Improving Intelligent Fault Diagnosis with Semantic Segmentation for Industrial Applications

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***Abstract*—The rapid advancement of AI-based signal processing technologies and the exponential growth of sensor data have accelerated innovation in intelligent fault diagnosis (IFD) methodologies. In particular, the autonomous data analysis and end-to-end fault diagnosis capabilities of deep learning have marked a significant breakthrough compared to traditional manual feature extraction approaches. However, the increasing reliance on deep learning models has also heightened the demand for interpretability and transparency in results. The "black box" nature of deep learning models poses a significant challenge, potentially undermining the reliability of diagnostic outcomes and the transparency of decision-making processes, thus limiting their practical applicability in real-world systems. This paper identifies the key factors necessary to enhance the reliability of intelligent fault diagnosis systems and proposes a semantic segmentation-based approach to address these challenges. Experimental results using autonomous driving fault diagnosis data demonstrate that the proposed methodology achieves over 99.9% classification accuracy and over 98% segmentation accuracy in real-time environments, showcasing its exceptional utility and reliability. These findings highlight the potential of the proposed approach to significantly improve the practical applicability of IFD systems.**

***Index Terms*—Semantic segmentation, intelligent fault diagnosis (IFD), model interpretability and transparency**

I. Introduction

Traditional fault diagnosis has heavily relied on the extensive experience and expertise of engineers skilled in signal processing techniques. However, recent advancements in AI-based signal processing technologies, coupled with the exponential growth of sensor data, have brought about transformative changes in the field of Intelligent Fault Diagnosis (IFD) [1]. These technological advancements enable the implementation of automated monitoring systems, reducing reliance on the expertise of operators while providing higher efficiency. In particular, deep learning technologies have opened new possibilities by replacing traditional manual feature extraction methods with end-to-end data analysis and fault diagnosis capabilities [2, 3].

Despite these advancements, existing deep learning-based IFD studies face challenges in achieving the reliability required for real-world applications and commercialization [4]. Overcoming these challenges demands a solution that simultaneously delivers high accuracy, broad generalizability, and strong interpretability. This paper identifies the critical requirements to enhance the reliability of IFD systems and proposes a semantic segmentation-based approach to address these challenges. Through extensive experimentation, the proposed methodology demonstrates its ability to overcome the limitations of existing approaches, providing outstanding utility and reliability.

In summary, our contributions are listed as follows:

- This paper introduces a novel semantic segmentation-based approach for intelligent fault diagnosis, enabling high-accuracy fault detection and robust interpretability by effectively analyzing time-frequency relationships in spectrogram data.
- Through extensive experiments using high-resolution spectrogram datasets from electric vehicle systems, this paper demonstrates the proposed method's superior performance in fault detection, classification, and segmentation compared to existing approaches.
- The proposed method addresses key challenges in real-world applications by ensuring scalability across diverse fault scenarios and optimizing the model for real-time processing in resource-constrained environments.

The structure of this paper is as follows. Section II defines the key requirements for ensuring reliability in intelligent fault diagnosis technologies. Section III proposes a fault diagnosis methodology utilizing semantic segmentation models, discussing its advantages and the considerations for implementation. Section IV describes the fault diagnosis datasets and experimental environments used in this study and presents the experimental results and their analysis. Finally, Section V summarizes the key findings of this research and suggests directions for future work.

II. Requirements for Ensuring Reliability

This section defines the key requirements that must be met to implement a reliable intelligent fault diagnosis (IFD) system. Fig. 1 visually organizes the primary factors that can affect intelligent fault diagnosis. Based on these factors, the critical considerations for implementation are outlined as follows:

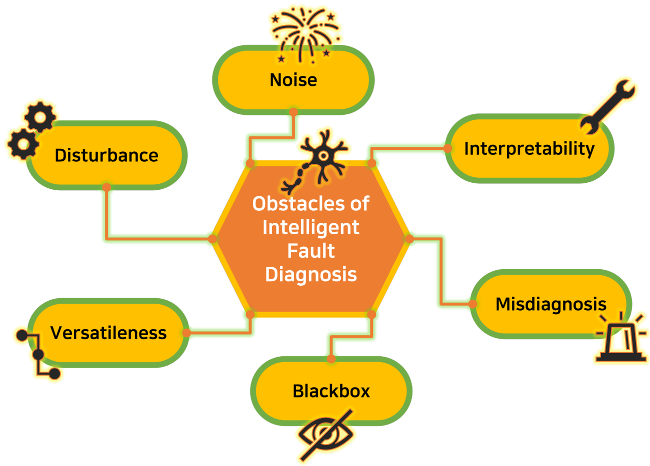

Fig. 1: Key factors that can impact intelligent fault diagnosis.

A. High Detection Accuracy and Low Error Rates

To ensure the reliability of an IFD system, achieving high detection accuracy and low error rates is essential. In particular, for monitoring systems directly linked to industrial equipment and safety, diagnostic errors can escalate risks rapidly, leading to catastrophic consequences. Therefore, such systems demand strict standards and sophisticated approaches to simultaneously enhance both the sensitivity (diagnostic accuracy) and specificity (error prevention) of fault detection.

B. Scalability for Complex Systems

In real-world operational environments, unlike controlled laboratory settings, complex and nonlinear signals frequently occur. These signals arise from various factors such as component interactions, external noise, and unexpected disturbances, exhibiting characteristics that are difficult to replicate under laboratory conditions. Therefore, it is essential to design generalized analysis models capable of effectively reflecting these irregular and complex environments. Such models enable the development of highly reliable diagnostic systems that can operate stably in actual environments.

Moreover, modern industrial settings demand integrated analysis of multi-component systems, making the scalability of diagnostic models a critical requirement. For instance, it is necessary to develop comprehensive diagnostic systems that can integratively analyze various signals (e.g., current, vibration, temperature, infrared) generated from a single component or simultaneously process signals from multiple components [5]. These systems must efficiently analyze multidimensional data while quickly identifying and addressing faults in complex systems. Furthermore, by analyzing various faults within a single system simultaneously, the system's ability to respond to unexpected scenarios can be significantly enhanced.

To achieve this, flexible and generalized model designs are required, capable of efficiently handling the dynamic characteristics of systems and diverse fault types. Such models would enable swift and accurate fault diagnosis, significantly improving adaptability to complex, real-world operational environments.

C. Interpretability

Deep learning provides exceptional decision-making capabilities, but its inner workings are often opaque, leading to its characterization as a "black box" [6]. This black-box nature complicates the interpretation of diagnostic results, posing risks to reliability and transparency. To implement a highly reliable fault diagnosis system, it is essential to clearly explain the causal relationships between inputs and outputs and to enable the tracking or explanation of the causes when faults are detected.

One promising approach to addressing this issue involves integrating physical characteristics into deep learning-based diagnostic systems [4]. Maintaining a connection between the physical properties of the data and the model's outputs is crucial to ensuring that diagnostic results are closely aligned with the actual system's behavior. Furthermore, explainable artificial intelligence (XAI) technologies, which aim to demystify the black-box structure and reveal the causal relationships behind individual decision-making processes, have recently been introduced in the field of fault diagnosis [7, 8]. These technologies enhance both the interpretability and reliability of diagnostic results, enabling the implementation of more transparent and trustworthy systems.

D. Real-Time Processing in Resource-Constrained Environments

In resource-constrained environments such as embedded systems or industrial sites, the ability of a model to detect and analyze faults in real time is crucial. These environments are typically characterized by limited computational power and energy resources, necessitating model optimization and lightweight design. Strategic approaches are required to maximize computational efficiency while maintaining high accuracy.

Energy efficiency has also emerged as a critical consideration for supporting real-time processing. This can be achieved by designing low-power systems that efficiently utilize computational resources. Such approaches significantly enhance the practical utility of fault diagnosis systems in industrial environments, playing a key role in implementing efficient and reliable solutions.

III. Fault Diagnosis Using Semantic Segmentation Models

This section proposes an intelligent fault diagnosis method based on semantic segmentation models and outlines the key requirements for its implementation.

A. Advantages of Semantic Segmentation Methodology

Semantic segmentation offers the advantage of preserving and analyzing the spatial relationships and contextual information between time-frequency components on multidimensional

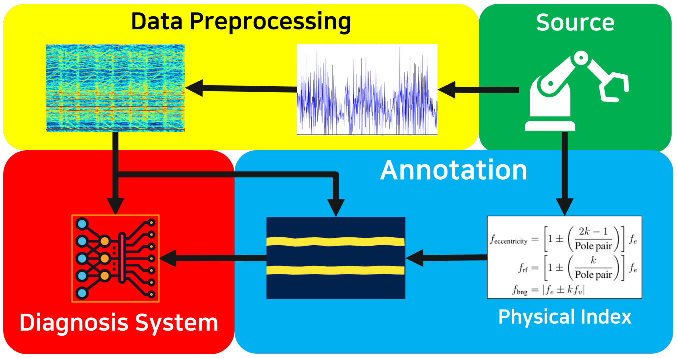

Fig. 2: Data preparation process for fault diagnosis using semantic segmentation models.

spectrograms, rather than being limited to one-dimensional spectrum analysis. This capability differentiates it from traditional classification and object detection techniques, making it particularly effective in complex environments characterized by nonlinear behaviors, where high accuracy is essential.

Additionally, semantic segmentation excels in efficiently processing high-dimensional data, making it well-suited for integrative utilization of multimodal data. This capability ensures robust performance even with small datasets or in complex fault diagnosis scenarios, significantly enhancing the reliability of systems in real-world industrial environments.

Another key advantage of semantic segmentation is its ability to provide visually intuitive results [9]. For instance, in fault diagnosis systems, it can distinctly highlight fault regions on a spectrogram that reflect physical characteristics, enabling precise identification of fault locations and types. This approach maintains the causal relationship between the model's input and output by linking diagnostic outcomes to physical evidence, thereby simultaneously improving the reliability and interpretability of the results.

Such characteristics enable system designers and operators to better understand the model's outputs, facilitating more informed decision-making based on clear and interpretable diagnostic insights.

B. Considerations for Implementation

To effectively integrate semantic segmentation techniques into fault diagnosis systems, several conditions must be met. Fig. 2 presents a diagram summarizing these conditions, which are detailed as follows:

- First, a preprocessing step is necessary to convert one-dimensional time-series data into two-dimensional data suitable for semantic segmentation. For instance, time-series data can be transformed into high-resolution spectrograms using short-time Fourier transform (STFT). This transformation is highly effective for extracting fault-related features in the time-frequency domain.
- Second, the labeling of preprocessed data must adequately reflect the physical characteristics of the system. This is crucial for enhancing the reliability of diagnostic outcomes and the accuracy of model training. For example, rotor faults in permanent magnet synchronous motors (PMSMs) manifest as fault frequencies in the harmonic and sideband components of the supply frequency [10, 11]. These characteristics are clearly visible in spectrograms, and high-quality labeled data reflecting these features directly influence the model's learning performance.
- Third, the model must be optimized for lightweight and efficient operation to enable real-time functionality in resource-constrained environments. Semantic segmentation models predict for each pixel of an image and require significant computational power and memory, especially during the process of restoring the original resolution. This demands optimization techniques that reduce resource consumption while maintaining model performance. Recent advances in lightweight models have demonstrated their capability to support real-time semantic segmentation, delivering excellent performance even with high-resolution datasets [12, 13, 14, 15].

IV. Experiments

This section introduces the experiments conducted to validate the effectiveness of the proposed semantic segmentation-based intelligent fault diagnosis method. First, the fault diagnosis dataset and experimental environment are described, followed by a presentation of the results and an analysis of the characteristics and performance of models suitable for fault diagnosis.

A. Dataset

All models in this experiment were trained and validated using the autonomous driving fault diagnosis dataset [18] provided by AI Hub. This dataset comprises 550,800 current and vibration spectrogram images collected from PMSMs and gearboxes of various electric vehicles. It includes high-quality polygon labels that cover various fault types and normal conditions, accurately representing the physical characteristics of faults, such as harmonics and sideband features in the fault signals [10, 11, 19]. The dataset is split into a 9:1 ratio for training and validation. Each image has a resolution of 2000×1280 pixels, making it suitable for evaluating the real-time capabilities of high-resolution image segmentation models.

B. Model Configuration

The experiment evaluates and compares the performance of ten state-of-the-art real-time semantic segmentation models. The input consists of three spectrogram images, measured simultaneously and concatenated channel-wise. To segment the five states from each sensor's data, the output channel number is set to 15. To measure fault classification performance alongside segmentation, a classifier is appended to the end of the backbone of each segmentation model. This classifier comprises a global average pooling (GAP) layer followed by a

TABLE I: Comparison of classification, segmentation, inference speed, computational load, and memory performance for state-of-the-art models on the autonomous driving fault diagnosis dataset

Models	F1-score (%)		MIoUs (%)					Speed	#GFLOPs	#Params.	#Params.
		Total	Normal	Ecc10	Ecc20	Demag	Reduc	(FPS)			(in paper)
BiSeNetV2-L [12]	97.81	92.58	99.40	83.46	90.38	93.26	96.38	69	123.8	5.2M	-
STDC2-Seg75 [16]	96.67	94.92	99.40	88.60	90.83	96.91	98.86	73	337.3	15.9M	-
DDRNet-23-slim [13]	99.38	97.17	99.75	97.18	97.01	93.94	97.96	158	47.5	5.7M	5.7M
DDRNet-23 [13]	99.82	94.96	99.75	93.89	96.04	87.08	98.02	62	184.1	20.3M	20.1M
DDRNet-39 [13]	98.24	92.37	99.32	81.09	86.36	98.36	96.71	36	359.2	32.7M	32.3M
SFNet-Lite(ResNet-18) [14]	99.96	98.68	99.87	98.11	97.90	98.37	99.15	36	220.7	12.3M	12.3M
SFNet-Lite(STDC-1) [14]	99.93	98.54	99.85	97.70	97.83	98.28	99.03	62	212.4	9.7M	9.7M
PIDNet-S [17]	99.92	98.43	99.82	97.64	97.56	98.08	99.07	114	59.5	7.6M	7.6M
PIDNet-M [17]	99.96	98.57	99.84	97.55	97.69	98.60	99.17	46	220.3	28.8M	34.4M
RegSeg [15]	99.93	98.77	99.86	98.22	98.16	98.35	99.25	82	49.1	3.34M	3.34M

single-layer perceptron. All backbone networks are initialized without pretraining.

C. Experimental Setup

The training and evaluation of the models are conducted in a computing environment based on a single RTX 4080 GPU. The experimental settings include the Adam optimizer with an initial learning rate of 10^{-5}, weight decay of 10^{-6}, learning rate 10^{-5}, batch size of 4, and three epochs of training as the main hyperparameters. During training, a focal loss [20] is used for loss calculation with focusing parameters set to $\alpha = 1.0$ and $\gamma = 2.0$. To ensure optimal performance and reproducibility, the training images are sorted by filename, and the random seed is fixed at 42. Inference speed and computational load are measured on a single RTX 4080 with an input tensor of $1280 \times 2000 \times 9$.

D. Experimental Results

1) Quantitative Evaluation: Tab. I presents the quantitative comparison of state-of-the-art real-time semantic segmentation models on the autonomous driving fault diagnosis dataset. The best performance is highlighted in red, and the second-best performance is marked in blue. Notably, RegSeg [15] demonstrated significantly superior semantic segmentation performance compared to DDRNet [13]. Interestingly, DDRNet exhibited a decline in performance as the number of parameters in its hierarchical structure increased. This finding supports *Roland Gao*'s assertion [15] that RegSeg outperforms DDRNet in detecting thin and elongated objects, making it more effective at capturing fine frequency details on spectrograms. Fig. 3 illustrates the classification results of each real-time segmentation model in the form of confusion matrices. All fault classes achieved high classification accuracies above 95%, with the most advanced models achieving near-perfect accuracy of 99.9%.

2) Qualitative Evaluation: In real-world mechanical systems, abnormal factors such as disturbances and variations in internal rotational speeds frequently occur, complicating

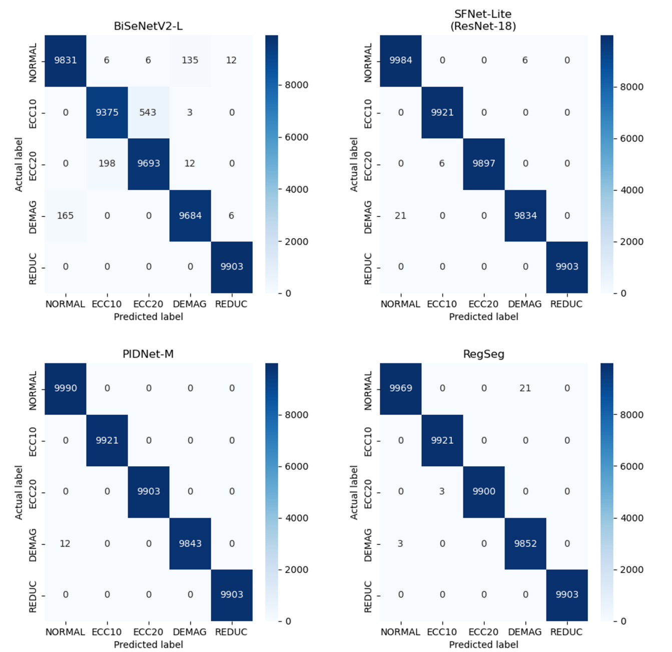

Fig. 3: Confusion matrices for fault classification using various real-time segmentation models on the autonomous driving fault diagnosis dataset.

fault diagnosis. Fig. 4 visualizes the prediction masks of the DDRNet-slim model (offering the highest inference speed and lowest computational cost) and the RegSeg model (achieving the highest accuracy) under such challenging conditions. The analysis shows that both models exhibited excellent fault frequency detection capabilities across various fault conditions, demonstrating stable operation even in complex environments. Specifically, both models delivered robust fault segmentation results under scenarios involving motor-gearbox speed variations (rows 1, 2, and 6) and conditions with noise

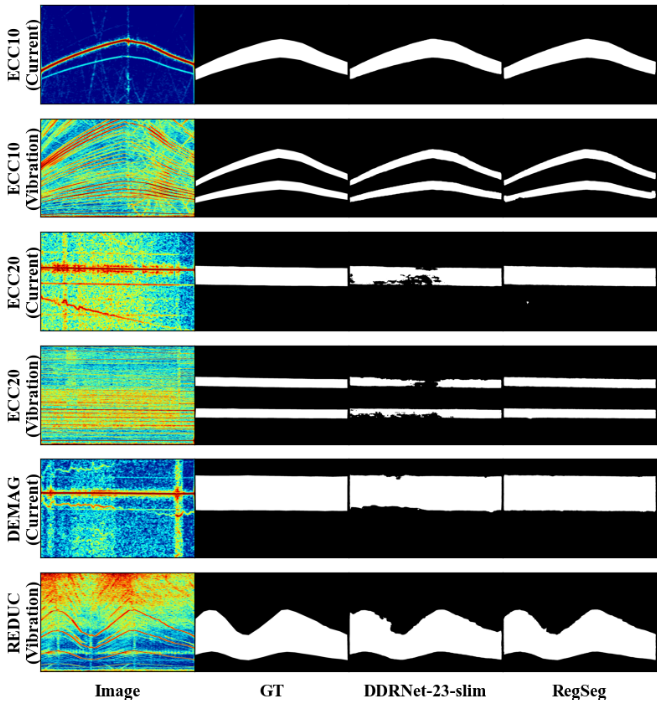

Fig. 4: Visual comparison of segmentation masks predicted by DDRNet-slim [13] and RegSeg [15] under harsh conditions.

and disturbances (current: rows 3, 4, and 5). However, the DDRNet-slim [13] model occasionally failed to accurately detect frequency boundaries in certain cases.

V. Conclusion

This paper proposed a novel semantic segmentation-based methodology to enhance the reliability and efficiency of intelligent fault diagnosis (IFD) systems. Extensive experimental results demonstrated that the proposed approach overcomes the limitations of existing methods, delivering high accuracy and superior interpretability. This research is expected to contribute significantly to improving the reliability and practicality of future IFD systems. Future work will focus on validating the applicability of the proposed approach across diverse industrial environments and developing lightweight and optimized models capable of maintaining high performance in resource-constrained settings.

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