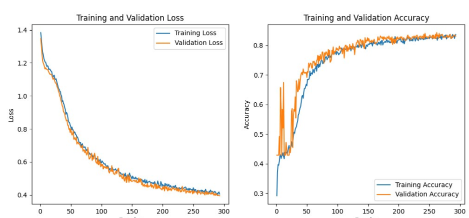
(b)



(c)



(d)



(e)

Figure 13: CNN Training Graph (0dB Dataset), (a) Fold 1, (b) Fold 2, (c) Fold 2, (d) Fold 4, (e) Fold 5

The Figure 13 demonstrate the training graph of CNN model on 0dB Dataset. (a) – (e) are the fold 1 – 5 of cross validation. Similar with previous figure that all loss graph are progressing to lower loss value the higher the epoch, but all of them never reach below 0.4, and each of them are similar with only slight differences. The accuracy also pretty similar with previous figure, it increases along with the epoch, with slight differences between each fold, and it also never reach above 0.9 accuracy score.

The detailed test results of the model performance that trained on each of these datasets are shown in Table 2, 3, 4, and 5. Each table will present the performance for each model and each fold in terms of accuracy. The ANN and CNN result are presented side by side to make analysis easier.

Table 2: Evaluation Result (Trained on 60dB Dataset)

Description	Accuracy	
	ANN	CNN
Fold 1	0.994285714	0.987142857
Fold 2	0.992857143	0.984285714
Fold 3	0.992857143	0.992857143
Fold 4	0.992857143	0.971428571
Fold 5	0.995714286	0.982857143
Average	**0.993714286**	**0.983714286**

Table 3: Evaluation Result (Trained on 30dB Dataset)

Description	Accuracy	
	ANN	CNN
Fold 1	0.991428571	0.982857143
Fold 2	0.984285714	0.977142857
Fold 3	0.984285714	0.971428571
Fold 4	0.984285714	0.975714286
Fold 5	0.985714286	0.978571429
Average	**0.986**	**0.977142857**

Table 4: Evaluation Result (Trained on 15dB Dataset)

Description	Accuracy	
	ANN	CNN
Fold 1	0.92	0.931428571
Fold 2	0.905714286	0.921428571
Fold 3	0.887142857	0.937142857
Fold 4	0.891428571	0.901428571
Fold 5	0.894285714	0.934285714
Average	**0.899714286**	**0.925142857**

Table 5: Evaluation Result (Trained on 0dB Dataset)

Description	Accuracy	
	ANN	CNN
Fold 1	0.827142857	0.834285714
Fold 2	0.824285714	0.838571429
Fold 3	0.812857143	0.83
Fold 4	0.828571429	0.831428571
Fold 5	0.808571429	0.827142857
Average	**0.820285714**	**0.832285714**

The analysis of Table 2, 3, 4, and 5 presented above indicates that both the ANN model and the CNN model have exhibited satisfactory results in terms of model evaluation. It is evident that the dataset containing 60dB white noise yields in Table 2 shows the most optimal model performance, whereas the dataset containing 0dB white noise results in Table 5 is the least favorable model performance. This finding suggests that the performance of deep learning ANN and CNN models in data classification improves when white noise is present in the dataset. Furthermore, the assessment results table indicates comparable outcomes for both ANN and CNN [34]. However, in terms of average accuracy on datasets with 60dB and 30dB, ANN outperforms CNN, whereas CNN exhibits superior average accuracy compared to ANN on datasets with 15dB and 0dB. This finding suggests that ANN exhibits superior classification performance compared to CNN in the presence of high levels of white noise. Conversely, CNN demonstrates better classification capabilities relative to ANN when the data contains low levels or no white noise.

4. CONCLUSION AND FUTURE WORKS

This study presents a deep learning approach for the detection of faults in diesel engines. Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) are utilized in the classification of 84 diesel engine features into four distinct classes. The implementation of five-fold cross-validation was utilized for the purpose of evaluation. The highest performing model in terms of evaluation was an ANN model, which achieved an average accuracy of 0.993714286. This model was trained using a 60dB dataset. Additionally, our findings indicate that ANN and CNN exhibit improved data classification performance in the presence of white noise. Specifically, we observed that ANN outperforms CNN in datasets with higher levels of white noise, whereas CNN has superior performance in datasets with lower levels of white noise.

For further research, it is worth to try use different model architecture to improve the model performance on low white noise data. Besides that, using the time-series classification approach can be suitable for this task and may improve the performance of the model. Real-time predictions model deployment is also plausible for future works, considering the performance of the model was already high on high white noise data.

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