Augmented Imagefication: A Data-driven Fault Detection Method for Aircraft Air Data Sensors

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Abstract

In this paper, a novel data-driven approach named Augmented Imagefication for fault detection (FD) of aircraft air data sensors (ADS) is proposed. Exemplifying the FD problem of aircraft air data sensors, an online FD scheme on edge device based on deep neural network (DNN) is developed. First, the aircraft inertial reference unit measurements is adopted as equivalent inputs, which is scalable to different aircraft/flight cases. Data associated with 6 different aircraft/flight conditions are collected to provide diversity (scalability) in the training/testing database. Then Augmented Imagefication is proposed for the DNN-based prediction of flying conditions. The raw data are reshaped as a grayscale image for convolutional operation, and the necessity of augmentation is analyzed and pointed out. Different kinds of augmented method, i.e. Flip, Repeat, Tile and their combinations are discussed, the result shows that the All Repeat operation in both axes of image matrix leads to the best performance of DNN. The interpretability of DNN is studied based on Grad-CAM, which provide a better understanding and further solidifies the robustness of DNN. Next the DNN model, VGG-16 with augmented imagefication data is optimized for mobile hardware deployment. After pruning of DNN, a lightweight...
model (98.79% smaller than original VGG-16) with high accuracy (slightly up by 0.27%) and fast speed (time delay is reduced by 87.54%) is obtained. And the hyperparameters optimization of DNN based on TPE is implemented and the best combination of hyperparameters is determined (learning rate 0.001, iterative epochs 600, and batch size 100 yields the highest accuracy at 0.987). Finally, an online FD deployment based on edge device, Jetson Nano, is developed and the real time monitoring of aircraft is achieved. We believe that this method is instructive for addressing the FD problems in other similar fields.

Keywords: Aircraft Air Data Sensors, Fault Detection, Deep Neural Networks, Data Augmentation, Interpretability Analysis, Online Monitoring

1. Introduction

1.1. Motivation

Fault detection (FD) is crucial for security of service of dynamical systems. Taking aeronautics field as a study case, aircraft air data sensors (ADS) provide measurements of aircraft’s airspeed, angle of attack (AOA), and sideslip angle. It is found that the erroneous sensor measurements is the main cause of many catastrophic flight accidents, such as the crashes of NASA X-31 [1], Airbus A330 [2], and recently Boeing B737 MAX [3]. A robust real time fault detection scheme with high performance and reliability in the application is imminent for the health monitoring of commercial airlines.

Nowadays hardware redundancy (HR) is widely used for FD problems. Particularly for ADS in the commercial airlines, HR strategy consists of installing multiple sensors to produce redundant measurements of the air data. Outputs from all the sensors are continuously monitored by a voting logic, which detects (and isolates) the defective sensor. The correct measurement is then reported using the remaining other sensors [4] [5] [6].

There are many shortcomings with the HR-based fault detection, on the one hand, HR leads to high cost of operation and maintenance, on the other hand, the weight penalty (due to the redundant sensors) strategy is needed well
designed for both efficiency and accuracy. Moreover, recent accidents indicate that HR is not sufficient in addressing the fault detection problem (e.g. the Boeing 737MAX accident due to AOA sensors). Alternative to HR, analytical redundancy (AR) has been proposed and investigated\[7\]. A majority of the AR methods adopted model-based approaches. Different from HR, AR investigates each sensor separately. For a certain sensor, a mathematical model is developed in conjunction with other sensors. An inferred sensor measurement is then estimated and compared with the sensor’s output and the a residual can be generated. If the residual exceeds a predefined bound, then fault is claimed to be detected for that sensor \[8\].

The model-based AR, nevertheless, hinges on the model that is derived from system specifics, which is sensitive to operational conditions. The development of model-based AR typically requires \textit{ad hoc} parameters tuning, which is time-consuming. Another research line of AR adopts model-free, and mostly data-driven methods. This does not require system specifics, but only the recorded data (e.g. sensors measurements and the associated faults). In particular for the ADS fault detection problem, deep neural networks (DNN) were widely used \[9\] \[10\] \[11\] \[12\] \[13\]. However, there is no universal and explainable rule for the architecture devising in DNN, so most works adopt the trial-and-error methodology. Mathematical operations enclosed within the DNN are also considered “black”, scalability of the DNN-based FD scheme is doubtful. Referring to the development of DNN in other fields (e.g. computer vision), many rules and experiences have been proposed and accepted in devising the DNN architectures (e.g. how many CNN filters should be used in each layer). For example, ablation studies \[14\] of DNN. However, it is very expensive and time-consuming to design such a new DNN with complex structures and mature DNN models is preferable if we can make full use of them. Besides, Many visualization methods of DNN are proposed, e.g., class activation mapping \[15\], which elevate the understanding of how DNN works. Similar concepts/approaches may also be used in analyzing the DNN-based FD scheme.

We thus summarize the motivation and goals of this paper: develop a DNN-
based methods (existing mature model is preferable) that yield accurate and scalable FD performances, then study the explainability in devising the DNN architecture and interpretability of the DNN operations. Exemplifying the FD problem of aircraft air data sensors, we propose an augmented imagefication method to develop a robust DNN-based FD scheme. Whilst the FD accuracy and scalability must be guaranteed, we also explain the rules in devising the DNN architecture, and interpret the operations enclosed in the DNN structure. Finally we plan to optimize the DNN model to develop an online FD system on edge device and achieve the online monitoring of aircraft conditions.

1.2. Related work

1.2.1. Model-based and Data-driven FD

Previous studies often use model-based approaches, which are sensitive to the specifics of a certain system, attenuating the robustness. Model-based FD hinges on a mathematical model to predict the sensor measurement, which being further used to generate a residual. It is found in a plethora of research literature that Kalman filtering (KF) is widely used. e.g., the extended KF [16, 17, 18], the unscented KF [19], the theoretical analysis of adaptive three-step KF [20], and implementation of the KF-based method to real data in [21]. Other KF-based works included [22, 23], wherein fuzzy logic was used in conjunction with KF to consolidate the sensors data [22], and hidden Markov model has been used to decide the sensors state (fault/healthy) based on the KF outputs in [23]. KF-based FD schemes, however, rely on the evolution model that is derived from the system dynamics/kinematics; ad hoc parameters tuning is imminent in adjusting KF to different systems (e.g. different aircraft) or operational cases (e.g. different flight conditions).

Other model-based FD methods adopted robust control theory in [24, 25, 26, 27], wherein the robustness synthesis-based filter was constructed to output the residual. But a sensor state evolution model is needed, and no rules pertaining to the parameters tuning was studied. In [28, 29, 30] moving horizon estimator was developed, which compensated for both sensor faults and wind speed estimation.
in the fault tolerant control. However, only limited aircraft/flight cases in these papers are discussed and the scalability of these proposed methods is unclear. A scheme designed particularly for systems with two time-scale dynamics (e.g. phugoid and short periods in the aircraft’s longitudinal plane) was discussed in [31, 32], wherein both nonlinear geometric approach and singular perturbation technique were involved. But computational load of the algorithm was relatively high, and parameters tuning was time-consuming. Barrier function-based learning observer was proposed in [33], and in [34] a set-value observer (SVO) was used. As acclaimed in the papers, these works significantly decreased the FD false alarm rate. The weaknesses of [33] and [34], however, are also typical: model sensitiveness and unclear scalability.

Data-driven methods have claimed accurate performances which scale well to different cases. Most of the data-driven schemes were found to use neural networks (NN). In [9, 10] fully connected cascaded NN was adopted, the authors discussed fault detection and isolation for inertial reference unit (IRU). Similar works were found in [35, 36], wherein feed-forward NN was used. In [37, 38] NN-based adaptive observer was developed to generate the sensor measurement residual; parameters of the NN were adjusted online via KF [37]. Also in [11, 12, 13], NN was used to establish nonlinear identification models, which being used as a state observer to generate the residual. The essence of all these works was to regress a functional relation that maps from the designated input to the desired output (i.e. fault cases). But traditional NN lacks the efficiency in abstracting high-level features. It is usually used in a hybrid form with other methods (e.g. KF). In addition, no research pertaining to the explainability and interpretability analysis was thoroughly illustrated in the associated publications.

Recent NN developments advocate the deep neural networks (DNN) in many academic/industrial fields [39]. DNN typically has more (‘deeper’) layers which are activated using designated function (e.g. ReLU). More dedicated operations were also designed in convolutional neural network (CNN) and long-short time memory (LSTM) blocks for extracting both spatial and temporal features.
enclosed in the DNN input. Early works along the DNN-based FD line were found in [40, 41, 42], wherein recurrent neural network (RNN) was used. Later works adopted a variant of RNN, i.e. LSTM, which attenuates the error vanishment/explosion problems in the traditional RNN. CNN was also widely used in conjunction with LSTM. New data formats defined as “state image” and “control image” were proposed in [43, 44], via which the sensor FD accuracy was significantly improved. The CNN-LSTM fusion-based DNN architecture has claimed promising results in [44] for air data sensors FD, and most recently in [45] for fault estimation. Despite the rapid developments of various DNN-based FD architectures, however, research efforts along the explainability and interpretability analysis line are still rare.

1.2.2. Interpretability analysis of DNN structures

DNN is commonly considered “black” for a long time. Why the DNN specifics are devised as such and how the enclosed operations work attract more and more attentions. To address such issue, we plan to explain the structure that corresponds to the DNN architecture specifics, and interpret the structure that depicts the operations enclosed in the DNN architecture. Similar works have appeared in literature.

The DNN structure corresponds to the specifics (e.g. CNN kernel size) that can be objectively optimized via certain metrics (e.g. DNN testing accuracy). To explain the large structure, comparative studies were commonly used. Different sets of parameters (number of CNN filters, kernel sizes, etc.) were assembled in the DNN and then the authors performed thorough training for each parameter set, finally decided the optimal one via gleaning the trained DNN [46]. Technical tools designed specifically for optimizing the DNN training were also found, of which the most peculiar one is the Microsoft’s NNI, which decides the best training coefficients (e.g. learning rate, iterative epochs) for a certain DNN architecture [47]. The Tree-structured Parzen Estimator (TPE) is a sequential model-based optimization (SMBO) approach, as a black-box optimization, which can be used in various scenarios and shows good performance.
Especially when limited by computation resources and can only try a small number of trials [18]. When an “optimal” DNN is found, ablation study is commonly used to verify the architecture (e.g. CNN branches, CNN-LSTM fusions), which involves cropping certain sub-architecture from the “optimal” one, and comparing the DNN performances. Typical examples are found in [14].

The DNN structure depicts the operations enclosed within the DNN (e.g. a certain CNN filter). It is usually analyzed via mirroring the DNN outputs to what humans understand in a certain context. For instance, in the visual object classification problem, CNN is commonly used. The understandable terms of humans in such a context are the visual features that one hinges on to classify an object (e.g. ‘ear’ or ‘nose’ of a cat/dog). Class activation mapping (CAM) thus was proposed in [15], and rapidly developed in [19] 50 51 52 53 54, which points out the highlighted region(s) wherein the CNN filters focus on. The CNN architecture may be considered reasonable (interpretable) if the highlighted region(s) corresponds to what humans tend to watch (e.g. the ‘ear’/’nose’).

Related studies in such line have made promising progresses which promoted both academic researches and industrial applications of CNN in vision-related problems—but “vision-related” only; very rare studies pertaining to such line was found in other DNN-based works (e.g. DNN-based fault detection).

1.2.3. Optimization methods of DNN

Once a prediction model is designed, it is ready to be optimized. Taking DNN as an example, a lot of factors (number of layers, kernel size, hyperparameters, etc.) may influence the performance of a DNN model. DNN model is designed and expected to be highly accurate, low delay and lightweight for real time prediction on edge devices, which are contradictory under certain circumstances. Therefore, it is important to clarify the application scenario and determine the goal and order of optimization.

Deep learning has been widely used because of its remarkable effect, but it is well known that deep neural network (DNN) has a great disadvantage that the amount of calculation is too large. More computing will directly lead to an
increase in cost. This shortcoming hinders the productization of deep learning methods, especially on some edge devices in aerospace engineering, which are not designed for computing intensive tasks. There will be many problems in power consumption and time delay if deep learning models are simply deployed. For the large-scale original model, it is the research focus that how to substantially simplify the model to reduce the amount of calculation and storage, which is called model compression and proposed as early as 1990 [55].

Model compression is a software method with low cost, which does not conflict and even can be added with the hardware acceleration method. The deep learning model can be compressed based on an assumption: over-parameterization of DNN, i.e. a large number of parameters of DNN are redundant and can be removed with little impact on the performance of DNN. The biggest advantage of model compression is the reduction of the computing time and power consumption. And it is more convenient to the deployment the DNN to edge devices or personal terminals when model size becomes smaller. There are many techniques of model compression, such as pruning, quantification, low rank decomposition, knowledge distillation, etc[56, 57, 58, 59, 60].

The hyperparameters have strong influences on the performance of deep learning model. Classifiers based on sophisticated feature extraction techniques have ten hyper-parameters or more, depending on how the experimenter chooses to parametrize the model, and how many hyper-parameters the experimenter chooses to fix at a reasonable default. Moreover, the evaluation of the fitness model is expensive when choose different combinations of hyperparameters. Consequently, optimization problem of hyperparameters could be difficult and time-consuming. Hyperparameter optimization is the problem of optimizing a loss function over a graph-structured configuration space[61]. There are also many algorithms to select the hyperparameters, which can be devided as model-free and model-based. For model-free methods, grid search[62] and random search[63] is typical representative, whose primary ideas can be inferred from their names. And the other model-based sounds more reasonable and convincing, including Bayesian optimization[64], evolutionary algorithms[65] and
other methods. Sequential Model-Based Global Optimization (SMBO) algorithms, which have been used in many applications where evaluation of the fitness function is expensive[66], will be adopted in this paper for model optimization.

1.3. Overview of this Paper

In this paper, exemplifying the FD problem of aircraft air data sensors, we aim to develop a DNN-based fault detection scheme with high accuracy and speed as well as lightweight so to deploy on the edge device. We highlight our work as:

- **Accurate and scalable FD performances**: We model the FD problem using aircraft IRU measurements as equivalent inputs; we also construct a dedicated dataset; via delicate architecture tuning, the DNN-based scheme claims accurate and scalable FD performances for different aircraft at various conditions.

- **Augmented Imagefication method for ADS data manipulation**: We propose the methodology in reshaping 1D data for the feature extraction and case prediction of DNN. The necessity of augmentation of ADS data and different kinds of augmented methods are discussed. The explainability of such methods specifics are studied based on Grad-CAM, which elevates the interpretability of how the DNN operations work.

- **Model optimization and online monitoring of flying condition based on edge device**: We adopt the model pruning and TPE-based hyperparameter finetuning to optimize the model for deployment on edge device. The online monitoring of flying condition is finally achieved, which provides a novel data-driven approach of fault detection on aircraft as well as and may bring inspiration to other engineering fields.

The remainder of this paper is organized as follows. Section 2 defines the problem. Section 3 illustrates the database. Section 4 proposes the imagefication method and experimental setup. Data augmentation in different ways are
detailed in Section 5. Section 6 studies the interpretability on augmented image augmentation method based on Grad-CAM. In Section 7, pruning and TPE-based hyperparameter finetuning are implemented for model optimization, and online FD deployment on edge device is achieved. Finally conclusions and future works are discussed in Section 8.

2. Problem definition

To define the FD problem of aircraft air data sensors, we start with the air data evolution equations:

\[
\begin{align*}
\dot{V} &= (A_x - gS_\theta)C_\alpha C_\beta + (A_y + gS_\phi C_\theta)S_\beta + (A_z + gC_\phi C_\theta)S_\alpha C_\beta \\
\dot{\alpha} &= (-A_x S_\alpha + A_z C_\alpha + gC_\phi C_\alpha C_\alpha + gS_\theta S_\alpha)/VC_\beta + w_y \\
&\quad - (w_x C_\alpha + w_z S_\alpha)S_\beta/C_\beta \\
\dot{\beta} &= -(A_x - gS_\theta)C_\alpha S_\beta + (A_y + gS_\phi C_\theta)C_\beta - (A_z + gC_\phi C_\theta)S_\alpha S_\beta)/V \\
&\quad + w_x S_\alpha - w_z C_\alpha
\end{align*}
\]

(1)

wherein \(S_*\) and \(C_*\) represent \(\sin\) and \(\cos\) operations, \(\{V, \alpha, \beta\}\) are airspeed, AOA, and sideslip angle, \(g\) is the gravitational acceleration, \(\{w_x, w_y, w_z\}\) and \(\{\psi, \theta, \phi\}\) denote rotational speeds and angles, respectively. In Eq. (1), \(\{A_x, A_y, A_z\}\) indicate the accelerations along different axes of the aircraft body, which are defined as \(\{A_i = F_i/m\}_{i=x,y,z}\), wherein \(m\) is the mass of the aircraft, and \(\{F_x, F_y, F_z\}\) are the external forces generated by the control actions:

\[
\begin{align*}
F_x &= F_x(\delta_{th}, V, \alpha, S, ...) \\
F_y &= F_y(\delta_r, \delta_a, V, \alpha, S, b, c, ...) \\
F_z &= F_z(\delta_e, V, \alpha, S, c, ...)
\end{align*}
\]

(2)

In Eq. (2), \(\delta_*\) indicates individual control input (e.g. throttle \(\delta_{th}\), elevator \(\delta_e\), aileron \(\delta_a\), and rudder \(\delta_r\)), \(S, c,\) and \(b\) are the aircraft wing area, mean chord length, and span, respectively.
Figure 1 depicts an overall flow for above equations. Traditional works hinge on model-based approaches to monitor the control inputs and sensors outputs. Implicitly in such model, the external control forces/moments must be considered, which are generated using associated control actions, and directly related to the aircraft specifics (e.g. wing area, mass) and flight conditions (e.g. airspeed, AOA). Parameters within such model-based FD scheme typically requires *ad hoc* tuning per aircraft/flight condition. Therefore, its scalability is doubtful.

Despite the high dependency of control forces/moments upon aircraft specifi-
cs/flight conditions, their outcome (i.e. \( A_i = x, y, z \) and \( w_i = x, y, z \)) can be directly measured using inertial reference unit (IRU). Via Eq. (3), rotational angles of the aircraft can also be calculated using \( w_i = x, y, z \) (although dedicated sensors do exist to directly measure them). We thus adopt IRU measurements as a probe into the overall system, model them as equivalent inputs to the air data evolution, and perform the air data sensors FD task directly.

To be specific, the problem in this paper is defined as, to detect (classify) different faults that occur in the air data sensors, given the air data measurements \( \{V, \alpha, \beta\} \), and other data resources which may include \( \{A_x, A_y, A_z\} \), \( \{w_x, w_y, w_z\} \), \( \{\psi, \theta, \phi\} \) and \( \{g_x, g_y, g_z\} \) (overload). The FD scheme is modeled as a mapping process (input: available data resources, output: fault case), which we aim to regress via deep neural networks.

3. Data preparation

3.1. Diverse aircraft and flight conditions

Data is essential for DNN training and validation. Most previous works discussed 1 aircraft only. In this paper, we allocate both simulation and real flight data from 5 different aircrafts which include 1 large cargo airplane (Y [67]), 2 passenger aircrafts (B1 and B2, [68, 69]), 1 general aviation (D [43, 44]), and 1 fighter aircraft (F [70]). We also involve 6 different flight conditions to cover the aircraft’s entire envelope, i.e. high, medium, and low altitudes for both cruise, manual free flight, and low-altitude landing/take-off cycle (LTO). Different control forms from both human pilot (manual) and automated control

| Aircraft | General configuration                  | Weight | Span  | Data source | Flight condition                |
|----------|---------------------------------------|--------|-------|-------------|---------------------------------|
| Y        | large cargo airplane, quadruple piston engines, high wing | 41.0t  | 38.0m | simulation  | low altitude, LTO, manual       |
| B1       | large passenger aircraft, quadruple turbo engines, low wing | 174t   | 59.6m | simulation  | high altitude, cruise, AP       |
| B2       | large passenger aircraft, double turbo engines, low wing  | 44.6t  | 35.8m | real flight | low altitude, LTO, manual       |
| D        | general aviation, double piston engines, high wing          | 3.12t  | 19.8m | simulation  | high altitude, cruise, AP       |
| F        | fighter aircraft, double turbo engines, delta wing          | 10.5t  | 11.4m | real flight | medium altitude, manual flight  |
laws (auto-pilot, AP) are also considered. See Table 1 for more details. In Figure 2, we also plot a sampled data we allocated in our database.

3.2. Measurement noises and disturbances

Both simulation and real flight data are considered in the paper. While measurement noises and disturbances exist naturally in the real flight, we adopt the model following [71] in simulation. Dryden atmospheric disturbances are injected to perturb the flight states, on which the measurement noises are added to generate the noise-corrupted data. Measurement noises are assumed to follow

| Sensor          | Standard deviation | Unit          |
|-----------------|--------------------|---------------|
| $V_m$           | 0.1                | $m/s$         |
| $\{\alpha, \beta\}_m$ | 0.1$\pi/180$     | $rad$         |
| $\{A_x, A_y, A_z\}_m$ | 0.01               | $m/s^2$       |
| $\{p, q, r\}_m$ | 0.01$\pi/180$     | $rad/s$       |
| $\{\psi, \theta, \phi\}_m$ | 0.01$\pi/180$ | $rad$         |
| $\{g_x, g_y, g_z\}_m$ | 0.01               | —             |
Gaussian process distribution. Standard deviations for the noise of each sensor are characterized in Table 2\[10\].

3.3. Designated training and testing

Training and testing data are strictly separated to avoid the over-fitting problem. We put all the real flight data in testing to fully evaluate the DNN performance. Diversity is crucial in specifying the training data, as the training algorithm is expected to extract from this data for an efficient FD mapping. We therefore adopt the real data from B\textsubscript{2}, F, and simulated data from D, B\textsubscript{1} manual flight for testing. As for training, we use the data from Y manual LTO and B\textsubscript{1} AP cruise, see Table 3. In the table, an overview of the data for each aircraft/flight condition is also characterized using the minimum, maximum, and standard deviation of key (clean) flight states (i.e. altitude, airspeed, AOA, and sideslip angle).

3.4. ADS fault modeling and injection

Different sensor fault types have been discussed in previous works, which include ramp bias, oscillations, and drift. For airspeed, most flight accidents happened due to the Pitot tube being clogged by ice/rain. We thus consider drift fault for airspeed (measurement loss). For AOA and sideslip angles, the deflection vanes may be stuck or perturbed by external atmosphere, which causes drift (constant bias) and extra noises. As in Table 4, a total of 5 ADS fault cases are discussed in this paper, wherein the magnitude for each case is specified following [44].

We implement the ADS faults in an additive form; i.e., the “clean” data (Case 0 in Table 4) are retrieved from real flight/simulation. Sensor faults are

| Table 3: Training and testing data specifics in this paper. |
|----------------------------------------------------------|
| Aircraft & Condition | Duration (min) | Altitude (km) | Airspeed (m/s) | AOA (°) | Sideslip angle (°) | Cases distribution in \([0−5]\) (%) |
|----------------------|----------------|--------------|----------------|--------|-----------------|-----------------------------------|
| **Training**         |                |              |                |        |                 |                                   |
| B1 Air cruise        | 207            | [9.63, 10.7, 0.35] | [227, 252, 9] | [−1.3, 0.6, 0.4] | [−1.9, 0.4, 0.6] | {27, 13, 16, 16, 14}             |
| Y Manual LTO         | 295            | [0.03, 0.66, 0.11] | [93, 167, 14]  | [−2.7, 7.7, 1.2] | [−2.2, 1.0, 0.3] | {28, 14, 13, 18, 16}             |
| **Testing**          |                |              |                |        |                 |                                   |
| B2 Manual LTO        | 67             | −            | [75, 151, 12]  | [0.8, 6.7, 0.8] | [−7.3, 2.7, 2.2] | {20, 10, 17, 15, 20}             |
| F Manual flight      | 30             | −            | [80, 141, 21]  | [10, 46, 11]  | [−8, 5, 1]       | {10, 10, 17, 15, 20}             |
| B1 AP cruise         | 162            | [3.50, 4.00, 0.19] | [68, 71, 0.38] | [0.5, 3.2, 0.37] | [−6.3, 2.7, 2.2] | {20, 16, 17, 14, 15}             |
| B2 Manual LTO        | 151            | [0.01, 1.61, 0.26] | [47, 270, 31] | [−14, 19, 4]  | [−8, 5, 1]       | {29, 16, 13, 14, 16}             |

*Note: minimum, maximum, and standard deviation of clean altitude and ADS states are characterized. Altitude was not recorded in B\textsubscript{2} and F real flight.*
Table 4: ADS fault cases adopted in this paper.

| Case | Sensor       | Fault type   | Magnitude* |
|------|--------------|--------------|------------|
| 5    | sideslip angle | extra noise  | $5^\circ \sim 10^\circ$ |
| 4    | sideslip angle | drift        | $\pm(5^\circ \sim 10^\circ)$ |
| 3    | AOA          | extra noise  | $5^\circ \sim 10^\circ$ |
| 2    | AOA          | drift        | $\pm(5^\circ \sim 10^\circ)$ |
| 1    |airspeed      | drift        | $-(50\% \sim 100\%)$ |
| 0    |clean measurement with noises and disturbances, no fault | |

* Noise standard deviation and drift values defined in this column.

Figure 3: Illustrative plot for the fault injection. Black lines denote clean states from real flight/simulation, red the fault-injected data. The FD scheme is expected to detect the different fault cases (blue thick line) based on available data measurements and proper DNN operations.

then injected into the ADS data. Following [44], this injection is performed in a randomized manner; i.e., for every 60 seconds in the data, the fault cases occur randomly at randomized moments, with its duration (also randomized) not exceeding the 60 seconds. In Figure 3 different fault cases are injected to both airspeed, AOA, and sideslip angle for illustrative purposes. Table 3 also presents the distribution of different cases in the final data we adopt for the DNN training/testing.
4. Imagefication method for ADS fault detection

4.1. Data-driven method for ADS fault detection

Deep neural networks are proven a very effective way for image classification problems. Our previous works advocated a fusion of CNN and LSTM in designing the DNN architecture \cite{43, 44} for parameter identification, icing detection, etc. In our recent study in fault diagnosis of Inertial Measurement Unit (IMU) sensors, a novel data driven method, CNN-LSTM-fusion architecture is used for fault classification\cite{72}.

In CNN \cite{73}, convolutional filters scan the input (e.g. an image), of which the results are concatenated as feature maps. Multiple filters yield various feature maps, which being stacked to construct the designated mapping. Activation functions and pooling operations may also be used, with the former adding to nonlinearity in the mapping, and the latter the noise-tolerance \cite{43, 44, 74}.

LSTM is typically used for sequential data. Different from the spatial local-connectivity features extraction in CNN, it aims to abstract the temporal knowledge. Previous DNN including RNN \cite{73} also targets the temporal features. RNN, however, may suffer error explosion/vanishing problems in the training. LSTM adopts gate operations to automatically select the historic input that may be useful in the mapping. As proved in many works, training efficiency, mapping accuracy, and deployment cost of LSTM can all be improved \cite{43, 44}.

It can be inferred that the deep neural networks also work for ADS fault detection problems. In coping with the dynamics problem, both CNN and LSTM may be useful. However, combination causes complexity. We want to find a simple way, if satisfactory enough, to model the fault detection problem. Therefore, The CNN is chosen to handle the problem. As there is not an input explicitly defined as “image”, the key in implementing CNN in these problems is to reshape the dynamics data (e.g. flight states, control commands) into an image-like format, i.e., Imagefication, which is elaborated in section 4.2.
4.2. Imagefication manipulation

Imagefication is a data manipulation process for 1 dimensional data (vector), such as ADS data from different channels, to generate the image-formatted data (matrix), so it can be treated as standard input to CNN. Take an example of $V$, $\alpha$, $\beta$, as shown in Figure 4. Via real flight or simulation, we have the records of different states. We inject faults into the ADS states, allocate all other flight data, and stack them into a 2D matrix (middle plot). In this matrix, each row stands for the historic measurements of a certain state, and column the value of that state at a certain moment. For each group of the aircraft flight state (e.g. air data, accelerations, rotational speed, and rotational angles), we stack this matrix separately.

Time window is also used. At each moment $t$, we consider the flight records in a range from previous $t - \Delta T$ to $t$ (both included), wherein $\Delta T$ is $30s$. For different aircraft, the data is recorded in various sampling rates (e.g. $20Hz$ for B1, $30Hz$ for F). We down-sample them to a unified frequency at $f_s = 1/\Delta t$, wherein $\Delta t = \Delta T/n = \Delta T/30 = 1s$. We then stack the state matrix using the re-sampled data.

1Following [43][44], this window may be understood as a compromise between the aircraft “fast” motion modes of which the periods are in seconds (e.g. longitudinal short period, lateral roll), and “slow” modes which typically last for tens/hundreds of seconds (e.g. longitudinal phugoid, Dutch roll).
In the down-sampled flight data, the range of each state varies significantly (see Table 3). In practice, this may create numerical difficulties in the DNN training (singularities, error vanishing/explosion). Normalization is adopted to process the sampled data. Following [43, 44], this normalization is performed linearly along each row of the stacked matrix. After normalization, the “image” we obtain in the right plot of Figure 4 is adopted as input to the CNN.

5. Data augmentation methods and comparison

5.1. Necessity of ADS data augmentation

After imagefication manipulation shown in Figure 1, the data of airspeed, angle of Attack, slideslip angle, accelerations, rotational speeds acquired from ADS (shown in Table 2) are constructed like grayscale images. Each image has the 2D matrix shape 15 × 31. In previous studies [72], a new deep neural network for fault detection is established, because this image shape is not commonly seen in image processing studies.

On the one hand, we find that the feature maps are becoming vectors (1D data) after several convolutional layers because of the quantity difference in different dimensions of the image matrix. It is inevitable when we set one dimension as the physical parameters (V, α, β, Ax, Ay, Az, p, q, r, ψ, θ, φ, g x, g y, g z) and the other as the sampling data of ADS. The more data we sample from ADS, the longer and narrower the matrix shape is. Consequently, the convolutional kernels (mostly 3×3 size) are not well functioned for extracting the feature of the data when performing the convolutional manipulation for 1D vector. The considerable connection between different physical parameters may be easily missed because of the first convolution at the beginning. In other words, the convolutional kernel is too large for the dimension of physical parameters. Even the smallest kernel size 2×2 is chosen (1×1 convolution completely ignores the relationship with surrounding data), it is still too large and it is preposterous to chose a fraction as kernel size, such as 1.1×1.1, 1.2×1.2, etc. Therefore, almost the only strategy is augmenting the image matrix data to fully utilize the
convolutional manipulation. On the other hand, there are many mature CNN models that have been proven to be effective, such as VGG net\cite{VGG}, ResNet\cite{ResNet} and so on. The input image size of these models is typically $224 \times 224$. It is more natural and easier to adopt the existing mature model than develop and test a new deep neural network with different structures. For these reasons, it is a necessary and logical way to augment the image-like data to typical size ($224 \times 224$) for modeling the fault detection network.

5.2. Experimental Setup

In training/testing the DNN, we record both training loss and validation accuracy (with all testing data designated as the validation dataset). Following \cite{44}, we repeatably perform 30 training runs for all DNN architectures, excluding the best/worst 5 runs, and summarize the outcome via the remained 20 records. We also adopt Pytorch 1.10 as backend and python version 3.8 in the programming. Our computational platform is configured with CUDA 11.3 (GPU: Nvidia RTX3090) in Windows 10 system. The platform has one i9-9900K CPU and 64GB RAM.

5.3. Comparison of different data augmentation methods

There are so many data augmentation ways: flip, rotation, scale, shear, translation, interpolation and even Generative Adversarial Networks (GANs)\cite{GANs} designed mainly to avoid overfitting of networks, which is some different from reconstructing the matrix shape in this paper, that is, to transfer the original shape of matrix from $15 \times 31$ to $224 \times 224$. Taking the dimension of ADS signal along with time as example, if we interpolate the points from 31 to 224, the fault with the type of sudden change (jump) will turn into a slowly rise or fall, which may hinder the feature extraction of convolution layer in CNN. Here we propose a data augmentation method called “duplication”, considering the existing flip method, the different combinations of these methods are discussed.

The scheme of data “duplication” is shown in Figure 5. Notice that the shape of imagefication matrix is $15 \times 31$ (upper left corner of the figure), then
we duplicate the data of each dimension until the shape of matrix is closest to 224×224, so the data from different views of dimensions are duplicated 7 and 14 times, respectively. Thus, a matrix shaped 210×217 can be obtained. Finally, the zero-padding operation is implemented for rounding up the shape. The edges of matrix, i.e., the up, down, left and right edges of the image are filled with 7, 7, 3 and 4 lines of zeros. In this way, a image with the shape of 224×224 for CNN model is constructed.

The key point of data augmentation in Figure 5 is how to duplicate the original matrix to 14×7 times. There are many kinds of methods and their combinations are also needed to be discussed. Let the imagefication matrix write as \( M_{(m \times n)} \) with dimensions \( m = 15 \) and \( n = 31 \), respectively. And \( a \times b \) is the duplication multiple of dimensions.

Flip is a typical transformation for a matrix. \( P \) with shape \( n \times n \) in Equation 7 is an anti-diagonal identity matrix whose all counter-diagonal elements are 1 and other elements are 0. Then we have

\[
M_{lr} = MP
\]  \hspace{1cm} (6)

Where \( M_{lr} \) is the left-right flip of the matrix \( M \). Similarly, the up-down flip \( M_{ud} \) can be performed by multiplying the anti-diagonal identity matrix in the
other dimension.

\[
P = \begin{pmatrix}
0 & 0 & \ldots & 0 & 1 \\
0 & 0 & \ldots & 1 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 1 & \ldots & 0 & 0 \\
1 & 0 & \ldots & 0 & 0 \\
\end{pmatrix}
\]  \quad (7)

There are two kinds of methods when copy the original matrix. One is called “repeat”, the other is “tile”. Repeat operation is from the perspective of elements \(x_{ij}\), which broadcast from \(1 \times 1\) to \(a \times b\), as shown in Equation 8. Tiling operation is repeating the whole matrix \(a \times b\) times in respective axes, seen in Equation 9. Therefore, the different three data augmentation methods and their combinations should be studied and compared, as shown in Figure 6.

\[
M_{\text{repeat}} = \begin{pmatrix}
\underbrace{x_{11} \ x_{11} \ x_{11}}_{(a \times b)} \\
x_{11} \ x_{11} \ x_{11} \ \ddots & \ddots & \ddots \\
x_{11} \ x_{11} \ x_{11} & \ddots & \ddots & \ddots \\
\vdots & \ddots & \ddots & \ddots & \ddots \\
x_{mn} \ x_{mn} \ x_{mn} & \ddots & \ddots & \ddots & \ddots \\
x_{mn} \ x_{mn} \ x_{mn} & \ddots & \ddots & \ddots & \ddots \\
\end{pmatrix}
\]  \quad (8)

\[
M_{\text{tile}} = \begin{pmatrix}
\underbrace{M \ \cdots \ M}_{(a \times b)} \\
\vdots & \ddots & \vdots \\
M & \cdots & M \\
\end{pmatrix}
\]  \quad (9)

Table 5 specifically explained the different data augmentation methods of Figure 6. In All_Flip, All_Repeat and All_tie augmentations, the same operation is implemented in two axes of the original matrix. The other 4 augmentation
methods are the combinations between flipping with repeat or tiling. When the matrix is flipped along one axis, it then will be tiled the whole data or repeated the elements along the other axis.

The deep neural network that we choose for fault detection is VGG-16\cite{VGG16}. VGG-16 is a preferred model with excellent generalization performance in deep learning, whose architecture is shown in Figure 7. The input channel is reset to 1 since the augmented grayscale image is a 2D matrix. And the output number of the final soft-max layer is set to 6, the number of fault types. The training and testing are implemented with all augmentation methods under the
Table 5: Different data augmentation operation.

| Number | Name           | Operation                                                                 |
|--------|----------------|---------------------------------------------------------------------------|
| 1      | All_Flip       | $M$ and $M_{lr}$, $M_{ud}$ are alternatively arranged in each axis respectively |
| 2      | All_Repeat     | Repeat all elements from $1 \times 1$ to $a \times b$                     |
| 3      | All_Tile       | Tile the whole matrix $M$ in all axes                                     |
| 4      | LR_Flip & Tile | $M$ and $M_{lr}$ are alternatively arranged in rows and $M$ is tiled in columns |
| 5      | UD_Flip & Tile | $M$ and $M_{ud}$ are alternatively arranged in columns and $M$ is tiled in rows |
| 6      | LR_Flip & Repeat | $M$ and $M_{lr}$ are alternatively arranged in rows and elements of $M$ is repeated in columns |
| 7      | UD_Flip & Repeat | $M$ and $M_{ud}$ are alternatively arranged in columns and elements of $M$ is repeated in rows |

same network VGG-16 with the same hyperparameters. In detail, epoch 500, learning rate 0.0001, batch size 100 and momentum 0.9.

The test accuracies every 5 epochs of networks with different augmentation methods are shown in Figure 8. It is satisfactory that all fault detection models with different augmentation methods converge after no more than 100 epochs, and the all the test accuracies are higher than 90%, which proves the effectiveness of the data augmentation method we proposed. Comparing these methods, many interesting useful conclusions can be drawn.

Firstly, comparing the same operations in two axes (operation No.1-3), it is obvious that the model with All_Repeat operation is the best with the highest accuracy, and the second is All_Flip, the last is All_Tile. Secondly, comparing
the Repeat and Tile operations (operation No.2 and 3, 4 and 6, 5 and 7), it can be concluded that Repeat operation yields higher accuracies than Tile operation. Thirdly, comparing the Flip and Tile operations (operation No.1, 3-5), it is obvious that Flip operation leads to higher accuracy than Tile operation, whether LR Flip or UD Flip.

However, comparing the LR Flip and UD Flip operations, the conclusion becomes more complicated. The LR Flip operation leads to lower accuracy than UD Flip under the Tile operation in the other axis (operation No.4 and 5), on the contrary, the higher accuracy than UD Flip with Repeat operation in the other axis (operation No.6 and 7). So it can be summarized that the LR Flip and UD Flip operations are coupled with the Tile and Repeat operations, of which combination is responsible for the performance of the fault detection network.

The best training accuracies and test accuracies are detailed in Table [6]. It is clear that the Repeat operation yields the higher accuracies, as revealed by operation No.2, 6 and 7. All Repeat lead to the best train and test accuracies (100% and 97.704%), LR Flip & Tile results in the lowest accuracy (98.898% in
train set and 92.296% in test set).

Table 6: Best accuracies of different data augmentation operation.

| Number | Operation          | Train accuracy /% | Test accuracy /% |
|--------|--------------------|--------------------|------------------|
| 1      | All_Flip           | 99.963             | 95.481           |
| 2      | All_Repeat         | 100                | 97.704           |
| 3      | All_Tile           | 99.611             | 93.370           |
| 4      | LR_Flip & Tile     | 98.898             | 92.296           |
| 5      | UD_Flip & Tile     | 99.061             | 94.741           |
| 6      | LR_Flip & Repeat   | 100                | 97.407           |
| 7      | UD_Flip & Repeat   | 99.996             | 95.556           |

Overall the All_Repeat operation leads to the highest accuracy (100% in train set and 97.704% in test set) and the fastest convergence speed among all methods, which indicates that the operation of repeating the elements is the most effective way of augmentation for ADS data. In next studies, the Repeat operation is determined as the data augmentation method.

6. Interpretability analysis on augmented imagefication method

Neural networks were considered as a “black box” for a long time. Why does the VGG-16 with All_Repeat data augmentation method work so well for fault detection? As shown in Figure 9, flight records corresponding to fault Case 4 (Table 4, sideslip angle drift) are plotted. The width of the image corresponds to the time window (30s), and the 15 rows (from top to bottom) indicates normalized $V, \alpha, \beta, A_x, A_y, A_z, p, q, r, \psi, \theta, \phi$, respectively. The sideslip drift fault is marked with a red box. Figure 10 depicts the imagefication visualization before and after augmentation for the records in Figure 9 (Note: the lines of borders in augmented image do not actually exists, just for visualization convenience of zero-padding in edges). It can be explained that the Repeat elements operation enlarges the fault characteristics so the ADS data with fault can be detected by convolutional neural networks. We want to explore the interpretability of the air data convolutional operations in VGG-16, as it affects the performance most significantly.
Figure 9: Normalized flight records for features visualization; as in Figure 4, the data has been downsampled to 1 Hz; the sideslip drift fault occurs at last 1/3 of the window, i.e 21~31s.

Figure 10: Typical fault (β drift) in original and augmented imagefication.

It is undoubted that we must build ‘transparent’ models that have the ability to explain why they predict what they predict. To better illustrate the features-extraction of VGG-16, we adopt the Gradient-weighted Class Activation Mapping (Grad-CAM) technique \[54\], which is a generalization of Class Activation Mapping (CAM). Suppose Grad-CAM \( L_{\text{Grad-CAM}} \in \mathbb{R}^{u \times v} \) with width \( u \) and height \( v \) for any class \( c \), \( \frac{\partial y^c}{\partial A^k} \) is the gradient of the score for class \( c \), \( y^c \) with respect to feature map activations \( A^k \) of a convolutional layer. These gradients flowing back are global-average-pooled 2 over the width and height dimensions.
(indexed by $i$ and $j$ respectively) to obtain the neuron importance weights $\alpha_k^c$:

$$\alpha_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}}$$

(10)

Where $Z$ is the number of pixels in the feature map ($Z = \sum_i \sum_j 1$). The weight $\alpha_k^c$ represents a partial linearization of the deep network downstream from $A$, and captures the ‘importance’ of feature map $k$ for a target class $c$. Finally, the Grad-CAM can be obtained by a sequential processing of linear combination (weighted combination of forward activation maps) and a nonlinear operation (ReLU function):

$$L_{\text{Grad-CAM}}^c = \text{ReLU} \left( \sum_k \alpha_k^c A_k \right)$$

(11)

Figure 11 is the visualization of the Grad-CAM plots for the case 4 in Figure 10. Note a “hotter” mapping on CAM indicates the highlighted regions that convolution hinges on to assert the FD output. In Figures 11, Grad-CAM corresponds to a more general and abstract understanding of the FD problem, as the highlighted hotter (red) regions overlap the areas that the fault occurs (marked by red rectangles). It is also noticed that there are some hot areas in the junctions between different physical parameters, which may indicate that some combinations of these parameters also contribute to the FD case prediction.

7. Model optimization for mobile hardware deployment

7.1. Model compression method-Pruning

7.1.1. Model pruning theories

In this paper, a pruning method is introduced for VGG-16 compression. Based on the assumption that parameters of DNN are independent, the main
The idea of pruning method is solving a combinatorial optimization problem:

\[
\min_{W} \Delta C(h_i) := |C(D \mid W') - C(D \mid W)| = |C(D, h_i = 0) - C(D, h_i)| \quad \text{s.t.} \quad \|W'\|_0 \leq B
\]

Where \(h_i\) is the output produced from parameter \(i\), \(h = \{z_0^{(1)}, z_0^{(2)}, \cdots, z_L^{(C_i)}\}\). \(D\) is the set of training examples \(\{x = \{x_0, \cdots, x_N\}, y = \{y_1, \cdots, y_N\}\}\), \(x\) and \(y\) represent an input and a target output, respectively. \(W\) is the parameters of DNN, \(\{\{w_1^{(1)}, b_1^{(1)}\}, \cdots, \{w_L^{C_i}, b_L^{C_i}\}\}\), which are to be optimized to minimize a cost value \(C(D \mid W)\). \(W' = gW\), \(g\) is vectorized pruning gate \(g \in \{0, 1\}^{C_i}\). \(C(D, h_i = 0)\) is a cost value if output \(h_i\) is pruned, while \(C(D, h_i)\) is the cost if it is not pruned. the \(l_0\) norm in \(\|W'\|_0 \leq B\) bounds the number of non-zero parameters \(B\) in \(W'\). Equation (12) points out that we refine a subset of parameters that preserves the accuracy of the adapted network when pruning. The criteria for pruning is Taylor expansion. Approximating \(C(D, h_i = 0)\) with a first-order Taylor polynomial near \(h_i = 0\), we have

\[
C(D, h_i = 0) = C(D, h_i) - \frac{\delta C}{\delta h_i} h_i + R_1(h_i = 0)
\]
where $R_1(x)$ is the first-order remainder and can be neglected due to the significant calculation required as well as a smaller second order term deduced from the widely-used ReLU activation function. Ignoring the remainder, we have $\Theta_{TE}: \mathbb{R}^{H_i \times W_i \times C_i} \rightarrow \mathbb{R}^+$, with

$$
\Theta_{TE}(h_i) = |\Delta C(h_i)| = \left| C(D, h_i) - \frac{\delta C}{\delta h_i} h_i - C(D, h_i) \right| = \left| \frac{\delta C}{\delta h_i} h_i \right| \quad (14)
$$

$\Theta_{TE}$ is computed for a multi-variate output, such as a feature map, by

$$
\Theta_{TE}(z_{(k)}(l)) = \left| \frac{1}{M} \sum_m \frac{\delta C}{\delta z_{(k)}(l,m)} z_{(k)}(l,m) \right| \quad (15)
$$

where $M$ is length of vectorized feature map.

### 7.1.2. Pruning result of VGG-16

Based on the above technique, the VGG-16 model with highest accuracy by All Repeat data augmentation method in Section 5.3 is to be pruned. The performance indexes of pruning that we concern are best test accuracy, number of parameters, size of model, and time delay of evaluating. Time delay is the average time of making a prediction form input data to output case and can be calculated by $T = T_{total}/M$, where $T_{total}$ is the time cost of evaluating all the input data, $M$ is the number of all samples.
The hardware platform we choose to be deployed in this paper is an edge device, NVIDIA Jetson Nano[79], as shown in Figure 12. It is a powerful, small and easy to use computer with low power consumption for image classification, object detection, speech processing, etc. The VGG-16 model is pruned and retrained with the same hyperparameters on Jetson Nano and the results are shown in Table 7. The relative change is calculated by $\frac{|(\text{After} - \text{Before})|}{\text{Before}}$. It is obvious that the pruning result is satisfying. The best test accuracy is slightly up by 0.27%, the number of parameters is significantly reduced by 98.79% and the model size is 98.79% smaller than original VGG-16. Time delay is reduced by 87.54%, which means the recognition speed of pruned model is more than 8 times as quick as original model. In general, the pruned model with high accuracy and low time delay is very suitable for deployment on the edge device.

|                | Accuracy  | Parameters No. | Size/Mb | Time delay/ms |
|----------------|-----------|----------------|---------|---------------|
| Before         | 97.704%   | 134283974      | 524.56  | 297           |
| After          | 97.963%   | 1624003        | 5.96    | 37            |
| Relative Change| 0.27% ↑   | 98.79% ↓       | 98.86% ↓| 87.54% ↓      |

7.2. hyperparameter optimization base on Tree-structured Parzen Estimator (TPE) approach

7.2.1. Tree-structured Parzen Estimator approach

In an application where the true fitness function $X \rightarrow \mathbb{R}$ is costly to evaluate, model-based algorithms approximate $f$ with a surrogate that is cheaper to
evaluate. The algorithm is shown in Function \[16\]

\[
\text{SMBO} (f, M_0, T, S) \\
1 \quad H \leftarrow \emptyset \\
2 \quad \text{For } t \leftarrow 1 \text{ to } T \\
3 \quad x^* \leftarrow \text{argmin}_x S (x, M_{t-1}) \\
4 \quad \text{Evaluate } f (x^*) \quad \triangle \text{ Expensive step} \\
5 \quad H \leftarrow H \cup (x^*, f(x^*)) \\
6 \quad \text{Fit a new model } M_t \text{ to } H \\
7 \quad \text{return } H
\]

where \(x^*\) is the point that maximizes the surrogate (or its transformation), \(f\) is the true function that should be evaluated via observation history \(H\). The algorithms in this work optimize the criterion of Expected Improvement (EI) \[80\]. Expected improvement is the expectation under some model \(M\) of \(f \colon \mathcal{X} \rightarrow \mathbb{R}^N\) that \(f(x)\) will exceed (negatively) some threshold \(y^*\):

\[
\text{EI}_{y^*} (x) := \int_{-\infty}^{\infty} \max (y^* - y, 0) p_M(y|x) dy \tag{17}
\]

The tree-structured Parzen estimator (TPE) \[81\] deviates from the standard SMBO algorithm in that it creates two hierarchical processes, \(l(x)\) and \(g(x)\) acting as generative models for all domain variables, which are defined as follows:

\[
p(x|y) = \begin{cases} 
        l(x) & \text{if } y < y^* \\
        g(x) & \text{if } y \geq y^*
\end{cases} \tag{18}
\]

where \(l(x)\) is the density formed by using the observations \(\{x^{(i)}\}\) such that corresponding loss \(f (x^{(i)})\) was less than \(y^*\). \(g(x)\) is the density formed by using the remaining observations.
According to the Bayes formula, the EI can be written as:

\[
EI_{y^*}(x) = \int_{-\infty}^{y^*} (y^* - y) p(y|x) dy
= \int_{-\infty}^{y^*} (y^* - y) \frac{p(x|y)p(y)}{p(x)} dy
\tag{19}
\]

By construction, \( \gamma = p(y < y^*) \), and \( p(x) = \int_{\mathbb{R}} p(x|y)p(y)dy = \gamma \ell(x) + (1 - \gamma)g(x) \), so we have

\[
\int_{-\infty}^{y^*} (y^* - y) p(x|y)p(y)dy
= \ell(x) \int_{-\infty}^{y^*} (y^* - y) p(y)dy
= \gamma y^* \ell(x) - \ell(x) \int_{-\infty}^{y^*} p(y)dy
\tag{20}
\]

Finally,

\[
EI_{y^*}(x) = \frac{\gamma y^* \ell(x) - \ell(x) \int_{-\infty}^{y^*} p(y)dy}{\gamma \ell(x) + (1 - \gamma)g(x)}
\propto \left( \gamma + \frac{g(x)}{\ell(x)} (1 - \gamma) \right)^{-1}
\tag{21}
\]

Therefore, to maximize improvement the points \( x \) is supposed to be with high probability under \( \ell(x) \) and low probability under \( g(x) \). On each iteration, the TPE algorithm returns the candidate \( x^* \) with the greatest EI.

### 7.2.2. Hyperparameters optimization of DNN based on TPE

To further improve the performance of deep learning model in deployment, the pruned VGG-16 model in section 7.1.2 is chosen for the next optimization. The learning rate, number of epochs and batch size are selected to be optimized and the optimization target is the accuracy of predictions. The value of learning rate is a choice of \( \{0.001, 0.0001, 0.00001\} \), the value of number of epochs is a choice of \( \{1000, 800, 600\} \), the value of batch size is a choice of \( \{120, 100, 80\} \). Considering that the optimization of different combinations of hyperparameters
could be time-consuming, the total number of trails is set as 10.

![Figure 13: Optimization results of hyperparameters based on TPE.](image)

The toolbox NNI developed by Microsoft [47] for optimization is adopted. Given different DNN architectures, NNI probes into the architecture, analyzes the training data, and decides an optimal combination of the training parameters. Different DNN architectures are trained separately in associated “optimal” ways, which we believe provides more solid ground for comparative studies. After training and optimization running process, different combinations of learning rate, epochs, and batch size are examined, the results are acquired and shown in Figure 13. It can be concluded that not one single hyperparameter, but the coupling effect of these hyperparameters influence the performance of DNN. The combination of learning rate 0.001, iterative epochs 600, and batch size 100 yields the optimal DNN training outcome, i.e., highest accuracy at 0.987.

7.3. Online fault detection deployment

Based on above optimization processes, a lightweight fault detection DNN model with high performance is obtained and can be very fit for online deployment. Just as we originally envisaged, an online fault detection deployment based on edge device is designed and developed. The online fault detection scheme is shown in Figure 14 where the different kinds of ADS data (normal
and fault) are simulated on PC and transmitted to Jetson Nano for online processing. The PC and Jetson Nano are connected via WiFi in local area network (LAN), and the User Datagram Protocol (UDP) is chosen for data transmission because of its simplicity, resource saving and high speed. Then the ADS data pass through augmented imagefication module and feed into optimal FD model. Finally, the prediction of flying condition can be made and hence the real-time monitoring of aircraft is achieved.

![Diagram](image)

Figure 14: Online fault detection scheme.

8. Conclusion and Future Works

Exemplifying the fault detection (FD) problem of aircraft air data sensors, a augmented imagefication method DNN-based FD scheme is proposed in this paper.

- The FD problem is modeled using aircraft inertial referent unit measurements as equivalent inputs, and a dedicated database is constructed which involves different aircrafts/conditions, providing a solid basis in training/testing the DNN.
- An ADS data reconstructing method named Augmented Imagefication is proposed for the DNN-based prediction of flying conditions. The raw
data are reshaped as a grayscale image for convolutional operation, and
the necessity of augmentation is analyzed and pointed out. Different kinds
of augmented method, i.e. Flip, Repeat, Tile and their combinations are
developed and compared, the result shows that the All_Repeat operation
in both axes of image matrix leads to the best performance of DNN.

• The interpretability of DNN is studied based on Grad-CAM, as the high-
lighted hotter (red) regions overlap the areas that the fault occurs, which
corresponds to a more general and abstract understanding of how DNN
works the FD problem out.

• The DNN model, VGG-16 with augmented imagefication data is optimized
for mobile hardware deployment. After pruning of DNN, the best test ac-
curacy is slightly up by 0.27%, the number of parameters is significantly
reduced by 98.79%, the model size is 98.79% smaller than original VGG-16
and time delay is reduced by 87.54%, which shows that the pruned model
with high accuracy and low time delay is very suitable for deployment on
the edge device. Then the hyperparameters optimization of DNN based
on TPE is implemented and the best combination of hyperparameters is
obtained, that is, learning rate 0.001, iterative epochs 600, and batch size
100 yields the highest accuracy at 0.987. Finally, an online FD deploy-
ment based on edge device, Jetson Nano, is developed and the real time
monitoring of aircraft is achieved.

As a continuation of the work in this paper, it is promising to implement
similar augmented imagefication method to other FD problems, e.g. aircraft
actuators faults, communication datalink failures in commercial airlines. Moreover, interpretation of other DNN operations in the fault diagnosis field will also be studied.
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