In: Proceeding of the 2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC),
24 - 27 September 2024, Edmonton, Canada, pp. 1145-1150
DOI: 10.1109/itsc58415.2024.10920046

Mitigating No Fault Found Phenomena through Ensemble Learning: A Mixture of Experts Approach

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***Abstract*— In the aviation industry, the reliance on precise fault diagnostic decision-making is critical for equipment maintenance. A significant challenge encountered is the erroneous categorization of components under "No Fault Found" (NFF), which subjects these components to unwarranted repairs or further testing. Such misclassifications not only trap on airlines through costly cycles of unnecessary maintenance but also exacerbate degeneration and potential safety hazards. Consequently, there is a heightened demand for the development of effective fault diagnosis models that are adapting to the aircraft complex systems and adeptly addressing issues related to the NFF phenomenon. In this study, we draw inspiration from ensemble learning and propose a multiple Naive Bayes experts (MNBMoEs) approach based on a mixture of experts (MoEs) model. This method leverages the predictive advantages of each sub-model on specific features, allowing the hybrid expert decision to outperform any single expert. It also includes a quantitative analysis method for the NFF issue, derived from the confusion matrix according to the industrial definition of NFF. Experiments evaluated on public datasets results show that the ensemble learning approach, based on Mixture of Multiple Naive-Bayes expert models, can effectively utilize the strengths of different models, improving fault diagnosis accuracy to 96.96%, with a maximum reduction in NFF occurrence rates of up to 94.17% and 84.2% model performance improvement.**

I. INTRODUCTION

With the practical deployment of Electric Vertical Take-Off and Landing (E-VTOL) aircraft [1], the development of aerial intelligent transportation systems has rapidly accelerated. The advent of E-VTOLs has conferred multiple benefits in daily life, such as reducing road congestion through three-dimensional air traffic and minimizing travel time and collision incidents caused by human factors through intelligent route planning [2]. In the coming years, the implementation of more advanced intelligent transportation systems will increasingly rely on the reduction of human intervention, necessitating high reliability in each system component. The aviation industry, with its routine inspection and maintenance procedures and strict regulatory standards, serves as an exemplary model for designing a low-cost maintenance framework for low-altitude E-VTOL operations.

Despite the availability of various models based on differing principles for fault diagnosis and maintenance strategies, an inevitable issue arises with electronic components due to inherent design flaws, manufacturing errors, and software-hardware incompatibilities [3], leading to incidents of No Fault Found (NFF). NFF refers to instances where components reported as faulty show no defects upon retesting. The ARINC 672 standard defines NFF as: "Removals of equipment from service for reasons that cannot be verified by the maintenance process (shop or elsewhere) [4]." The occurrence of such issues significantly escalates maintenance costs for aviation transport enterprises. For instance, British Airways reports that of the 8,000 parts removed monthly, 14% are due to NFF issues, with 30% of avionics equipment experiencing NFF, causing losses exceeding $20 million annually. Another survey by American Transportation Association (ATA) estimates that each aircraft spends $100,000 annually addressing NFF issues, with each airline incurring over one million dollars in wasted funds due to NFF annually [9]. For E-VTOLs, which have a higher proportion of electronic equipment [11], NFF issues, while ensuring reliability, consume a greater part of maintenance budgets. These costs are distributed over the cost per kilometer of E-VTOL operations. As consumers are price-sensitive, they may opt for cheaper travel alternatives [12], undoubtedly hindering the development of low-altitude intelligent transportation.

To enhance the efficiency, sensitivity, and reliability of the maintenance process, thousands of fault diagnosis, reasoning, and decision-making models have been developed, typically falling into four categories: model-based, signal-based, knowledge-based, and hybrid/active approaches [13][14]. While these studies have yielded excellent results for specific components or cases, their decision-making efficacy for complex systems or entire equipment assemblies remains to be improved. Empirical research and specific applications of machine learning have confirmed that a given classification method may outperform all others on specific problems or subsets of input data, yet finding one method that achieves optimal results across an entire problem domain is unusual [15]. Therefore, in this paper, we explore the application of combining classifiers in overall fault diagnosis through a tiny Mixture of Experts (MoEs) model and data-driven predictive features. Our aim is to leverage the strengths of different classifiers in handling specific data to make safe decisions through a gating network. We also employ simulation to elucidate how the NFF issue is mitigated in this process. Subsequently, this approach can serve as a standard for assessing the reliability of E-VTOLs, balancing between scheduled maintenance and condition-based maintenance to minimize the incidence of NFF issues.

Our research contributes to the field in three significant

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The final published version (version of record) is available online at DOI:10.1109/itsc58415.2024.10920046. Please refer to any applicable publisher terms of use.

ways:

- First, we introduce the application of the Mixture of Experts (MoEs) model to fault diagnosis. By leveraging the universality of data-driven simulation optimization algorithms and utilizing the AirLab Failure and Anomaly (ALFA) public dataset, we demonstrate in our numerical experiments a combined Naive Bayes (NB) model approach to diagnosis. Our approach reduces the incidence of NFF by up to 94.17% compared to the worst-performing model and by at least 3.1% compared to the best-performing model, which means the performance increased by 84.2%. It has practical significance to compare with the worst-performing model, which will be explained in a later section.
- Second, we propose a method for visualizing the occurrence of NFF issues during simulation experiments using the Confusion Matrix. This approach transforms NFF issues from being merely post-facto testable and analyzable in terms of reliability to being real-time measurable parameters.
- Third, our research shifts focus towards simpler, more cost-effective, and technically efficient methods for addressing NFF issues, rather than delving into more customized mathematical optimizations, complex definitions, and high-accuracy fault diagnosis algorithms that require substantial computational resources.

Although this represents a different perspective on the same problem, this approach can rapidly implement cost-reducing, sustainable, and low-emission methods in practical applications.

II. RELATED WORK

A. Aircraft Fault Diagnosis

Aircraft fault diagnosis is a key aspect of ensuring the safety and reliability of aircraft systems [16]. Various research efforts have been directed towards developing intelligent methods for aircraft fault diagnosis.

Model-based fault diagnosis can be regarded as a control problem [17], which includes three tasks: fault detection, fault isolation, and fault identification [18]. Redundancy and observers are important structures in the model that estimate the system's state based on its inputs and outputs [19][20]. By adjusting the observer's gain, the performance of fault detection and diagnosis can be improved. A notable method in the model-based approach is the linear matrix inequality (LMI) based method. An example includes the design of a nonlinear observer that utilizes the Lipschitz formula and linear parameter varying (LPV) methods to reduce the conservative LMI conditions [26]. This method has been applied to fault diagnosis in satellite formations. Additionally, for fault prediction in LPV systems, the sliding mode control observer developed by Chen [27] is also influential.

Signal-based methods utilize measured signals for fault diagnosis. Faults during processes are reflected in these signals, and diagnostic decisions are made by extracting features from these signals and using prior knowledge [21]. Various studies have explored different methods and approaches to diagnosing faults in aircraft systems using signal processing techniques. For example, one study focused on signal analysis based on Lamb waves for detecting icing on aircraft surfaces to diagnose potential issues related to icing [22]. Furthermore, Liang et al. have proposed a non-destructive diagnosis method for aircraft engine blades based on signal classification, highlighting the importance of using signal-based methods for aviation fault diagnosis [23]. Similarly, in the knowledge-based approach, well-known methods include expert systems, support vector machines, and neural networks, which all rely on learning from historical data for fault diagnosis [14]. Cartocci et al. [24] addressed the robust data-driven multi-sensor fault diagnosis problem in aircraft, proposing and validating a universal robust data-driven scheme for fault detection, isolation, and estimation. NASA's Diagnostics & Prognostics Group has been working on developing data-driven diagnostics and prognostics algorithms for aircraft [25]. Overall, the literature review emphasizes the importance of data-driven approaches in aircraft fault diagnosis and prediction, showcasing the advancements and challenges in this field.

B. Mixture of Experts

Mixture of Experts (MoEs) is a robust technique that has been applied across various domains to enhance model performance and tackle complex data structures. Miller et al. introduced a hybrid expert classifier that leverages both labeled and unlabeled data for learning [30]. Avnimelech et al. proposed an enhanced expert mixing approach as an integrated learning solution for general classification and regression problems [31]. In recent years, Riquelme et al. introduced a Visual MoE (V-MoE) for image recognition, which is a sparse version of the visual converter [32]. This V-MoE model matches the performance of state-of-the-art networks while demanding less computational resources during inference. Mustafa et al. introduced the Language Image MoE (LIMoE), a sparse expert hybrid model that can simultaneously utilize images and text for multimodal learning [33]. They proposed an entropy-based regularization method to address the challenges of training stability and balancing expert utilization. Overall, the extensive applications of expert mixing across diverse domains offer an excellent template for its first integration in the field of fault diagnosis, significantly contributing to this research.

C. No Fault Found Issue

The No Fault Found (NFF) issue is not merely a challenge in fault diagnosis decision-making; the academic community generally attributes its origins to four aspects: technical, organizational, behavioral, and procedural [8][9]. Currently, in academic papers and related books, the NFF issue may also be referred to by other terms such as Cannot Duplicate (CND), Fault Not Found (FNF), No Trouble Found (NTF), No Defect Found (NDF), Hidden Failures, and False Failures [8][10]. In principle, this refers to a situation where a fault is reported in some manner but subsequent retesting in the

workshop reveals no issues. This can occur at the component, subsystem, or system level. Although factors like system design, human factors, and data management can influence the occurrence of this issue, addressing it from a technical perspective in the context of fault diagnosis scenarios is currently seen as the most impactful approach.

A substantial number of scholars have investigated the fault diagnosis and fault tolerance capabilities of airborne equipment, achieving a series of notable results. Model-based approaches employ mathematical models to describe equipment, offering high diagnostic accuracy, yet the validity of model parameters significantly influences the outcomes. Signal-based methods, requiring high-quality signals, are primarily applied to equipment that exhibits time or frequency domain characteristics. Knowledge-based approaches rely heavily on extensive, reliable prior knowledge and high-quality historical data. The aforementioned traditional methods of fault diagnosis prove challenging to apply in evaluating NFF issues, as they already achieve high diagnostic accuracy, yet NFF remains a prevalent issue in practice. Therefore, a shift in perspective is necessary, exploring evaluation models for the NFF issue through generic, unoptimized algorithms, and subsequently verifying if these approaches effectively address the NFF problem.

III. METHODOLOGY

Our framework primarily comprises two components: a Random Forest Gating Network and a Hybrid Naive Bayes Classifier.

A. Random Forest Classifier

Random Forest is an ensemble learning method often utilized for classification and regression tasks [29]. It comprises multiple decision trees, where the prediction outcome is derived from either averaging or majority voting based on the predictions of individual trees. A random forest is essentially a collection of tree-structured classifiers $\{h(x,k), k = 1, \dots\}$ where the $\{k\}$ are independent identically distributed random vectors, and each tree casts a unit vote for the most popular class at the input x.

In our study, the decision trees within the random forest use the Gini Impurity metric for feature selection, calculated using the formula:

$$G(D) = 1 - \sum_{i=1}^{k} p_i^2 \tag{1}$$

where p_i represents the relative frequency of class i in dataset D. This methodology is elaborated in detail in literature sources [6][7].

B. Hybrid Naive Bayes Classifier

In the selection of sub expert models, our requirement is to be simple, efficient, transparent, and interpretable, while not necessarily having good predictive results. There are four naive Bayesian models in the Python library, and it has been experimentally proven that Bernoulli NB does not have fault prediction ability on our test set. Therefore, we use three models, Gaussian NB, Multinomial NB, and Complement NB, as the basic models for MoEs.

Let us assume we have a training set $\mathbf{D} = \{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^{N}$, where each $\mathbf{x}^{(i)}$ is a d-dimensional feature vector, and $y^{(i)}$ is the corresponding class label. Our objective is to construct a classification model that can provide class predictions for a new observation $\mathbf{x}$. In the Mixture of Experts model, we define a set of Naive Bayes experts $\mathbf{E} = \{\mathbf{NB}_G, \mathbf{NB}_M, \mathbf{NB}_C\}$ and a gating network $\mathbf{G}$. Each expert $\mathbf{NB}_j$ corresponds to different data distributions:

- **Gaussian Naive Bayes Expert $\mathbf{NB}_G$**:

$$P(y \mid \mathbf{x}; \theta_G) = \frac{1}{Z_G(\mathbf{x})} \exp\left(-\frac{1}{2} \sum_{k=1}^{d} \frac{(x_k - \mu_{y,k})^2}{\sigma_{y,k}^2}\right) \tag{2}$$

  where $\mu_{y,k}$ and $\sigma_{y,k}^2$ are the mean and variance of feature k under class y, and $Z_G(\mathbf{x})$ is the normalization constant.
- **Multinomial Naive Bayes Expert $\mathbf{NB}_M$**:

$$P(y \mid \mathbf{x}; \theta_M) = \frac{1}{Z_M(\mathbf{x})} \prod_{k=1}^{d} \left(\frac{N_{y,k} + \alpha}{N_y + \alpha d}\right)^{x_k} \tag{3}$$

  where $N_{y,k}$ is the count of feature k occurrences in class y, N_y is the total count of all features in class y, α is the smoothing parameter, and $Z_M(\mathbf{x})$ is the normalization constant.
- **Complement Naive Bayes Expert $\mathbf{NB}_C$**:

$$P(y \mid \mathbf{x}; \theta_C) = \frac{1}{Z_C(\mathbf{x})} \prod_{k=1}^{d} \left(\frac{N_{\bar{y},k} + \alpha}{N_{\bar{y}} + \alpha d}\right)^{x_k} \tag{4}$$

  where $N_{\bar{y},k}$ is the count of feature k occurrences in all classes except y, $N_{\bar{y}}$ is the total count of all features in all classes except y, and $Z_C(\mathbf{x})$ is the normalization constant.

In the testing phase of the Mixture of Multi-Naive Bayes Experts (MNBMoEs) methodology, the input $\mathbf{x}$ is concurrently provided to both the MNBMoEs experts and the

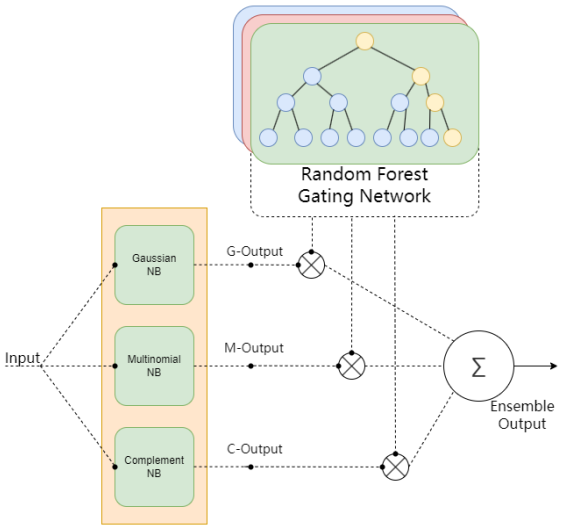


Fig. 1. Diagram for the Testing Step in the Mixture of NB-Experts Method

gating network. The outputs from the gating network undergo processing via a Random Forest algorithm. The ensemble system then computes its final output by performing a weighted average of the outputs from the base Naive Bayes experts. This approach ensures a robust decision-making process by integrating multiple expert assessments.

IV. EXPERIMENTS AND ANALYSIS

In our experiment, we utilized the AirLab Failure and Anomaly (ALFA) dataset, which was made publicly available by the Robotics Institute at Carnegie Mellon University. This dataset, released in 2020, offers authentic flight data captured from fixed-wing unmanned aerial vehicles (UAVs) experiencing various faults.

ALFA datasets include flight logs from 47 autonomous flights, encompassing 23 instances of sudden engine failures and 24 instances of failures across 7 different types of control surfaces (actuators). These datasets provide a total of 66 minutes of normal flight conditions and 13 minutes of post-fault flight data. As shown in Table I, we extracted 8 types of faults from the dataset and extracted features from the original sensor data. For each different types of failure, the diagnostic features were calculated in time and frequency, as detailed in Table II, the calculation was performed on flight windows last 1s with an overlap of 0.5s. The data pre-processing method adopts Fabio Carosi's open-source algorithm on GitHub [5]. It is easy to observe that the dataset is highly imbalanced, so we trained using the top 80% of the data and tested it on the global set.

We first discovered the hidden NFF information in the confusion matrix, which is a diagram used in machine learning to evaluate the performance of classification models. It displays the correspondence between the predicted results of a classifier on different categories and the actual labels.

TABLE I

FAULT TYPE AND AMOUNT

Fault Type	Label	Amount
No Fault	0	6721
Engine Full Power Loss	1	718
Rudder Stuck to Left	2	18
Rudder Stuck to Right	3	64
Elevator Stuck at Zero	4	46
Left Aileron Stuck at Zero	5	252
Right Aileron Stuck at Zero	6	319
Both Ailerons Stuck at Zero	7	71
Rudder & Aileron at Zero	8	54

TABLE II

FEATURE EXTRACTION METHOD

Features over time	Frequency Features
Mean	Peak Frequency
Variance	Peak Power
MAE (Mean Absolute Error)	Band Power
RMS (Root Mean Square)	Mean
RMSE (Root Mean Square Error)	25%/50%/75% percentile
25%/50%/75% percentile	
Kurtosis	
Skewness	
Impulse Factor	

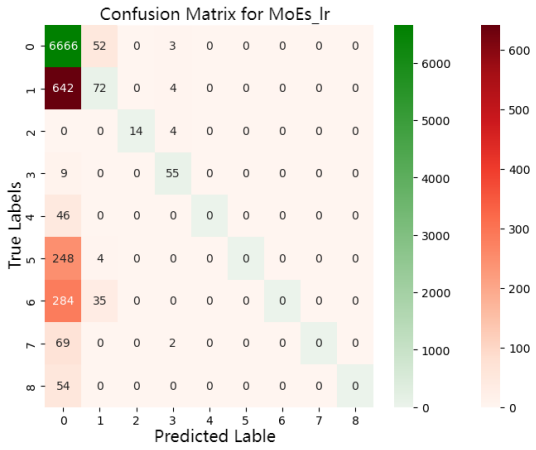


Fig. 2. Confusion Matrix Visualization for a Logistic Regression Gating Network

Usually, a confusion matrix is a two-dimensional matrix, where rows represent actual categories and columns represent predicted categories. According to the definition of NFF, if the actual category has no faults but the predicted category has faults, it can be considered a potential NFF event, as shown in the first row of the Fig. 2. It can be described by:

$$\text{NFF Rate} = \frac{\sum(\text{TL} = 0 \cap \text{PL} \in \{1,2,\ldots,8\})}{\text{Amount of No-Fault Components}} \quad (5)$$

Where TL is the value in the True Lable boxes, PL is the value in Predicted Lable boxes.

This just serves as an example, where we observe that the gating network exhibits minimal predictive capacity for faults 4 to 8. Therefore, it becomes imperative to replace the gating network with a different model.

Our Multiple Naive Bayes MoEs (MNBMoEs) model is significantly influenced by gating networks, as evidenced by the results depicted in Fig. 3. Utilizing a random forest routing mechanism yields a performance that is 61.6% superior

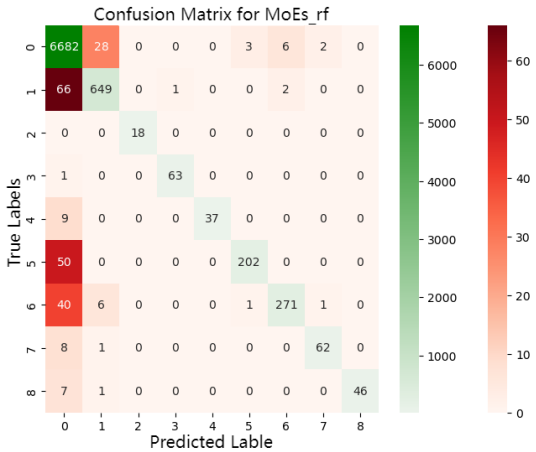


Fig. 3. Confusion Matrix Visualization for a Random Forest Gating Network

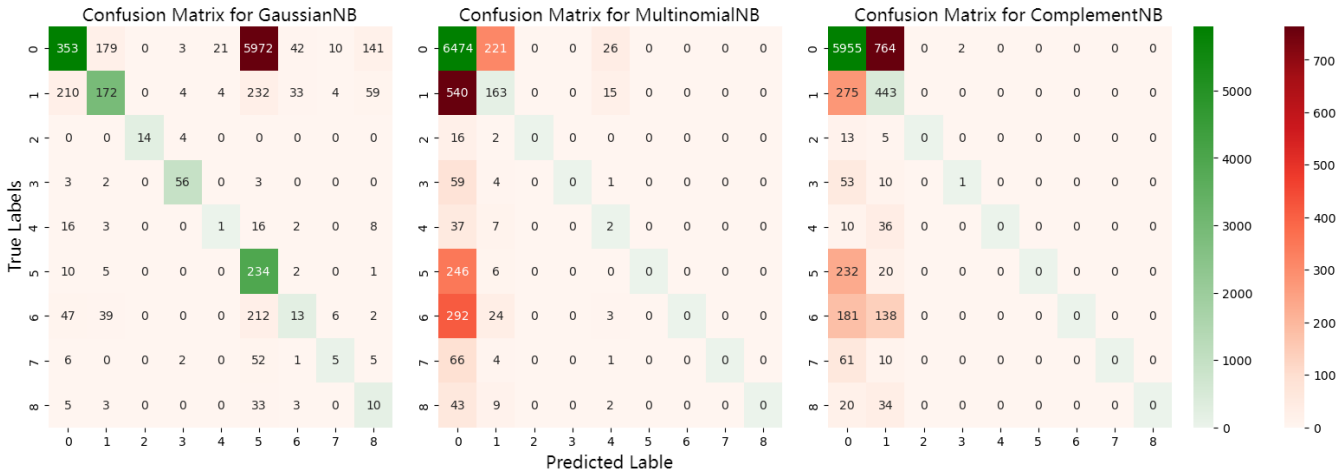


Fig. 4. Confusion Matrix Visualization for Multiple Naive Bayes Classifiers

TABLE III
PERFORMANCE METRICS FOR VARIOUS MODELS

Model	Accuracy	Precision	Recall	F1-Score	Infer. Time (ms)	NFF Rate
GaussianNB	0.10383	0.35936	0.35461	0.27275	24.704	94.75%
MultinomialNB	0.80346	0.80480	0.13708	0.13516	1.723	3.68%
ComplementNB	0.77441	0.83472	0.16874	0.14638	1.229	11.40%
MOE_lr	0.82379	0.89799	0.30324	0.30848	0.844	0.82%
MOE_rf	0.96962	0.97174	0.88396	0.92439	34.123	0.58%

to that achieved with the simplest logistic regression approach, which the ratio is derived from the difference in F1-score. Furthermore, a balance between diagnostic accuracy, inference time and the incidence of NFF is attained when the number of estimators is set at 30. If the inference time of the model exceeds 50 milliseconds, it will no longer be considered real-time.

In Fig. 4, we have highlighted the confusion matrix results for different sub-experts. Despite none of the sub-experts achieving satisfactory diagnostic outcomes individually, the MoEs model still demonstrates its competitiveness, outperforming all sub-expert models. This confirms that an ensemble of low-computation-cost classifiers, through combination, can enhance overall predictive performance beyond that of any single classifier.

In Table III, we present the scoring for five different models. Some might argue that the diagnostic results of the sub-experts are not sufficiently precise; however, the objective of our experiment was not to develop an optimized fault diagnostic algorithm, but rather to mitigate the frequency of NFF occurrences in this process. Overly precise fault diagnostic algorithms require researchers to invest more time and computational resources, while also obscuring the full scope of NFF events within the overall spectrum of faults.

Finally, our experiments have demonstrated that even simple learning models like Naive Bayes, when considered for inference time and result quality, become one of the best approaches after being integrated into an MNBMoEs framework. Our proposed MNBMoEs method reduces the incidence of NFF events to approximately 0.47% among all non-fault events and 2.53% among all fault events. It means in 6,721 NFF labels, our proposed MNBMoEs model incorrectly identified 39 instances, whereas the best-performing single model, MultinomialNB, incorrectly identified 247 instances. Consequently, the MNBMoEs model demonstrates an error rate approximately 84.20% lower than that of the MultinomialNB model. Compared to the least effective Gaussian NB method, the NFF incidence is reduced by as much as 94.17%. In this point, the comparative analysis of the results with the least effective model holds practical significance. This is primarily because one critical factor contributing to the NFF issue is the utilization of improper testing methodologies. The observed improvement in the performance of MoEs when compared with the single least effective model indicates that the detrimental effects of NFF reports, attributed to improper testing method, can be mitigated through the implementation of a mixed experts decision-making approach.

According to British Airways' disclosure, NFF constitutes approximately 14% of all failures, and deploying MNBMoEs will yield a cost savings of 81.93%, equivalent to $16,386,000.

$$\text{Cost Savings Rate} = 1 - \left(\frac{\text{NFF Events Amount}}{14\% \times \text{All Faults Amount}} \right) \quad (6)$$

Another advantage is evident in real-world scenarios where airlines might struggle to ensure optimal diagnostic performance across all systems based on fault patterns and

prior operating conditions. Thus, our MNBMoEs approach, which does not require high precision from sub-experts, further simplifies the entire process, mitigates the frequency of NFF events, ensure real-time diagnostic capability when supported by strength hardware and achieves the goal of reducing costs and enhancing efficiency.

V. CONCLUSIONS

In this study, we introduce a fault diagnosis methodology utilizing the Mixture of multi-Naive Bayes Experts (MNBMoEs) model, which quantifies the incidence of No Fault Found (NFF) events via confusion matrix analysis. This approach can be expanded into a sophisticated research framework that markedly diminishes NFF occurrences and curtails unnecessary maintenance expenditures for airlines. This is achieved by selecting and fine-tuning optimal gating networks, concurrently preserving the overall accuracy of real-time fault diagnosis. Drawing upon current simulation data and publicly accessible maintenance cost figures for NFF components, this methodology is anticipated to reduce wastage by approximately $16 million annually. Additionally, this technique offers significant advantages to designers of Electric Vertical Take-off and Landing (E-VTOL) vehicles, facilitating the development of more precise maintenance strategies, decreasing operational costs per kilometer, and advancing the progress of smart transportation systems.

ACKNOWLEDGMENT

I would like to express my gratitude to Dr. Huamin Jia, Dr. Lejun Chen and Prof. Saba Al-Rubaye for their guidance and support throughout this research endeavor.

REFERENCES

[1] J. Pritchard, "AutoFlight completes world's first inter-city eVTOL aircraft flight between Shenzhen and Zhuhai in China," *eVTOL Insight*, Feb. 27, 2024. [Online]. Available: https://evtolinsights.com/2024/02/.

[2] Cummings, C. & Mahmassani, H. Measuring the impact of airspace restrictions on air traffic flow using four-dimensional system fundamental diagrams for urban air mobility. *Transportation Research Record*. **2677**, 1012-1026 (2023)

[3] Visser, I. Analyzing user perceived failure severity in consumer electronics products: incorporating the user perspective into the development process. (2008)

[4] ARINC Working Group 672, Guidelines for the reduction of no fault found (NFF): ARINC; 2008.

[5] F. Carosi, "FaultDetection_ALFA-Dataset," GitHub repository, 2023. [Online]. Available: https://github.com/FabioCarosi/FaultDetection_ALFA-Dataset.

[6] Łuczak, T. & Pittel, B. Components of random forests. *Combinatorics, Probability And Computing*. **1**, 35-52 (1992)

[7] Antoniadis, A., Lambert-Lacroix, S. & Poggi, J. Random forests for global sensitivity analysis: A selective review. *Reliability Engineering & System Safety*. **206** pp. 107312 (2021)

[8] Jennions, I., Phillips, P., Hockley, C. & Khan, S. No fault found: the search for the root cause. (SAE International,2015)

[9] Khan, S., Phillips, P., Jennions, I. & Hockley, C. No Fault Found events in maintenance engineering Part 1: Current trends, implications and organizational practices. *Reliability Engineering & System Safety*. **123** pp. 183-195 (2014)

[10] Khan, S., Phillips, P., Hockley, C. & Jennions, I. No Fault Found events in maintenance engineering Part 2: Root causes, technical developments and future research. *Reliability Engineering & System Safety*. **123** pp. 196-208 (2014)

[11] Swaminathan, N., Reddy, S., RajaShekara, K. & Haran, K. Flying cars and eVTOLs—technology advancements, powertrain architectures, and design. *IEEE Transactions On Transportation Electrification*. **8**, 4105-4117 (2022)

[12] Abdullah-Al-Mamun, M. & Robel, S. A critical review of consumers' sensitivity to price: Managerial and theoretical issues. *Journal Of International Business And Economics*. **2**, 01-09 (2014)

[13] Gao, Z., Cecati, C. & Ding, S. A survey of fault diagnosis and fault-tolerant techniques—Part I: Fault diagnosis with model-based and signal-based approaches. *IEEE Transactions On Industrial Electronics*. **62**, 3757-3767 (2015)

[14] Zhiwei, G., Cecati, C., Ding, S. & Others A survey of fault diagnosis and fault-tolerant techniques—Part II: Fault diagnosis with knowledge-based and hybrid/active approaches. *IEEE Trans. Ind. Electron.* **62**, 3768-3774 (2015)

[15] Dietterich, T. Ensemble methods in machine learning. *International Workshop On Multiple Classifier Systems*. pp. 1-15 (2000)

[16] Johnson, D. A review of fault management techniques used in safety-critical avionic systems. *Progress In Aerospace Sciences*. **32**, 415-431 (1996)

[17] Ding, S. Model-based fault diagnosis techniques: design schemes, algorithms, and tools. (Springer Science & Business Media,2008)

[18] Willsky, A. A survey of design methods for failure detection in dynamic systems. *Automatica*. **12**, 601-611 (1976)

[19] Frank, P. Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: A survey and some new results. *Automatica*. **26**, 459-474 (1990)

[20] Garcia, E. & Frank, P. Deterministic nonlinear observer-based approaches to fault diagnosis: A survey. *Control Engineering Practice*. **5**, 663-670 (1997)

[21] Gangsar, P. & Tiwari, R. Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review. *Mechanical Systems And Signal Processing*. **144** pp. 106908 (2020)

[22] ZHANG, Y., ZHANG, H., Xian, Y., Binrui, W., Xianlei, G. & XIONG, J. Analysis method and experimental study of ice accumulation detection signal based on Lamb waves. *Chinese Journal Of Aeronautics*. (2024)

[23] Liang, Z., Wang, A., Yu, Y. & Yang, P. Research on early weak structural damage detection of aeroengine intershaft bearing based on acoustic emission technology. *Structural Health Monitoring*. **20**, 3113-3122 (2021)

[24] Cartocci, N., Napolitano, M., Costante, G., Valigi, P. & Fravolini, M. Aircraft robust data-driven multiple sensor fault diagnosis based on optimality criteria. *Mechanical Systems And Signal Processing*. **170** pp. 108668 (2022)

[25] Adhikari, P., Rao, H. & Buderath, M. Machine learning based data driven diagnostics & prognostics framework for aircraft predictive maintenance. *Proceedings Of The 10th International Symposium On NDT In Aerospace, Dresden, Germany*. pp. 24-26 (2018)

[26] Nemati, F., Hamami, S. & Zemouche, A. A nonlinear observer-based approach to fault detection, isolation and estimation for satellite formation flight application. *Automatica*. **107** pp. 474-482 (2019)

[27] Chen, L., Edwards, C., Alwi, H., Sato, M., Nateghi, S. & Shtessel, Y. Sliding mode observers for robust fault estimation in linear parameter varying systems. *International Journal Of Robust And Nonlinear Control*. **33**, 9084-9108 (2023)

[28] Masoudnia, S. & Ebrahimpour, R. Mixture of experts: a literature survey. *Artificial Intelligence Review*. **42** pp. 275-293 (2014)

[29] Zhang, C. & Ma, Y. Ensemble machine learning: methods and applications. (Springer,2012)

[30] Miller, D. & Uyar, H. A mixture of experts classifier with learning based on both labelled and unlabelled data. *Advances In Neural Information Processing Systems*. **9** (1996)

[31] Avnimelech, R. & Intrator, N. Boosted mixture of experts: An ensemble learning scheme. *Neural Computation*. **11**, 483-497 (1999)

[32] Riquelme, C., Puigcerver, J., Mustafa, B., Neumann, M., Jenatton, R., Susano Pinto, A., Keysers, D. & Houlsby, N. Scaling vision with sparse mixture of experts. *Advances In Neural Information Processing Systems*. **34** pp. 8583-8595 (2021)

[33] Mustafa, B., Riquelme, C., Puigcerver, J., Jenatton, R. & Houlsby, N. Multimodal contrastive learning with limoe: the language-image mixture of experts. *Advances In Neural Information Processing Systems*. **35** pp. 9564-9576 (2022)



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2024-09-24
IEEE
https://doi.org/10.1109/itsc58415.2024.10920046
Liu Z, Kong X, Chen Y, et al., (2024) Mitigating no fault found phenomena through ensemble learning: a mixture of experts approach. In: Proceeding of the 2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC), 24 - 27 September 2024, Edmonton, Canada, pp. 1145-1150

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