Using 1DCNN for Diagnosis Fault in Electricals Power System

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Abstract

A fault is a non-desirable deviation of a system or one of its components from normal behaviour. Fault diagnosis is the process of detecting, isolating, and identifying such a fault.

In this paper, a method to diagnose the fault in Unmanned Aircraft Vehicles (UAVs) systems is proposed. These systems consist of several components along with sensors to measure some properties such as current, voltages, and temperatures. In such a system, faults are unavoidable and could lead to the failure of the whole system without timely treatment, and cause human losses. The proposed method adopts a deep learning technique to build a model called diagnose. Convolutional Neural Network (CNN) made.

This thesis adopted the "ADAPT" dataset, acquired from NASA Research Center will be considered. for a case study to represent an electrical power system of an Unmanned Aircraft Vehicle (UAV). Which contains 227 scenarios for a single fault. Finally, the classification accuracy for the proposed system for single fault classifier achieved for detection 96.70%, for isolation 98.51%, and for identifying 98.67%.

Keywords: Deep Learning, One Dimensional Convolutional Neural Network (1DCNN), Fault Diagnosis, unmanned aircraft vehicle (UAV).

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1. Introduction

Recently, Unmanned Aircraft Vehicles (UAVs) have been used in several fields, such as load transport, archaeology, hobbies, defences, filmmaking, and recreational. The UAVs are aircraft characterized by the absence of a human pilot on board [1]. Power systems are quickly developing in the latest years because of the implication of the latest digital technologies [2]. The automatic control of such systems is considered an essential part. This may be suffered by problems as a result of a fault in it or one of its components, undetected failures can lead to critical damage. To eliminate problems in the system Diagnosis Algorithms (DA) are used. The DA uses observations coming from the system being monitored to determine whether a fault has occurred (fault detection) and which fault has occurred (fault classification). Thus, fault diagnosis plays a substantial role in ensuring system safety and reliability [1].

An electrical power system has several components and sensors. Faults in the power system of UAV may occur in both components and sensors. This brings more difficulty and uncertainty to the problem of fault diagnosis. Assuming that there exists a set fault types F1,…Fn, each of which has a different number of fault modes. Then, we say that a fault of type Fi occurs if a fault of a certain mode in that typically occurs. In the first place, we will concentrate on the diagnosis of a single fault.

Faults are very expensive for every industry because they impose a repair of the machine, and stop periods in the entire process, with consequent loss of and delay in mission. To overcome these difficulties, companies resort to predictive repair. Fault detection and isolation play a significant role in ensuring system reliability and safety. To achieve precise control and navigation of the UAV, the reliability of the sensor system must be ensured [3]. The use of fault diagnosis (FD) techniques is becoming increasingly important to ensure high levels of safety and reliability in automated systems and autonomous or remotely controlled systems. The main purpose of the FD algorithm is to monitor the system during its operation to detect the occurrence of faults (fault detection), locate faults (fault isolation), and determine their temporal evolution (fault identification) [1][4]. We use one-dimensional convolutional neural network for Diagnosis.

1. Related Works

Due to the development in industry and the requirements to increase the safety and correctness of EPS, the fault diagnosis algorithm has become the focus of most studies and research. Therefore a review of the most relevant work is provided.

1. Jing-li .yet al (2016)[5], have shown that self-validating multifunctional sensors have been used in most industries. They used gas data sample implemented by board PCI-6014, which contained four type of faults. So the method was used to detect, isolate and diagnose their faults complete ensemble empirical mode decomposition with sample entropy weighted energy and multiclass SVM.

2. Jiangmeng. Fu et al(2019).[6], used Deep-learning approach to diagnose faults in six-rotor UAVs based on hybrid CNN-LSTM. They used four experiment of flight UAV data. The proposed method used sliding window technique and then extracts features using the networks for diagnose actuator faults. Accuracy calculated for each experiment then average accuracy calculated CNN-LSTM model. An inadequate in this work they used few datasets.

3. Aslam. M et al.(2019) [7], overviewed an application in power system, they used deep LSTM to present novel case study on the solar irradiation forecasting, single input, two hidden layers, and one output layer used in this work .KMA 'Korea

Meteorological Administration' dataset is used from 2001 to 2017.Authors used data from 2001 to 2016 for predicate 2017 then compare predicted with actual data. This work required only for yearly forecasting photovoltaic generation.

4. Jing. R et al. (2019)[8], Used deep learning, convolutional neural network, for fault detection and classification in unmanned ground vehicle. Authors generated dataset by take one input signal and two output signal then converted them to 2D time-frequency images by use continuous wavelet transform (CWT) to feed them to DNN as Inputs. Authors improved ability of their model to detection faults and classification, they generate four scenario contain three type of faults as well to no fault. Accuracy calculated for each scenario, then take average accuracy. An inadequate in this work algorithm need to extend for more types of faults and investigate the fault tolerance control algorithms for unmanned ground vehicles as well.

5. Lerui.C et al.(2020)[9], used a combination of nonlinear generalized frequency response function(GFRF) and convolutional neural network(CNN) for fault diagnosis in Permanent magnet synchronous motor (PMSM). PMSM data is used, which contain normal and three type of faults. Authors suggest to test the versatility of the proposed method by diagnosing other nonlinear systems as feature work.

6. M Ganesan et al.(2020) [10], used One Dimensional convolutional neural network(1DCNN) for detect fault in electrical power system of satellite. They use ADAPT dataset of six univariate experiments, they take only read of sensor voltage and ignore other from these experiments. S-transform used for process data before input to CNN and compared with used of sliding windows Fast Fourier Transform (FFT) and Wavelet Transform (WT). An inadequate in this work they didn't determine type of fault but detected faults occur or not.

7. Ahmad. A and Dahrouj .Z.(2020)[11], used Decision Tree matrix C4.5(DTMatrix) for detecting fault in UAV. Instead of employing a single large Decision Tree, they employed small Decision Trees. FLTz dataset from NASA was used, these dataset consist of 20 flights (sample of data), which have four type of faults. Authors used 15 flights of these dataset (8 for trained and 7 for tested) to build binary classifier to detect fault occurred or not. DT required time for sliding windows approach and for train and test.

2. proposed work

The design of any system is very important because it shows how the system works and explains the exact and practical steps that will be carried out to obtain the required need from it. The proposed diagnosis system consists of four main phases, as follows: preprocessing dataset, preparing dataset, training, and testing. The first phase, which is the preprocessing includes imputing missing values, making a dataset for abnormal class labels, Normalized values, and encoding class label. The second phase includes splitting data into two parts training and testing. The third phase involves building a diagnosis classifier system to detect, isolate, and identify fault mode. The final phase for testing the classifier model and predicted faults location and faults mode type.

Generally, the proposed diagnosis system detects the faults and classify them on the basis of the values of sensors reads into normal or abnormal. If abnormal, isolate the location of faults then identify the fault type mode. The overall proposed system structure of diagnosis system is illustrated in figure (1).

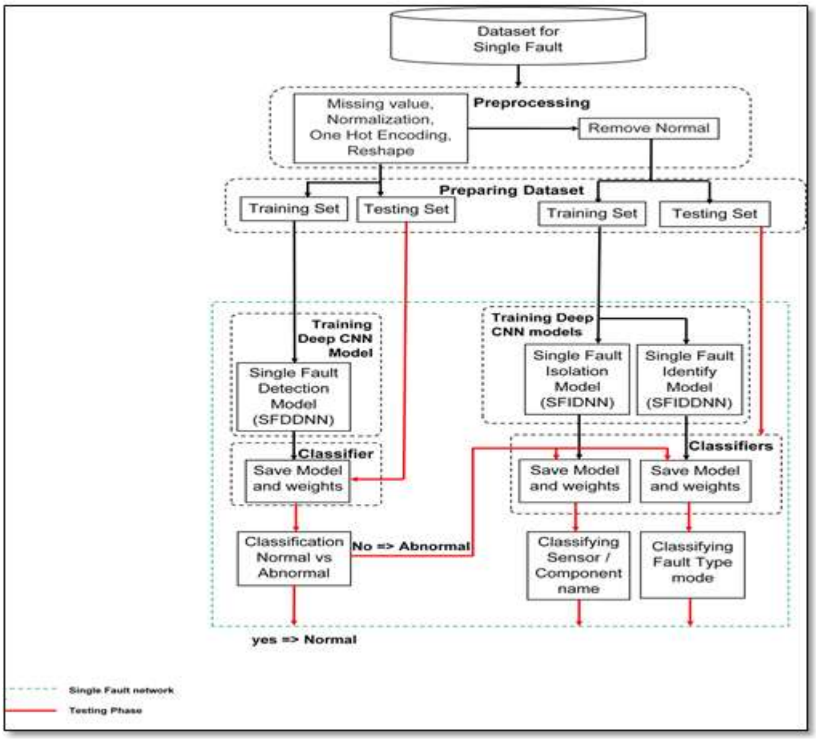


Figure .1: proposed system.

2.1. Pre-processing phase

The need for the pre-processing phase appears due to the entered data needs to be complete. The pre-processing improves and organizes the input data to prepare it for the training and testing phase. The pre-processing phase consists of three steps include: impute missing data, Normalization, and label encoding.

2.1.1. Dataset

The dataset is acquiring from NASA Ames Research Centre for the electrical power system of UAV the Advanced Diagnosis and Prognostics Testbed, [12]capturing a number of scenarios for single faults. Each scenario consists of a sequence of sensors reading of time-series. There are 226 samples each of which has approximately 2400 instances (reading) of sensor and command data (sensors and user commands data). Time-series data of each scenario has collected within 4 minutes. The number of features (sensors) in all scenarios of a single fault is 12. All of 227 were collected together in one CSV file. Figure (2) represents the raw dataset with missing values.

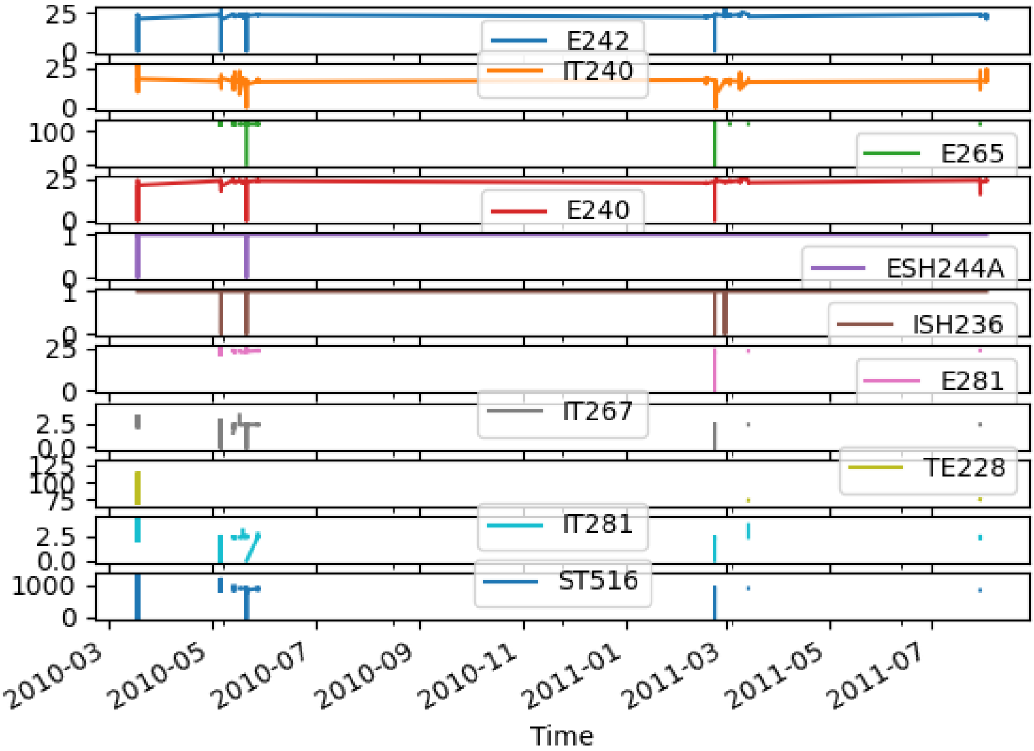


Figure - 2 raw dataset.

2.1.2. Impute data

The first and the most important step in the preprocessing is filling the missing values. For several causes, datasets of real-world may contain missing values, often indicated as NULs or NaNs. Furthermore, values of all sensors are not reading in synchronizable, and deep learning does not deal with this form of data. Therefore, the imputation methodology (SimpleImputer) uses for handling missing values by calculating the mean for each feature from the known portion of the data [13].

2.1.3. Normalization

Usually, the data set needs to be normalized when analyzing multiple sensors simultaneously. For example, one sensor may measure temperature, while another may measure voltage. Due to these values being measured on different scales Thus cannot be usefully compared. Therefore, the standardization technique uses to adjust for such differences and produce stander scalar values. Figure 3 represents the dataset after pre-processing (handle missing values and scaling values).

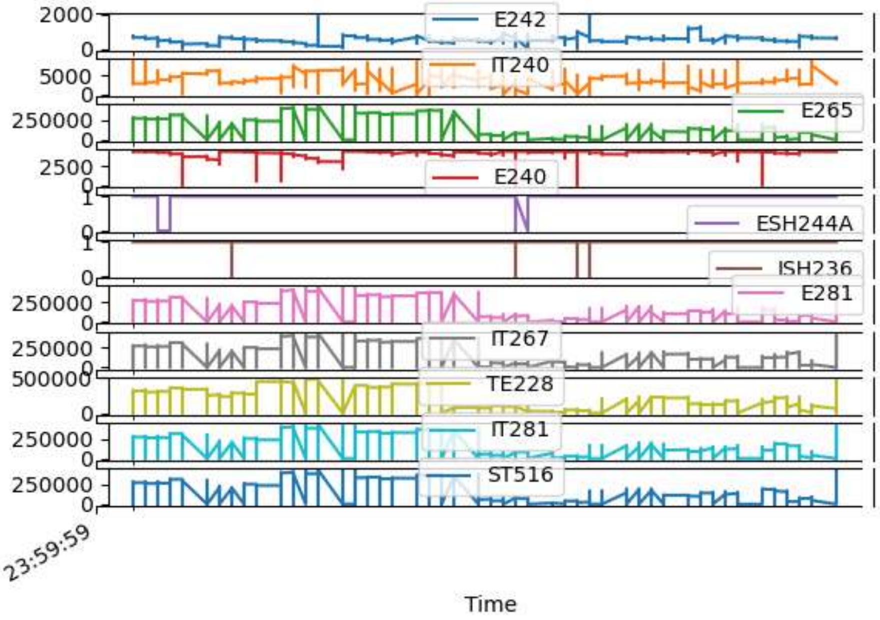


Figure - 3 pre-processing dataset.

2.1.4 One Hot Encoding

Due to the dataset Class Label being categorical, these values cannot be directly fed to Network. Therefore, categorical must be converted to a numeric value using the one-hot encoding method. In this method, the classes arrange alphabetically, then transform into binary vectors. Each class label indicates a binary vector for a length equal to the number of classes, where (0) means absence and (1) mean presence class. For instance, the class labels Normal and Abnormal represent as

Normal	[0	1]
Abnormal	[1	0]

Where the presence of class encoding with 1 while absence with 0 [14].

2.2 Split dataset

After a pre-processing dataset is split into two parts train, and test[15]. In our model, we use 70% of the dataset for training and 30% for testing.

2.3 Single Fault Diagnosis Classifier (SFD)

This stage includes building general and fast Fault Diagnosis Classifier. Which is responsible for working on single fault data, which mean that a single fault occurs in one of the sensors or components. SFD consist of three effective models as described below.

- **Single Fault Detection Model(SFDDNN)**

The Single Fault Detection model determines if faults occur or not. SFDDNN consists of eight one dimensional 1D convolution layers with a rectified linear activation function (ReLU) except the last layer with a linear activation function. The first six convolution layers are connected with the maxpooling layer with pool-size (1), last two convolution layers without the maxpooling layer. The numbers of filters used with the convolution layers are (16, 32, 64,128,256, 512, 1024, and 35) respectively with kernel size (3) and stride size (1).

The 1D convolution layer performs the role of feature extract to construct the feature maps of the input sample. A Flatten layer convert feature maps to vector, Output of flatten layer is used as input to fully connected layers (FC) to classify a fault with probabilistic values between 0 and 1. The weights of each layer are saved to generate the output of these layers, and after that output of the current layer is passed to the next layer as inputs until reaches to finally layer. The prediction for this model determines the model's overall functioning. If it is normal, there is no need to go through isolate model and the identifier model, otherwise, it will pass two models to determine the location and type of fault. The architecture of the SFDDNN Model illustrate in figure (4).

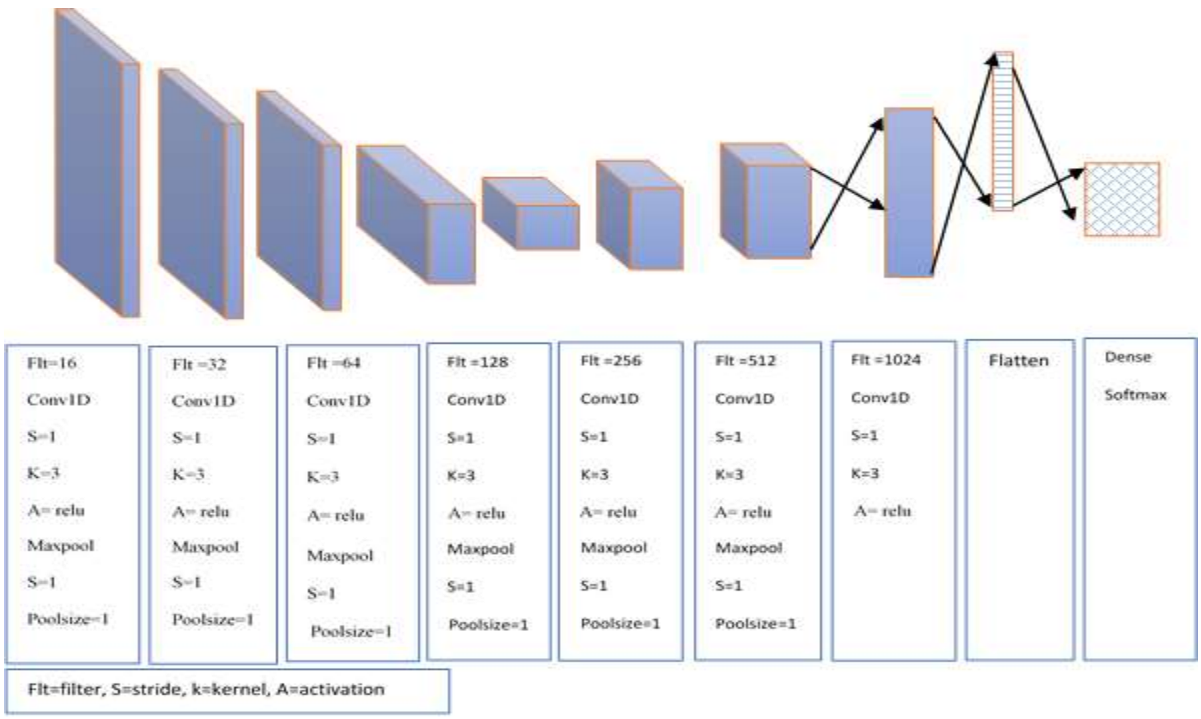


Figure 4 the structure of SFD Model.

- **Single Fault Isolate Model (SFIDNN**)

The SFIDNN model works if the prediction of the SFDDNN model is (abnormal), which is responsible for determining the location of the fault.

The model layers are similar to the layers of the SFDDNN model with little difference in filters number of the last convolution layer 145 and number of class labels in the Dense layer 24.

- **Single Fault Identify Model (SFIDDNN**)

The last model of the SFD works in synchronization with the SFIDNN model. SFIDDNN is responsible for classifying the fault type mode, which consists of layers similar to the SFDDNN model except the last convolution layer have 85 filters and the number of classes in the Dense layer (12). The weights of each model are different from others. A trained SFD obtain after completing training SFDDNN, SFIDNN and SFIDDNN models on the training dataset.

2.3 .1 Training phase

Each deep neural network (DNN) in the SFD is trained separately, the goal of training the networks separately is to determine if a fault occurs or not, find the location and fault types mode. To train each network separately the training data must be provided for each network. Following Algorithm illustrates the training process of the SFD system for each model.

Algorithm 1. Training 1D-CNN.
Input: training dataset(TRD) features, labels.
Output: fault diagnosis 1D-CNN model.
1 Initialize:biases and weights randomly.
2 For each epoch Do:
Process records of TRD data.
Per each Batch Size update and save the weights.
3 Save model and weights.
4 **End**

2.4 Model testing

Testing set used to provide an evaluation of a final model fit on the training dataset.

In the testing phase, weights of each trained model in SFD were used to test the classifier from the unseen dataset. Inputs of each model in SFD are features vectors, which uses to predict the system in Normal mode or faults, location and faults type mode. If the prediction of SFDDNN in SFD is Abnormal, features vectors pass to SFIDNN to predict fault location and to SFIDDNN to predict fault type mode.

3 Evaluation Metrics

Evaluating the overall fault diagnosis system performance requires evaluating the performance of each model in classifiers on the testing dataset. The metrics used in the evaluation are confusion matrix, accuracy, precision, recall, and F1-Mesure [16], as shown in equations bellow [17][18].

- True-positive (TP): correct-positive prediction
- False-positive (FP): incorrect-positive prediction
- True-negative (TN): correct-negative prediction
- False-negative (FN): incorrect-negative prediction

$$FN_i = \sum_{\substack{J=1 \\ j \neq i}}^{n} class_{ji} \qquad 1$$

$$FP_i = \sum_{\substack{J=1 \\ j \neq i}}^{n} class_{ji} \qquad 2$$

$$TP_i = \sum_{j=1}^{n} class_{jj} \qquad 3$$

$$TN_i = \sum_{\substack{J=1 \\ J \neq i}}^{n} \sum_{\substack{k=1 \\ k \neq i}}^{n} class_{jk} \qquad 4$$

$$Accuracy = \frac{TP_{all}}{TP_{all}+FP_{all}+TN_{all}+FN_{all}} \quad 5$$

$$Precision = \frac{TP_{all}}{TP_{all}+FP_{all}} \qquad 6$$

$$Recall = \frac{TP_{all}}{TP_{all}+FN_{all}} \qquad 7$$

$$\mathrm{F-score} = 2 * \frac{precision*recall}{precision+recall} \qquad 8$$

4 Experiments and Results

In this research, we use a deep learning technique for SFD. CNN was used to extract the best features from the dataset. The optimal number of filters used by CNN layers over the range of (16 filters to 1024 filters), after each conv1D layer max-pooling with bool size = 1 is used to extract the best feature from the feature map, table (1) illustrate parameters of SFD and performance matrix.

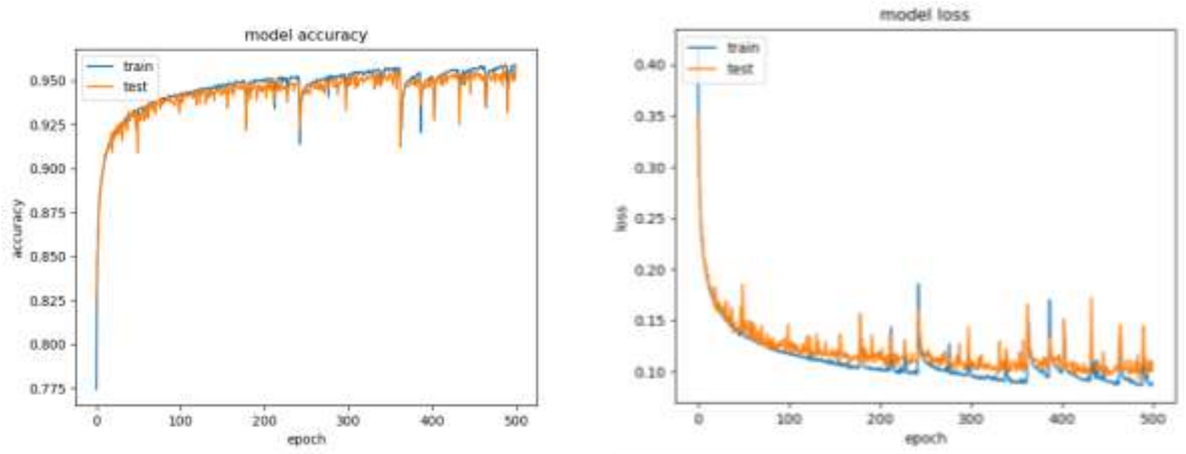
Our result get higher Accuracy compared with different techniques and the complexity of datasets for fault diagnosis, as illustrate in table (2). Figure 5 show accuracy and loss function for each model in SFD. Experiment run on a computer with Inter Core i710750h CPU, 16GB memory, and NVIDIA 1660TI GPU. The Programming language is Python 3.7 with the deep learning package “Tensor flow 2.3.1”. The total training time of all epochs is 1500 seconds (three second per epoch).

Table 1 parameters and performance matrix of SFDC**.**

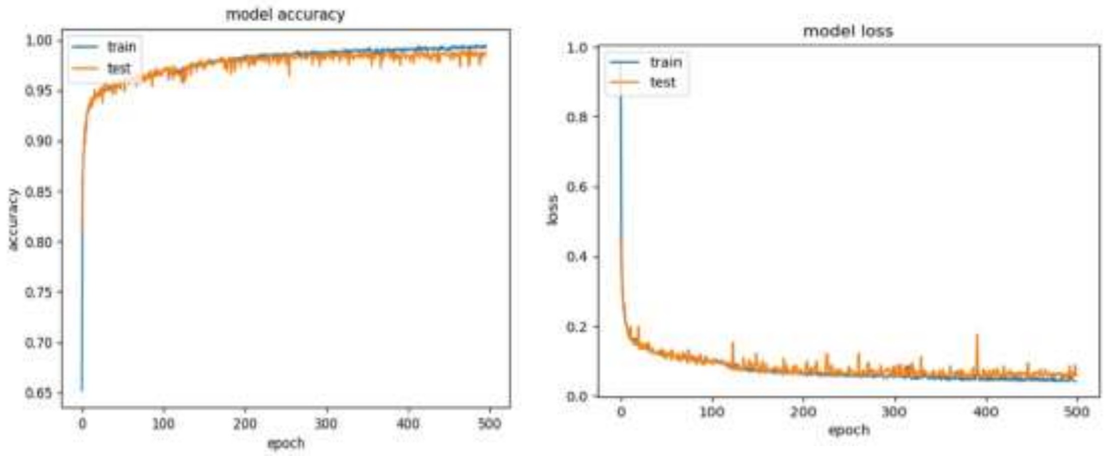
Model	Epochs	Batch size	learning rate	parameters	Accuracy	precision	recall	F1-measure
SFDDNN	500	1024	0.0016	823,947	0.96707	0.96710	0.96708	0.96708
SFIDNN	500	1024	0.0016	940,129	0.98513	0.985127	0.98513	0.98512
SFIDDNN	500	512	0.0016	876,157	0.98675	0.98677	0.98675	0.98676

Table 2 show compares between proposed approach with others methods.

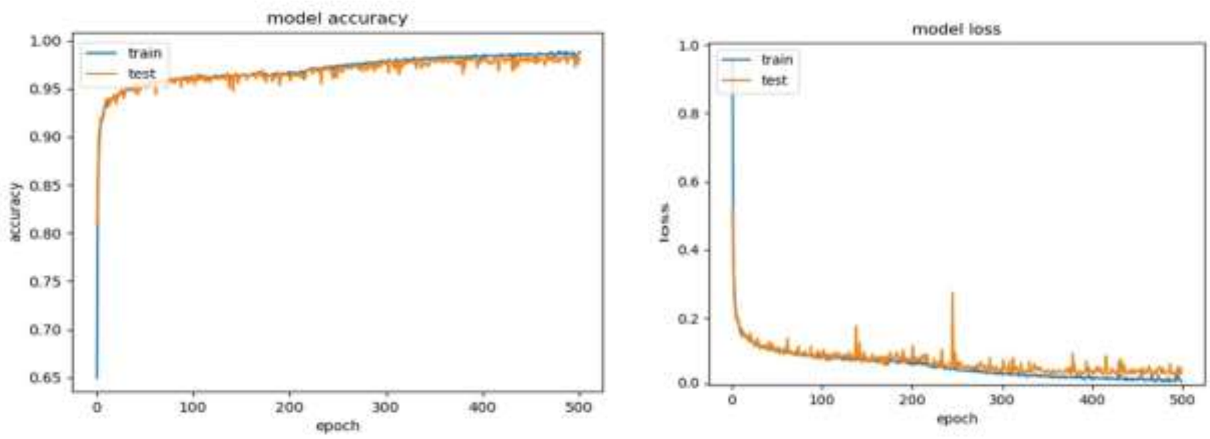
	M Ganesan et al [10]			Proposed*		
Dataset	Univariate			Multivariate		
	ADAPT single fault dataset (six experiments) **(**120 samples for each experiment)			ADAPT single,multi-fault dataset (227 experiments for single,2400 samples for each experiment)		
Pre-processing	Stockwelltransform with remove missing values.			Impute missing values and StanderScaler		
Approach	1DCNN for detection			1DCNN for diagnosis(detection , isolation, Identify)		
layers	Convolution, pooling and ReLU			Convolution, maxpooling , ReLU/Leaky Relu, and linear		
Hyperparameter	Learning rate		0.001	Learning rate		0.0016
	Batch Size		16	Batch Size		1024
	Number of Filters		50	Number of Filters		(16-1024)
	Strides		1	Strides		1
	Drop out		0.2			
Accuracy and Loss		Accuracy	Loss	Single	Accuracy	Loss
	Train	96.6	0.114	Train	96.77	0.1022
	Test	96.7	0.118	Test	96.71	0.1248



(a) SFDDNN



(b) SFIDNN



(c) SFIDDNN

Figure - 5 show curve of accuracy and loss for SFD models

6. Conclusion

Increasing the use of UAVs in different fields and increase trouble takeover in its power system lead to an increase in the need for fault diagnosis. In this paper, we have shown the ability of deep learning in fault diagnosis algorithm for a single fault in the power system of UAV. In the future, we will extend the algorithm for multi faults in the electrical power system of UAV.

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