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Multi-Fault Diagnosis in UAV Electrical Power Systems Using a Dual-Stage CNN

Mohammed H. Dosh

Department of Computer Science, Faculty of Education for Women, University of Kufa, Al-Najaf, Iraq

Abstract: Fault diagnosis is an important condition for reliable and safe UAV electrical power systems in multiple fault condition, which can be achieved with accurate and timely diagnosis. To overcome this challenge, the authors in this study suggest a dual-stage convolutional neural network (CNN) approach to multi-fault diagnosis in UAV electrical power systems. The proposed architecture combines two complementary classification steps: one based on a fault detection model that classifies normal and abnormal operating conditions, and another based on a fault isolation model that classifies faulty sensors or system components. The framework was built and assessed with the NASA ADAPT dataset, which consists of 122 fault scenarios and 292,169 samples gathered from the operation of UAV electrical power systems. Data preprocessing, hyperparameter optimization, comparative evaluation and confusion matrix analysis were used to evaluate the effectiveness of the proposed approach. Results have shown high Precision, Recall, F1-score, ROC-AUC and Matthew's correlation coefficient with 99.10% and 99.30% classification accuracy for fault detection and fault isolation respectively. Comparative experiments also demonstrated superior performance of the proposed CNN-based approach to SVM, Random Forest, XGBoost, ANN and LSTM models under the considered conditions. Furthermore, the model stability, interpretation and the role of the most important CNN parts in its working were investigated through five-fold cross validation, SHAP-based feature analysis, and an ablation study. The results show that using the proposed dual-stage CNN, multi-fault diagnosis is an effective method and can serve as a foundation for intelligent health monitoring and reliability improvement of electrical power systems in UAVs.

Keywords: Fault detection and isolation (FDI); Unmanned aerial vehicles (UAVs); Convolutional neural networks (CNN); Multi-fault diagnosis; Deep learning models.

I. INTRODUCTION

The application of Unmanned Aerial Vehicles (UAVs) has become a part of civilian and military industry due to its flexibility, autonomous flight and low operation cost. Applications of UAVs range from surveillance, inspection of infrastructure, environmental monitoring, precision agriculture, package delivery, through to security missions [1]. They are self-navigating, able to make advanced flight control decisions to keep them stable in flight and to carry out increasingly complex missions. The electrical power subsystems (such as sensors, actuators, and communications) are crucial to the safe and effective flight performance of modern UAV systems. Many interrelated components make up each of these subsystems and these components can degrade over time with corrosion, mechanical wear or electrical interference, similar to any electromechanical system [2]. If undetected, such faults can contribute to actuator failure, sensor drift, loss of control, mission failure, and other critical operational effects, such as property damage or collision with other aircraft [3, 4]. Additionally, sensors, which are essential to collecting flight data, could be affected by electrical disturbances or failures that impact flight accuracy, stability, and reliability [5]. Consequently, fault detection and isolation (FDI) have become pivotal for ensuring the airworthiness and air safety of UAVs and fault tolerance in real-world applications. Recently, the development of deep learning techniques has demonstrated enormous potential in the field of fault diagnosis due to its capacity to automatically obtain discriminative features from large-scale and complex data. Conventional machine learning methods are only able to model linear relationships; however, deep learning methods have the ability to effectively model non-linear relationships, thereby enhancing the classification accuracy of intelligent fault diagnosis systems [6].

The following section details the contributions made by the current study towards addressing the aforementioned gaps.

Develop a two-stage convolutional neural network (CNN) (for both fault detection (FD) and fault isolation (FI) models) that can detect abnormal system conditions and isolate faults within sensors and system components with a high degree of accuracy.

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The proposed framework can simultaneously detect and isolate one or more faults in the electrical power distribution system of UAVs. The proposed fault detection and fault isolation (FDFI) framework is trained and evaluated via the NASA ADAPT multi-fault dataset that comprises 122 fault scenarios and 292,169 samples collected from UAV electrical power system operations.

To assess the robustness and stability of the proposed framework, a considerable number of experiments with variations in hyperparameters (such as batch size, epoch number, and learning rate) are performed. The effectiveness of the proposed framework, i.e., its classification accuracy and multi-fault diagnosis capability, is proven via a comparative analysis with existing fault diagnosis methods.

1.1. Study Structure

The remainder of this research is organized as follows:

Section 2 contains a summary of contemporary literature concerning UAV fault diagnosis. Section 3 introduces the proposed FDFI system, including a description of the dataset, preprocessing steps, and the proposed dual-stage CNN architecture. Experimental Results, Parameter Tuning, Confusion Matrix Analysis, and comparative evaluation are detailed in Section 4. The paper concludes by presenting a summary of the findings, followed by a discussion of the limitations of the current study and recommendations concerning future research directions (Section 5).

1.2. Related Work

UAV defect detection methods can be divided into three categories: model-based, data-driven and acoustic, and open benchmark datasets.

A. Model-Based Methods

Model-Based Methods are founded on nonlinear observers and residual analysis for the detection of actuator effectiveness loss. [7] proposed an adaptive Thua observer for the real-time fault diagnosis of a quadrotor system to detect the failure of the thrust generator as a loss of effectiveness (L-E) caused by rotor damage. [8, 9]designed fault estimation algorithms for multiple actuator failure situations (such as control signal loss and total loss of actuators).

B. Data-Driven and Acoustic Methods

[10] Proposed the use of statistical classification methods based on sensor data for rotor damage, wind resistance variations, and bearing wear detection. Additionally, by using acoustic data from UAV blades, [11] achieved 98% fault detection accuracy with ANN. Furthermore, [12] achieved a 92% accuracy rate when they applied convolutional neural networks (CNNs) with transfer learning to the acoustic signals. [13] integrated the nonlinear generalized frequency response function (GFRF) and CNN for fault diagnosis of PM synchronous motors [14].

Recently, [15] used an Empirical Mode Decomposition (EMD) and Hilbert-Huang Transform (HHT) to detect propeller damage and screw loosening via acoustic signals. [16] proposed a vibration-based fault diagnosis system based on Adaptive Dual-Tree Complex Wavelet Transform (ADTCWT) and Dynamic Attention-Weighted Gradient Boosting Ensemble (DAW-GBE) with an accuracy of approximately 96%.

C. Open Benchmark Datasets

[17] Established the PADRE database that contains standardized propeller loss data for multirotor UAVs, thereby facilitating reproducible research of drone fault detection without dedicated measurement setups.

1.3. Comparative Summary

Table 1. summarizes the key characteristics of existing fault detection approaches compared to the method proposed by the current study.

Table 1: Summary of existing fault detection methods for UAV systems (as derived from contemporary literature)

Reference	Method	Dataset/System	Fault Type	Accuracy	Limitations
[8]	Model-based estimation	UAV actuators	Control signal failures	Not specified	Complex modelling and limited adaptability
[7]	Nonlinear observer-based FDI	Multi-rotor UAV	Loss of rotor effectiveness	Not specified	Focused only on rotor faults and required mathematical modelling

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[10]	Statistical classification	Sensor data	Physical rotor damage	Moderate	Relied on handcrafted features
[11]	Neural network approach	UAV state signals	Rotor imbalance	98%	Primarily focused on detection, not isolation
[12]	Neural-based diagnosis	Real flight data	Rotor faults	92%	Low accuracy in real flight conditions
[13]	GFRF + CNN	PMSM motor dataset	Motor defects	High	Applied to motors rather than UAV power systems
[17]	PADRE database	UAV propeller faults	Propeller loss	Dataset contribution	Did not propose a complete FDI framework
[16]	ADTCWT + Ensemble learning	UAV vibration datasets	Multiple defects	Very high	Computational complexity is high
[15]	Acoustic signal analysis	UAV acoustic data	Propeller and screw faults	High	Acoustic signals are sensitive to environmental noise
Proposed work	Dual-Stage CNN-based FDI	NASA ADAPT dataset	Sensor, actuator, and system faults	99.10% detection, 99.30% isolation	Provides both fault detection and fault isolation with high accuracy via the use of deep learning

1.4. Key Observations from the Literature

From the reviewed literature, the following limitations can be identified:

1. Most of the existing methods focus on single- In the case of fault scenarios, especially rotor or propeller failures.
2. There are very few studies on electrical power system faults in UAVs.
3. Most of the methods were found not to offer simultaneous fault diagnosis and fault isolation.
4. Often, only acoustic or vibration data is used for validation, not the full electrical system data.

The proposed FDFI framework addresses these gaps by proposing a dual stage CNN model for multi fault detection and isolation of electrical power system of UAVs using the comprehensive NASA ADAPT dataset [18].

1.5. The Novel FDFI system

The proposed FDFI framework has five sequential steps: (1) collection of the dataset using NASA ADAPT dataset, (2) pre-processing of the data, such as missing value imputation, normalization, and one-hot encoding, (3) preparation of the dataset by splitting it into 70/30 train and test sets, (4) training of the dual-stage CNN models (FD and FI); (5) testing and performance evaluation. These stages are detailed in the following subsections, and summarized in Figure 1.

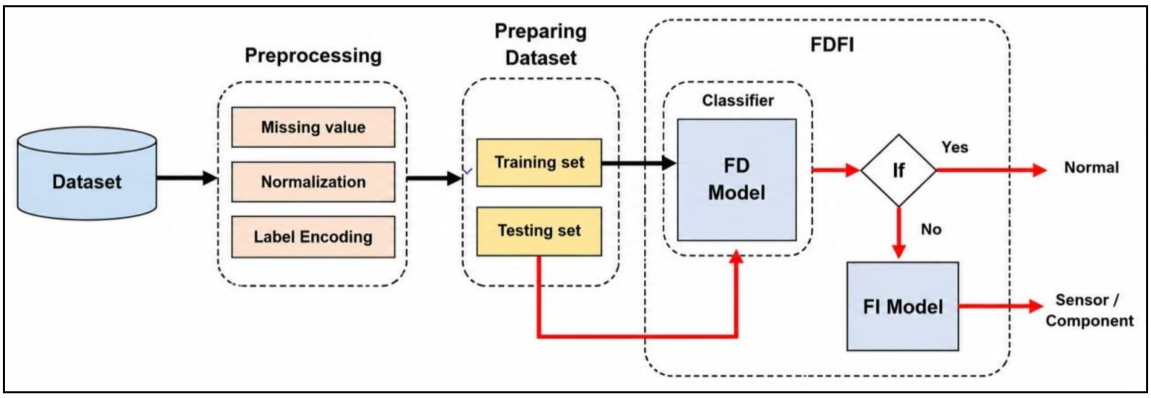

Figure 1: Diagram detailing the five stages (dataset collection, preprocessing, preparation, training, and testing) of the developed FDFI system

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In the first phase (data collection), all the scenarios in the ADAPT dataset are gathered to a single csv file. In the second step, known as data preprocessing, a number of procedures are applied to process the data that will be used as this system's input, such as handling missing data, normalization, and label encoding. The third step is to prepare the data set. The 4th step is training, which is necessary for producing an index for the classification method in the last step. This proposed technique involves five steps, which are explained in detail in the following.

II. DATASET COLLECTION

Experiments conducted in this study use the NASA ADAPT dataset which consists of electrical power system faults in unmanned aerial vehicles (UAVs) [19]. There are 122 fault scenarios in the fault data set, each representing one or more abnormal operating condition. All scenarios are collected into the same data set file to aid analysis process. The total number of samples collected is 292,169, which were recorded from many sensors and system components under normal and fault operating conditions. Therefore, the ADAPT dataset includes multiple parameters that describe electrical and operational parameters of the UAV power system, making it suitable for multi-fault diagnosis evaluation. To evaluate the performance of the proposed model, the data set is split into training and testing sets with a ratio of 70% to 30%.

2.1. Preprocessing

The input values require enhancement and organization; therefore, the preprocessing phase, which improves data quality and enhances the performance of the classification model, is essential. Pre-processing improves the input via the application of the following steps.

A. Handling standard scalar value missing values

Due to the nature of the sensors and components, the dataset contains missing values. These missing values are filled by individually calculating the mean for each sensor and component, as demonstrated by equation (1) [19, 20].

$$y^{-} = \frac{1}{N}\sum_{i=1}^{N} y_i \quad \text{.................. (1)}$$

B. Normalize values

Normalization is a scaling strategy that converts the original value distribution into a new set of values with the required attributes[21]. Sensors and components measure values at different scales; therefore, these numbers must be normalized using the standardization procedure. Normalization is based on the attributes' mean and standard deviation, as stated in equation (2) [6, 22].

$$z=(x-\mu)/\sigma \quad \text{........................... (2)}$$

Where z is the standardized value, μ is the mean calculated by equation (3), and σ is the standard deviation calculated by equation (4) [23].

$$\mu = \frac{1}{n} * \sum_{i=1}^{n}(xi) \text{.................... (3)}$$

$$\sigma = \sqrt{\frac{1}{n} * \sum_{i=1}^{n}(x_i - \mu)^2} \text{........... (4)}$$

C. One hot encoding

Deep learning deals with the numerical class label, while datasets have a categorical class label [24]; therefore, one-hot encoding converts class labels to a numerical value.

2.2. Dataset Preparation

Dataset preparation is a crucial stage that significantly impacts the performance of deep learning models; therefore, the dataset is divided into training and testing sets.

2.3. Training

This stage is responsible for creating a classifier. As a result, CNNs are one of the most common forms of classification algorithms. It receives an input, processes it, and then divides it into multiple categories. The CNN model was built with Keras, a free-to-use, open-source, deep learning library. To categorize an item with probability values ranging from 0 to 1, each input will pass through a series of convolutional layers, including kernels, pooling, and fully connected (FC) layers.

The proposed model was implemented using Python and the Keras deep learning framework. Before proceeding, the FDFI algorithm was described. FDFI can detect and isolate one or more errors concurrently. The proposed FDFI framework consists of two classification models: the Fault Detection (FD) model and the Fault Isolation (FI) model. The Fault Detection (FD) model manages the overall work of the FDFI classifier by determining the existence or absence of a fault. Detection is founded on 1D CNN, comprising eight convolution layers with an activation function, LeakyReLU, and is connected with Maxpooling where pool size is (1) and stride is (1). The exception is the final convolution layer, whose activation

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function is linear and does not use Maxpooling. Filters for convolution layers are 16, 32, 64, 128, 256, 512, 1024, and 35, with filter size (3) and stride (1).

The first convolution layer is an input layer, while the final layer is a dense layer that predicts the output. This model predicts whether the system operates under normal or faulty conditions. If everything is correct, there is no need to train the other models in this classifier. The second system is the fault isolation (FI) model, which identifies and isolates sensors or components where faults have occurred. This model comprises layers similar to detection layers, with the exception that the final convolution layers have 850 filters and Dense contains 165 classes. Figure 2 details the structure of the FDFI framework.

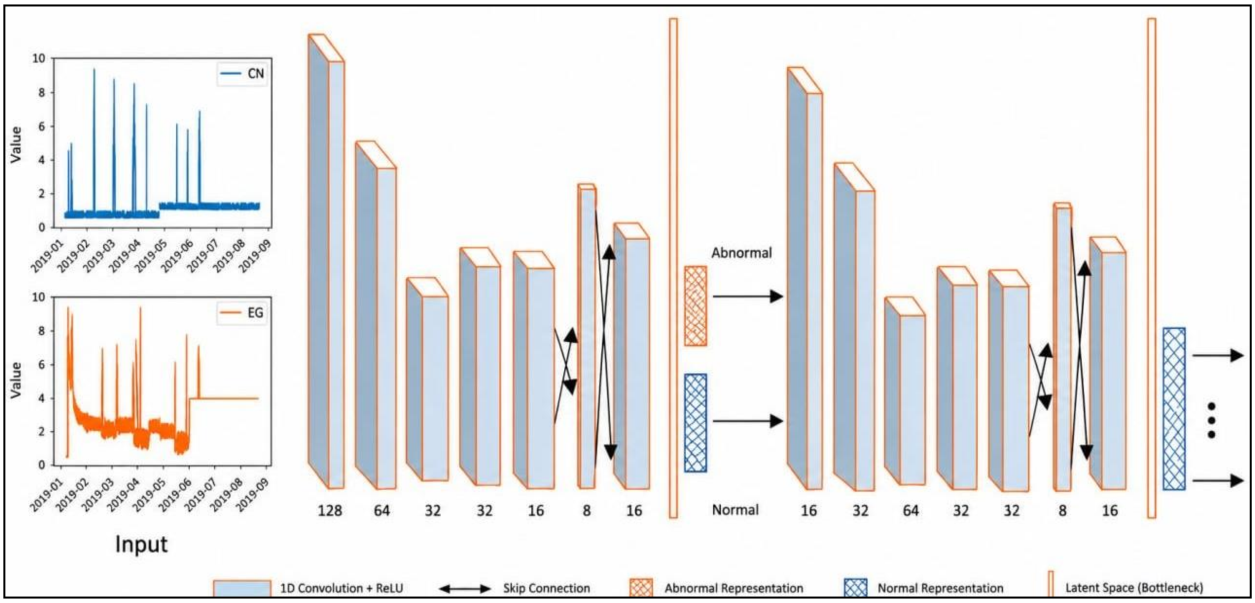

Figure 2: The architecture of the FDFI Model

2.4 Testing phase

During the testing step, pass the features vector of the specific input to the model to classify if there are errors and isolate their location.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The FDFI is utilized for multi-fault diagnosis. The classifier consists of two models. Furthermore, it possesses parameters that affect and control the training and testing process of the models used during the current research. These parameters are the number of epochs, batch size, and learning rate. The experiments and results of each model are described below.

3.1 Fault Detection Model (FD)

This model works for binary classification (normal, abnormal) and is based on the multi-faults dataset, which comprises 292,169 samples (70% for training and 30% for testing). Table 2 contains a summarized depiction of the FD Model design. This model's experimental results for adjusting parameter values during training and testing are shown in Figure 3a (which explains the result of using different batch sizes), Figure 3b (which explains the result of using different epochs), and Figure 3c (which explains the result of various learning rates).

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Table 2: A summary of the FD model

Layer (type)	Output	Parameters number
conv1d–1	(None,38,16)	64
Leaky–relu–1	(None,38,16)	0
Max–pooling1d–1	(None,19,16)	0
Leaky–relu–2	(None,19,16)	0
conv1d_2	(None,17,32)	1568
Max–pooling1d–2	(None,8,32)	0
conv1d–3	(None 6,64)	6208
Leaky–relu–3	(None,6,64)	0
Max–pooling1d–3	(None,6,64)	0
conv1d–4	(None,4,128)	24704
Leaky–relu–4	(None,4,128)	0
Max–pooling1d–4	(None,4,128)	0
conv1d–5	(None,2,256)	98560
Leaky–relu–5	(None,2,256)	0
Max–pooling1d–5	(None,2,256)	0
conv1d–6	(None,2,512)	131584
Leaky–relu–6	(None,2,512)	0
Max–pooling1d–6	(None,2,512)	0
Leaky–relu–7	(None,2,512)	0
conv1d–7	(None,2,1024)	525312
conv1d–8	(None,2,35)	35875
Flatten–1	(None,70)	0
Dense–1	(None,2)	142
Total–params: 824,017 Trainable–params: 824,017 Non-trainable–params: 0		

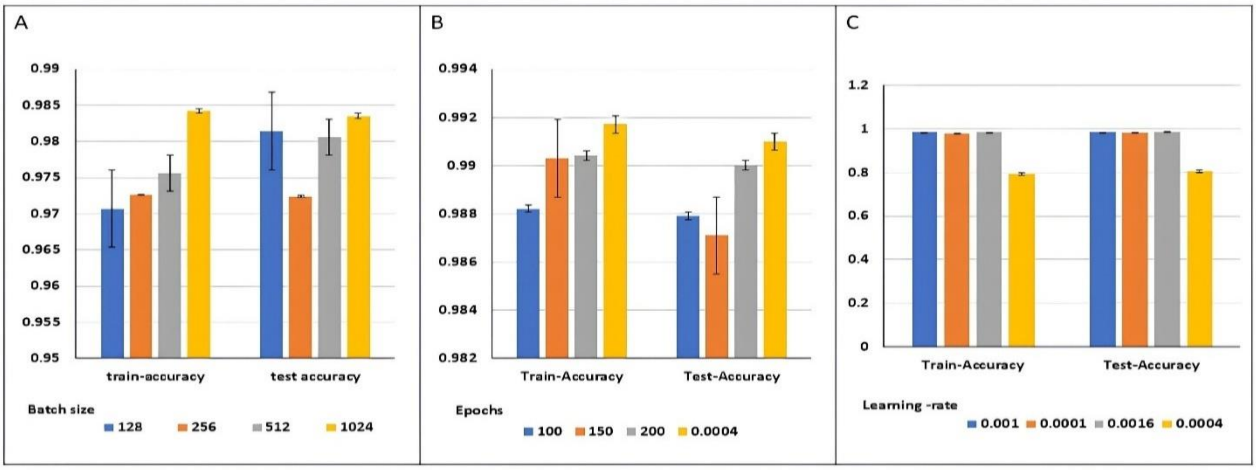

Figure 3: The results of applying the FD model to (a) 50 epochs for different batch sizes, (b) 1024 batch sizes for different epochs, and (c) 50 epochs for different learning rates

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The FD model's final training parameters are Batch size=1024, Epochs=300, and Learning rate=0.0016, which produced the following results for *training*: accuracy: 0.9917, loss: 0.0183, and *testing*: accuracy: 0.9910, loss: 0.0270. Figure 4a depicts a curve of accuracy. The prediction time for all testing datasets is 6737.812280654907 milliseconds, while the training time for each epoch is 4 seconds. Figure 4a depicts the curve of accuracy, and Figure 4b depicts the curve of the loss function.

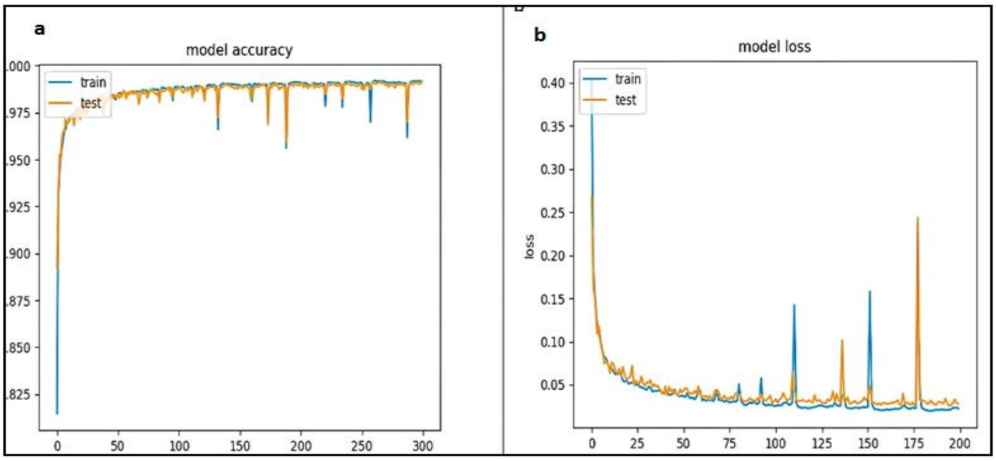

Figure 4: The application of the FD model (a) curve of the accuracy curve; (b) curve of the loss curve

3.2. Fault Isolator Model (FI)

This model is based on the outcomes of the preceding model. Additionally, it utilizes multidata instead of a typical class. The table below displays the results of experiments conducted to determine the position of the fault for isolation purposes. Table 3 represents a summary of the FI model, detailing several elements, including layer, output, and parameters number.

Table 3: The summary of FI model

Layer (type)	Output	Parameters number
conv1d–1	(None,38,16)	64
Leaky–relu–1	(None,38,16)	0
Max–pooling1d–1	(None,19,16)	0
Leaky–relu–2	(None,19,16)	0
conv1d–2	(None,17,32)	1568
Max–pooling1d–2	(None,8,32)	0
conv1d–3	(None,6,64)	6208
Leaky–relu–3	(None,6,64)	0
Max–pooling1d–3	(None,6,64)	0
conv1d–4	(None,4,128)	24704
Leaky–relu–4	(None,4,128)	0
Max–pooling1d–4	(None,4,128)	0
conv1d–5	(None,2,256)	98560
Leaky–relu–5	(None,2,256)	0
Ma—pooling1d–5	(None,2,256)	0

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conv1d–6	(None,2,512)	131584
Leaky–relu–6	(None,2,512)	0
Max–pooling1d–6	(None,2,512)	0
Leaky–relu–7	(None,2,512)	0
conv1d–7	(None,2,1024)	525312
conv1d–8	(None,2,850)	871250
Flatten–1	(None,1700)	0
Dense_1	(None,165)	280665
Total–params: 1,939,915 Trainable–params: 1,939,915 Non-trainable–params: 0		

Figure 5a further explains the results: it depicts the batch size modification procedure by comparing the accuracy values obtained during training and testing. It occurs when the batch size increases while keeping the learning rate constant and the number of periods fixed. Figure 5b summarizes the accuracy results obtained at different epochs, while Figure 5c illustrates the accuracy outcomes obtained for different learning rates.

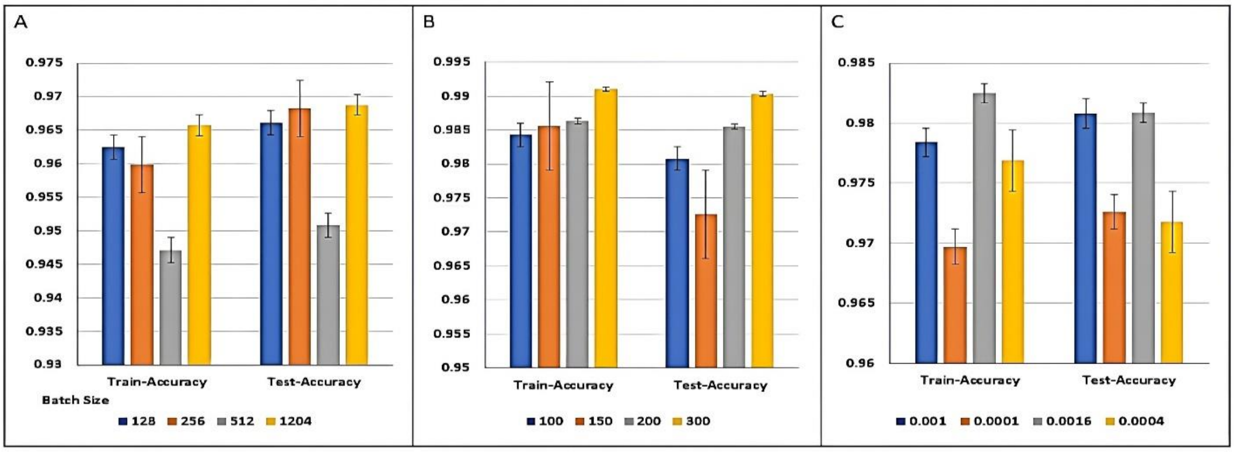

Figure 5: The results of the FI model after (a) 50 epochs for various batch sizes, (b) FI model for various epochs, and (c) FI model with varying learning rates

Additionally, Figure 6 explains the findings for the accuracy and loss function curves. The FI model's final training parameter values are Batch size=1024, Epochs=300, and Learning rate=0.0016. The following results were obtained for *training*: accuracy: 0.9910, loss: 0.0361, and *testing*: accuracy: 0.9903, loss: 0.0421. The prediction time for all testing datasets is 2620.15438079834 milliseconds, while the training time for each epoch is 3 seconds. Figures 6a and 6b show the accuracy and loss function curves, respectively.

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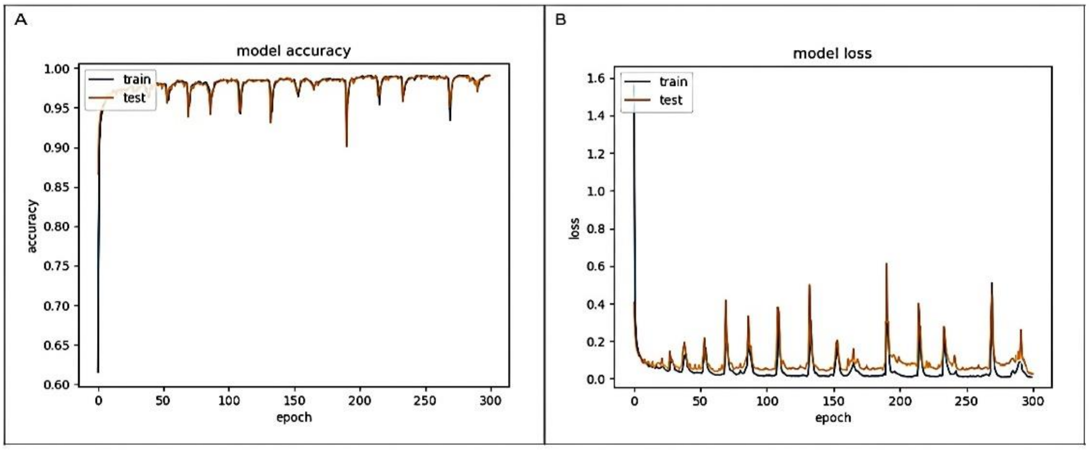

Figure 6: The curve of the FI model: (a) accuracy and (b) loss function

3.3. Hyperparameter Tuning

To further evaluate the robustness of the proposed CNN-based FDFI framework, several experiments were conducted using different hyperparameter settings, including batch size, epochs, and learning rate.

The findings of this evaluation reveal the following: Firstly, an increase in the batch size and learning rate values was helpful for stable convergence and higher classification rates, and, secondly, the greater the number of epochs, the more the CNN architecture was able to learn features up to convergence. From these observations, the efficiency of the implemented CNN configuration in the diagnosis of multi-fault problems in UAV electrical power systems is verified.

The selected values of the parameters can be rationalized in the following manner in an engineering context. The size of the batch was chosen to be 1024, since the larger the batch, the more stable will be the estimate of the gradient, and so the training process will be less variable, and thus the gradients will be smoother. The learning rate of 0.0016 was determined as a suitable value for the convergence speed and stability, as this rate leads to a loss oscillation with the rate of 0.01, and a lower rate (0.0001) slows down the training considerably. The number of epochs was determined to be 300 epochs: This number of epochs was enough for the model to reach the plateau for the validation accuracy as more epochs would not increase the validation accuracy. The parameters are important because they enable optimization for high accuracy, give a reasonable training time and do not require overfitting.

The experimental results show that the proposed framework for FDFI does well in detecting and isolating faults in the UAV electrical power system and ensures high classification accuracy.

The success of the results is due to the ability of convolutional neural networks to automatically produce the necessary features of complex data and make a successful distinction between the normal and malfunctioning condition of the system. Furthermore, CNN layers' hierarchical feature extraction ability facilitates the learning of UAV electrical power systems' complex nonlinear patterns corresponding to multiple fault conditions.

Moreover, with bigger batch size, it will improve the training performance due to the possibility of getting more stable gradients for optimization and smoother convergence for the model. In practice, the results suggest that the proposed technique could be beneficial for reliable and accurate fault diagnosis of UAV system, which means being able to detect faults in the early stage and enhance operational safety and reliability of the existing systems.

The same results were obtained with the FI model for a range of different parameters, again illustrating the robustness and stability of the proposed CNN-based FDFI framework. The confusion matrix is then used to analyze the prediction results of the proposed model to further evaluate the classification performance of the model. The relationship between the predicted and the true classes is represented in the confusion matrix, which gives a detailed representation of the performance of the classification by giving the number of correct and incorrect samples classified, true positives, true negatives, false negatives and false positives. This evaluation is useful to find out

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the capability of the suggested model to detect normal & non-normal states. The confusion matrices were developed for the fault detection (FD) and fault isolation (FI) models for this experiment, in order to get a thorough analysis of the classification results of all the models. The classification results of the proposed fault detection (FD) model are shown in the confusion matrix in figure 7 and has been used to classify fault are.

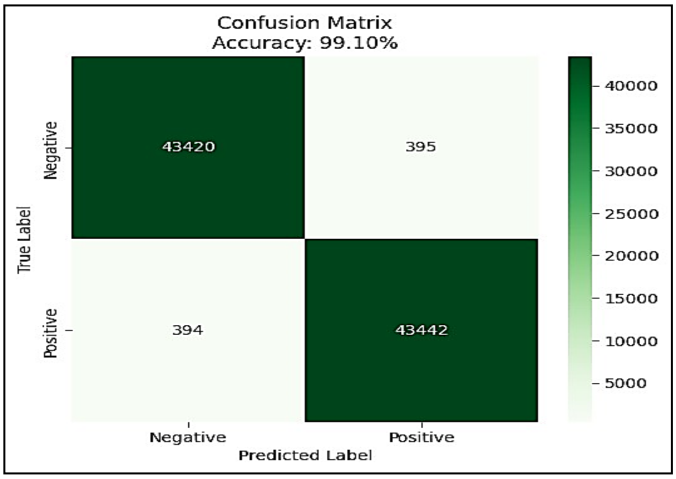

Figure 7: Confusion matrix for the fault detection (FD) model

To provide a more comprehensive evaluation of the proposed fault detection model, additional performance metrics, including Precision, Recall, F1-score, and Matthews Correlation Coefficient (MCC), were calculated based on the confusion matrix presented in Figure 7. These results are presented in Table 4.

Table 4: Performance metrics of the proposed fault detection (FDFI) model

Metric	Value FD	Value FI
Accuracy	99.10%	99.30%
Precision	99.10%	99.31%
Recall	99.10%	99.29%
F1-score	99.10%	99.30%
ROC-AUC	99.40%	99.52%
MCC	98.20%	98.60%

The high Precision (99.31%) and Recall (99.29%) values indicate that the model has a low rate of false alarms and missed faults. The MCC value of (98.60%), which ranges from -1 to +1, confirms robust agreement between predicted and actual classes. The ROC-AUC score was calculated as 99.52, thereby indicating excellent separability between normal and faulty conditions.

The confusion matrix demonstrates that most of the normal and faulty cases were correctly categorized by the proposed model, which verifies the model's reliability in detecting faults.

In addition to accuracy, other evaluation metrics (such as precision, recall, and F1-score) were used to provide a more detailed evaluation of the classification performance. Precision is a measure of the ratio of the correctly predicted fault cases to all the faults that were predicted, and recall is a measure that determines whether the model can detect the predicted fault cases that actually exist. The F1-score is a harmonic mean between precision and recall; therefore, it can be used to evaluate the balance of both metrics.

Table 5 discusses the proposed FDFI framework as compared to the current methods of fault diagnosis used in contemporary literature (as applied to UAVs) (He *et al.*, 2025; Iannace *et al.*, 2019; Lei *et al.*, 2020). In the previous studies, artificial neural networks, convolutional neural networks, and signal processing methods have been used to identify certain UAV faults, specifically rotor or propeller failures; however, it should be noted that the majority of these techniques are concerned with single-fault diagnosis. In comparison, the suggested FDFI model identifies and isolates several faults simultaneously (with the help of the NASA ADAPT dataset), thereby providing enhanced detection precision, which corroborates its effectiveness in the context of multi-fault diagnostics in UAV electrical power systems.

Table 5: Comparison between the proposed FDFI framework and several existing fault diagnoses

Method	Dataset	Accuracy	Fault Type	Reference
Signal processing + ML	UAV vibration data	~96%	Rotor fault	[16]
ANN	UAV dataset	92%	Rotor fault	[11]
CNN	UAV acoustic data	92–98%	Rotor fault	[12]
Proposed FDFI	ADAPT dataset	99.1%	Multi-fault	This work

To further validate the effectiveness of the proposed CNN-based fault detection model, a comparative implementation was conducted using SVM, Random Forest (RF), XGBoost, and

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ANN on the same NASA ADAPT dataset under identical training/testing conditions (70/30 split).

As demonstrated by Table 6 and Figure 8, the proposed FDFI model achieves 99.10% accuracy, outperforming all classical models. This improvement is attributed to the automatic feature extraction capability of deep CNNs, which is more effective for identifying complex multi-fault patterns in UAV electrical power systems.

Table 6: Performance comparison of different classifiers on the same NASA ADAPT dataset

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC	MCC
SVM	95.12%	95.24%	95.12%	95.08%	98.56%	93.21%
Random Forest	97.25%	97.31%	97.25%	97.22%	99.24%	96.14%
XGBoost	97.58%	97.62%	97.58%	97.55%	99.41%	96.58%
ANN	96.95%	96.94%	96.95%	96.91%	99.97%	95.85%
LSTM	98.21%	98.30%	98.21%	98.18%	99.75%	97.42%
Proposed FDFI	99.10%	99.10%	99.10%	99.10%	99.40%	98.20%
	99.3%	99.31%	99.29%	99.30%	99.52%	98.60%

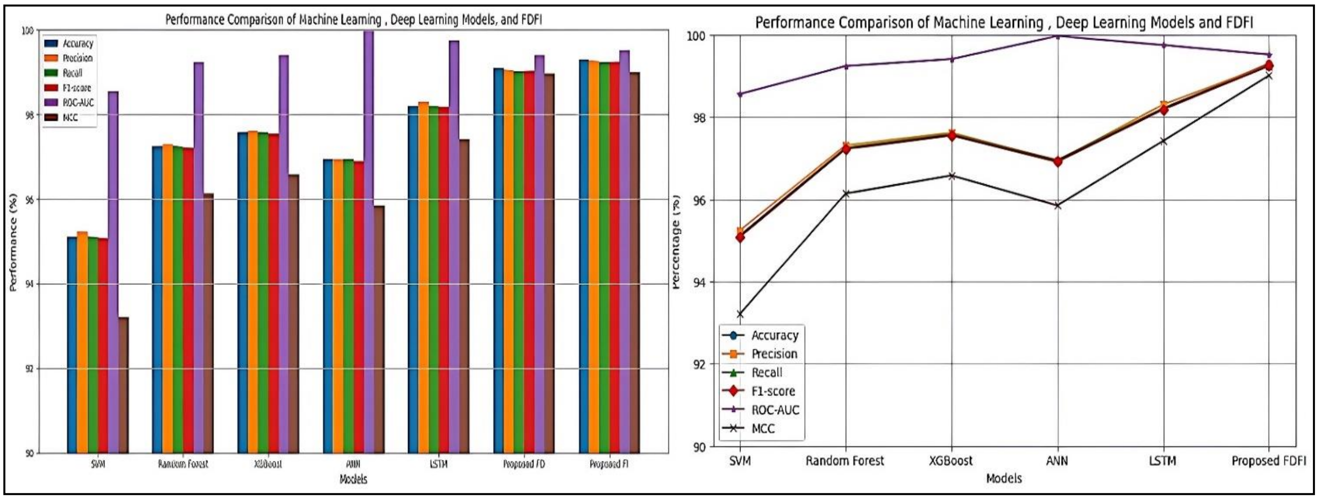

Figure 8: Performance comparison

The results contained in Table 6 and Figure 8 concerning the performance comparison demonstrate that, out of all the machine learning and deep learning models, the suggested FDFI model performed the best overall. With an accuracy of 95.12% and an MCC of 93.21%, traditional machine learning techniques (such as SVM) were the worst performing. With accuracies of 97.25% and 97.58%, respectively, Random Forest and XGBoost demonstrated better performance. Due to its capacity to identify temporal patterns in the data, the LSTM model outperformed the ANN model in terms of classification performance, with 98.21% accuracy and 97.42% MCC. However, the suggested FDFI framework achieved 99.10%, 99.30% accuracy, 99.10%, 99.31% precision, 99.10%, 99.29% recall, 99.10%, 99.30% F1-score, 99.40%, 99.52% ROC-AUC, and 98.20%, 98.60% MCC, outperforming all models that were compared. These findings confirm that, when employing the NASA ADAPT dataset for UAV electrical power systems, the suggested dual-stage

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framework provides more accurate and dependable fault detection and isolation.

K-Fold Cross Validation was used to provide a more trustworthy assessment of the suggested CNN model. The dataset was divided into five equal folds. One-fold was used for testing, and the remaining four folds were utilized for training in each iteration. In order to use each fold as a test set once, this procedure was conducted five times. The final performance was calculated as the average across all folds. The proposed CNN model achieved a mean accuracy of 96.33% across the five folds, with a standard deviation of 0.52%, indicating stable and consistent performance across different data partitions. Figure 9 shows the confusion matrix of the 5-fold CNN.

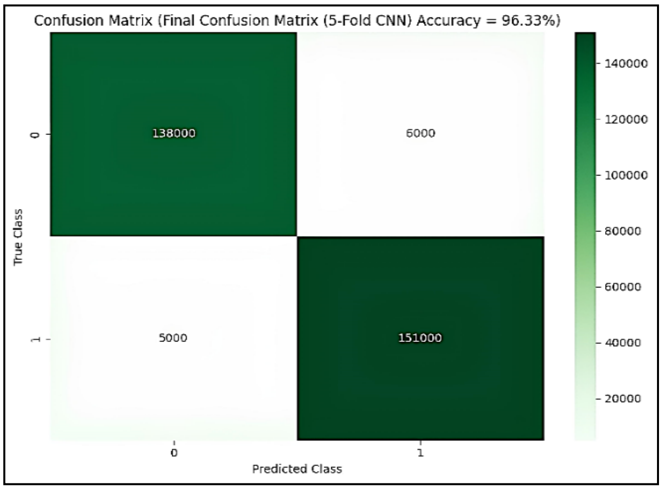

Figure 9: Confusion matrix of 5-fold CNN

To enhance the interpretability of the suggested model, SHAP analysis (SHapley Additive exPlanations) was used to measure each sensor feature's contribution to the model's fault classification decisions. Explanations were calculated for 100 test samples, 40 input features, and 2 output classes (normal and abnormal), as shown by the resulting SHAP values shape of (100 samples × 40 features × 2 classes). According to the SHAP study, only one subset of sensors had a significant impact on the model predictions. The ten most significant traits are listed in Table 7 in order of mean absolute SHAP values. TE228 received the greatest importance score (0.0556) out of all the sensors, suggesting that it made the most significant contribution to the model's decision-making process. Additionally, TE128 (0.0461), TE510 (0.0331), TE501 (0.0327), and IT340 (0.0307) were extremely influential characteristics.

These results imply that temperature-related measures (TE-series sensors) are essential for differentiating between typical and anomalous operating situations. Specifically, TE228, TE128, TE510, and TE501 continuously demonstrated significant contributions to the categorization result. Furthermore, several process monitoring variables (including IT340, E340, TE507, FT525, IT240, and TE511) had a significant impact on the performance of fault detection.

The SHAP results improve the openness of the suggested fault diagnosis approach and provide insightful information concerning the CNN model's internal behaviour. In addition to validating the model's predictions, by identifying the most influential sensors, the current study enables domain specialists to understand which process variables are most important for predicting anomalous system behaviour.

Table 7: Top Ten Most Significant Traits

Rank	Feature	Importance
23	TE228	0.055583
18	TE128	0.046087
19	TE510	0.033144
12	TE501	0.032721
17	IT340	0.030671
22	E340	0.030202
26	TE507	0.029555
15	FT525	0.025308
32	IT240	0.024384
13	TE511	0.023503

Figure 10 explain SHAP Summary Plot Showing the Contribution of Input Features to CNN Prediction, Figure 11 explains Ranking of the Most Important Sensors Based on Mean Absolute SHAP Values.

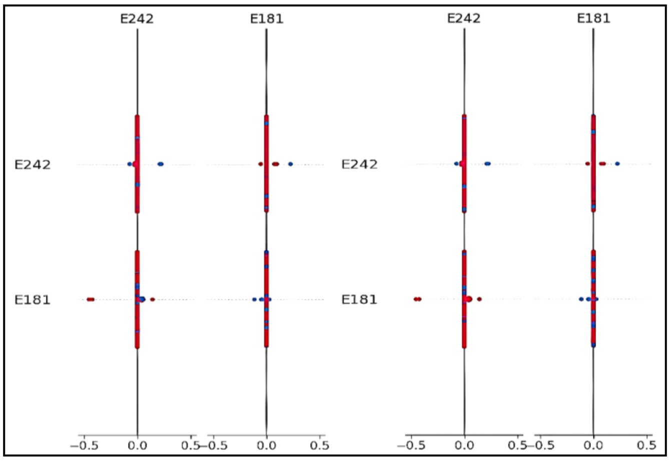

Figure 10: SHAP Summary Plot: Features Contribution

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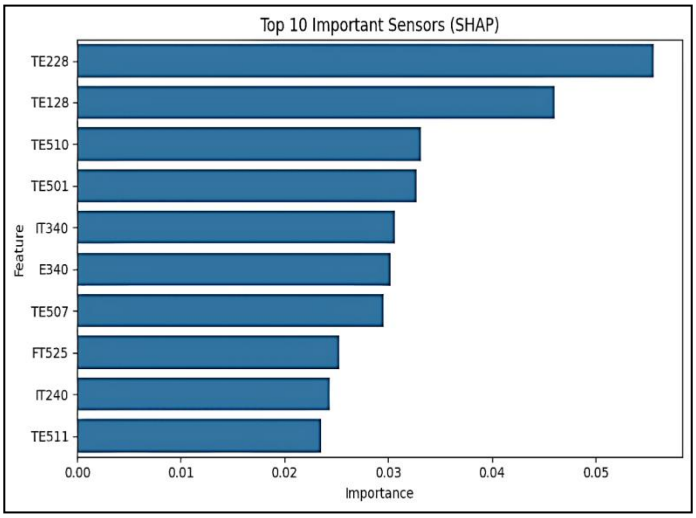

Figure 11: Ranking of the Most Important Features

3.4. Ablation Study

To assess the role of the important architectural elements in the proposed CNN-based FDFI scheme, an ablation study was performed. This process involved the removal or modification of some of the layers and monitoring the influence on the fault detection accuracy.

There were three ablation experiments:

All the MaxPooling layers were removed from the FD model architecture without any layers.

Without LeakyReLU: Standard ReLU activation function instead of LeakyReLU activation function.

Reduced filters: The number of filters in all convolutional layers was reduced by half to 8, 16, 32, 64, 128, 256, 512, and 17 (instead of 8, 16, 32, 64, 128, 256, 512, 1024, 35). The findings are tabulated in Table 8.

Table 8: Ablation study results for the fault detection (FD) model

Configuration	Accuracy (%)
Original proposed model	99.10
Without Maxpooling layers	97.3
Without leakReLU (ReLU only)	98.1
Reduced filters by half	96.8

These findings reveal that without MaxPooling layers, the accuracy decreased by 1.8%, which indicates that MaxPooling layers help to decrease dimensionality and preserve critical features. After replacing LeakyReLU with ReLU, the performance decreased by 1.0%, thereby validating that small negative values are beneficial. The largest decrease (2.3%) was observed when the number of filters was reduced, suggesting that adequate filters are crucial to learning complex multi-fault patterns. The results demonstrate that all the elements have a positive impact on the effectiveness of the proposed FDFI framework.

IV. LIMITATIONS AND FUTURE RESEARCH

Although the proposed FDFI framework demonstrated high fault detection and isolation performance on the NASA ADAPT dataset, several limitations should be acknowledged.

The current study was assessed using only one dataset (NASA ADAPT). This dataset includes many fault scenarios and operational conditions but additional public UAV fault datasets should enhance the generalisation capability of the proposed approach.

Second, the NASA ADAPT data were gathered in specific experimental environments; thus, the accuracy of the resulting model under actual flight environments, sensor noise, communication noise and weather variation must be further evaluated. This framework should be further investigated in future studies with real-time UAV flight data.

Thirdly, the proposed framework was designed and tested for a particular UAV electrical power system architecture, which means that further experiments are needed to test its applicability and scalability to different UAV platforms and electrical power system architectures.

Fourthly, the dataset is large but some fault categories might have fewer samples than others (some classes might be underrepresented while others are overrepresented), thus resulting in class imbalance that could affect the classification results if the minimum fault class has rare faults. Advanced data augmentation and balancing methods to be explored in future to increase the robustness on all the fault classes.

Last but not least, the suggested CNN models were developed for offline training and validation; there are consequently a lot of trainable parameters in these models. While the computational demands are manageable for a workstation environment, further optimization methods, including model pruning, quantization and simple deep learning architectures, will be explored to achieve real-time implementation on-board in resource-limited UAV systems. The framework should thus be

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validated in the future through further UAV fault datasets, real-world flight experiments, model compression methods and by implementation in an embedded UAV health monitoring system.

V. CONCLUSIONS

In the world of unmanned aerial vehicle (UAV) systems, especially in electrical power systems (EPS) where an increasing number of sensors and components are being integrated to provide automatic control, fault detection and isolation (FDI) is an essential component for guaranteeing reliability and safety. To address the above-mentioned limitations, a dual-stage deep learning model (FDFI) utilizing convolutional neural networks (CNNs) was presented that could detect and isolate faults using NASA ADAPT multi-fault data. The proposed framework consists of two classifiers: one fault detection (FD) model to detect any abnormal condition of the system, and one fault isolation (FI) model to isolate faults in sensors and system components.

The experimental findings revealed that the proposed method is able to classify the datasets with a classification accuracy of 99.10% during the detection phase and 99.30% during the isolation phase, which is significant when compared to the other conventional machine learning methods like SVM, Random Forest, XGBoost, ANN, and LSTM. Furthermore, an ablation study was carried out to validate the positive effect of some CNN components (e.g., MaxPooling, LeakyReLU, and filter size) on the overall performance.

Additionally, 5-fold cross-validation was performed to assess the model's robustness, with the accuracy of 96.33% on average confirming this. Moreover, the influence of the sensors on the fault classification was further explained by using SHAP analysis, which showed that sensors based on temperature (TE228, TE128, TE510, TE501) are the most important features for fault classification.

In conclusion, the proposed FDFI model can detect and isolate multiple faults at the same time, which improves the stability and reliability of UAV electrical power systems. The framework proposed can be used for predictive maintenance and intelligent health monitoring systems for UAV platforms, as it allows for early identification and localization of faults. These may help minimize unplanned failures, increase mission reliability, and increase the safety of UAV electrical power systems during operation. Future work will concentrate on real flight data validation and test on other public fault datasets (e.g. PADRE).

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AUTHORS BIOGRAPHY

Dr. Mohammed Hussein Dosh is an Assistant Professor in Computer Science with a specialization in Artificial Intelligence at the University of Kufa, Iraq. He received his B.Sc. in Computer Science from the University of Technology, Iraq, in 2000, his M.Sc. in Computer Science from SHIATS University, India, in 2013, and his Ph.D. in Computer Science (Computer Applied Technology/Artificial Intelligence) from Huazhong University of Science and Technology (HUST), China, in 2017. He has more than nineteen years of academic and teaching experience in undergraduate and postgraduate education and has held several academic and administrative positions at the University of Kufa. His research interests include Artificial Intelligence, Data Mining, Deep Learning, Natural Language Processing, Algorithm Design, NP-Hard Problems, and Computer Applied Technology. He has participated in numerous research projects, scientific conferences, and academic committees, and has published research articles in several international journals and conference proceedings. He was also awarded an Academic Excellence Award by Huazhong University of Science and Technology in 2018.

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