

Research Article

Two-Stage YOLOv4-Tiny for Vascular Stenosis Severity Classification and Hemodynamic Correlation Analysis Using AVF Shunt Sound

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ARTICLE INFO

Article History

Received 8 December 2025
Accepted 2 September 2026

Keywords

AVF shunt sound
Vascular stenosis
YOLOv4-Tiny
Spectrograms
Doppler ultrasound

ABSTRACT

The two stage YOLOv4-Tiny framework for vascular stenosis using arteriovenous fistula (AVF) shunt sound spectrograms is introduced. AVF sounds were recorded using a digital stethoscope and converted into spectrogram images for classification. In the proposed hierarchical framework, the first stage classified samples into normal and non-normal categories, while the second stage further separated non-normal cases into gray and abnormal conditions. To improve training diversity, 1-second and 3-second spectrogram slice configurations were investigated, with the 1-second slices achieving the best file-level accuracy of 67.92% for the final three-class classification task. To further investigate the physiological relevance of the model outputs, confidence-derived features generated by the proposed framework were analyzed in relation to Doppler ultrasound parameters, including Flow Volume (FV), Pulsatility Index (PI), and Resistance Index (RI). Pearson correlation analysis revealed moderate relationships between several confidence-derived features and Doppler ultrasound parameters, with FV showing comparatively stronger correlation tendencies ($r \approx 0.55-0.60$) than PI and RI. These findings suggest that the proposed framework can capture stenosis-related acoustic characteristics and may provide supplementary physiological information for non-invasive AVF monitoring vascular assessment.

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1. Introduction

Arteriovenous fistula (AVF) is widely recognized as the first-line vascular access for chronic hemodialysis superior long-term patency and lower complication rates compared with alternative vascular access methods. Nevertheless, vascular stenosis remains one of the primary causes of AVF dysfunction and eventual access failure. The progression of stenosis alters vascular hemodynamics and produces characteristic changes in AVF shunt sound patterns. Early identification of these abnormalities is therefore important to reduce thrombosis risk, maintain vascular access functionality, and minimize repeated clinical intervention [1],[2],[3],[4].

Recent advances in deep learning have demonstrated the effectiveness of spectrogram-based physiological signal analysis for vascular access monitoring and stenosis classification [5], [6], [7]. Previous studies have shown that AVF shunt sound analysis combined with artificial

intelligence can support automated stenosis assessment and vascular access surveillance. Deep learning approaches using acoustic blood flow analysis have demonstrated promising capability for detecting stenosis-related abnormalities from AVF sound recordings. Among existing architectures, YOLO-based models have attracted considerable attention because of their computational efficiency. Although YOLO architectures have been widely applied in medical imaging applications, their application to AVF shunt sound analysis remains relatively limited, particularly for lightweight systems suitable for practical deployment [7],[8],[9]. In addition, most previous studies have focused primarily on binary abnormality classification, while investigations involving hierarchical multi-stage classification for stenosis severity assessment remain limited.

Motivated by these limitations, two-stage YOLOv4-Tiny framework was developed for vascular stenosis classification using spectrogram images generated from

AVF shunt sound recordings [10]. YOLOv4-Tiny was selected because its lightweight architecture, computational efficiency and the confidence outputs from YOLOv4-Tiny can exhibit a clear separation between highly confident and low-confidence detections, which are desirable for potential practical and short-time AVF monitoring [11]. The first stage differentiates normal and non-normal conditions, while the second stage further separates non-normal samples into gray and abnormal categories. This hierarchical strategy was designed to improve the discrimination of borderline stenosis conditions. In addition, a conventional single-stage YOLOv4-Tiny model was evaluated as a baseline under the same three-class classification setting to assess the contribution of the proposed hierarchical strategy. Two spectrograms slice durations, 1-second and 3-seconds, were also investigated to evaluate the influence of temporal window length on classification performance.

Beyond stenosis classification, this study also explores whether the confidence distributions generated by the proposed framework contain physiologically meaningful information associated with vascular blood flow conditions [12],[13]. Confidence-derived features extracted from the classification outputs were analyzed in relation to Doppler ultrasound parameters, including Flow Volume (FV), Pulsatility Index (PI), and Resistance Index (RI). Previous studies have demonstrated the feasibility of utilizing AVF acoustic signals and deep learning approaches for stenosis assessment and vascular condition analysis [14],[15],[16]. Motivated by these findings, this study further investigates whether the confidence distributions produced by the proposed two-stage YOLOv4-Tiny framework preserve latent hemodynamic characteristics associated with vascular stenosis severity through correlation-based analysis.

2. Methodology

2.1. Overview of the Proposed Two-Stage YOLOv4-Tiny System

A hierarchical classification framework based on YOLOv4-tiny was developed to identify vascular stenosis conditions from AVF shunt sound spectrograms. The proposed approach was designed to improve the discrimination of intermediate stenosis patterns. The clinical severity categories were determined using a predefined classification rule based on normalized FV, RI and PI derived from ultrasound measurements. The dataset contained five clinical categories, normal, gray-normal (g-n), gray, gray-abnormal (g-a), and abnormal. For the final evaluation, g-n and gray were consolidated into the gray class, while g-a and abnormal were consolidated into the abnormal class. Thus, the five clinical categories were grouped into three clinically meaningful classes, normal, gray, and abnormal to simplify interpretation and support practical stenosis assessment, as shown in Figure 1.

Rather than directly performing three-class classification, a sequential decision process was adopted. The first YOLOv4-Tiny model functions as a screening

stage by separating normal samples from potentially abnormal recordings. Samples identified as non-normal are subsequently processed by a second YOLOv4-Tiny model that performs a finer distinction between gray and abnormal conditions. This hierarchical structure reduces the complexity of the classification task and allows the system to focus on subtle acoustic differences associated with borderline stenosis cases.

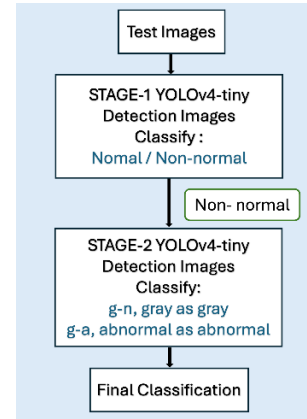


Figure 1 Architecture of the Proposed Two-Stages YOLOv4-Tiny Classification Framework

2.2. Spectrogram Slice Generation Using 1-Second and 3-Second Temporal Windows

AVF shunt sound recordings were transformed into spectrogram images using two temporal window configurations consisting of 1-second and 3-second slices. Each audio recording was segmented into overlapping temporal windows, and spectrogram representations were generated using the short-time Fourier transform (STFT). To ensure compatibility with YOLO-based processing, all spectrogram images were standardized using consistent resolution, scaling, and color mapping settings.

The temporal slicing strategy was introduced to increase training diversity and improve the representation of stenosis-related acoustic characteristics. Shorter slices were expected to emphasize localized acoustic patterns, whereas longer slices were intended to preserve broader temporal flow characteristics. By comparing the 1-second and 3-second configurations, this study further investigates the influence of slice duration on vascular stenosis classification performance and confidence-derived physiological correlation analysis. The workflow related to slicing and YOLO-based training shown in Figure 2.

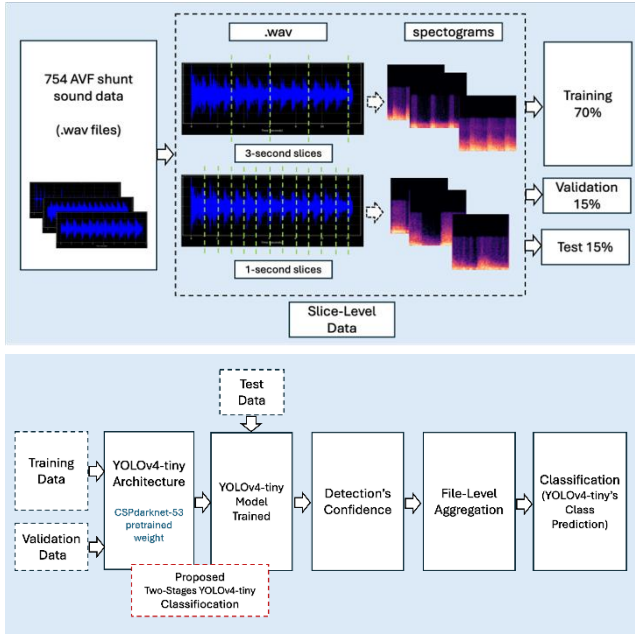


Figure 2 Workflow of the Proposed Method, including AVF Shunt Sound Spectrograms Slicing, YOLO-Based Training, Slice-Level and File-Level Classification Aggregation

2.3. AVF Shunt Sound Dataset

The experimental dataset consisted of AVF acoustic recordings obtained from hemodialysis patients using a digital stethoscope placed at designated location over the radial artery-cephalic vein arteriovenous fistula (AVF). Recordings were collected over a three-year period from 2021 to 2023, involving 282 unique patients and 377 recordings instances. This study was approved by the Miyazaki University Ethics Review Board (approval number: O-0943). Some patients contributed more than one recording instance because they were examined at different time points or under different stenosis conditions. All recording were stored in WAV format using identical acquisition and sampling parameters to maintain consistency across the dataset.

During acquisition, patients were placed in the supine position while the target arm was elevated vertically to stabilize blood flow conditions and improve acoustic consistency. Recordings were obtained under two physiological conditions: before stress (BS), with the arm positioned beside the body, and under stress (US), with the arm elevated. Each recording instance therefore provided two audio recordings corresponding to the BS and US conditions, resulting in a total of 754 audio recordings (377 recording instances x 2 conditions).

The audio recordings were subsequently converted into spectrograms and divided into either 1-second or 3-second temporal slices for the YOLOv4-Tiny analysis. Because the duration of the original recordings varied, the number of spectrogram slices generated from each recording was not identical. The dataset was divided into training, validation and test subsets using 70%, 15%, and 15% split,

respectively, after spectrograms slicing. To prevent data leakage, all slices originating from the same recording were assigned to the same subset. Furthermore, when a patient contributed multiple recording instances, all recording instances from that patient were kept within the same subset.

The dataset exhibited an imbalanced class distribution. Among the 377 recording instances, 208 were classified as normal, 77 as gray and 91 as abnormal, corresponding to 55.4%, 20.4% and 24.1% respectively. The gray class was therefore the least represented class. This imbalance together with the difficulty of distinguishing borderline stenosis conditions, motivated the adoption of the proposed two-stage hierarchical classification framework. The distribution of the final three classes is summarized in Table 1.

Table 1 Distribution of AVF Shunt Sound Data

Dataset Split	Normal	Gray	Abnormal	Total
Train	298	116	132	546
Validation	58	18	26	102
Test	62	20	24	106
Total	418	154	182	754

2.4. Confidence-Based Physiological Parameter Estimation

In addition to vascular stenosis classification, this study investigated whether the confidence outputs generated by the proposed framework contain physiological information related to vascular blood flow conditions. Confidence scores from the predicted classes were aggregated to construct confidence-derived features. Several statistical features, including confidence differences, confidence ratios, confidence standard deviation, and entropy-based uncertainty measures, were further generated to enhance feature representation.

Physiological interpretation of the confidence-derived features was investigated by examining their relationships with clinically measured Doppler parameters, including FV, PI, and RI. Correlation coefficients were computed for each feature parameter pair, and the resulting association patterns were presented in a heatmap representation. The purpose of this analysis was not to replace Doppler ultrasound examination, but rather to investigate whether the confidence distributions generated by the proposed framework preserve latent hemodynamic information associated with vascular stenosis severity.

3. Results

3.1. Classification results

Confusion matrices were used to evaluate the classification performance of the proposed two-stage framework using the 1-second and 3-second slice configurations. Figure 3 presents the confusion matrices obtained from both temporal window settings. For the 1-second slices, the model demonstrated relatively stable

classification behavior with fewer gray–abnormal misclassifications. The shorter temporal windows generated more localized spectral representations, enabling improved discrimination of intermediate stenosis conditions. However, several non-normal samples were still misclassified as normal, suggesting that shorter slices may not fully preserve subtle stenosis-related acoustic characteristics.

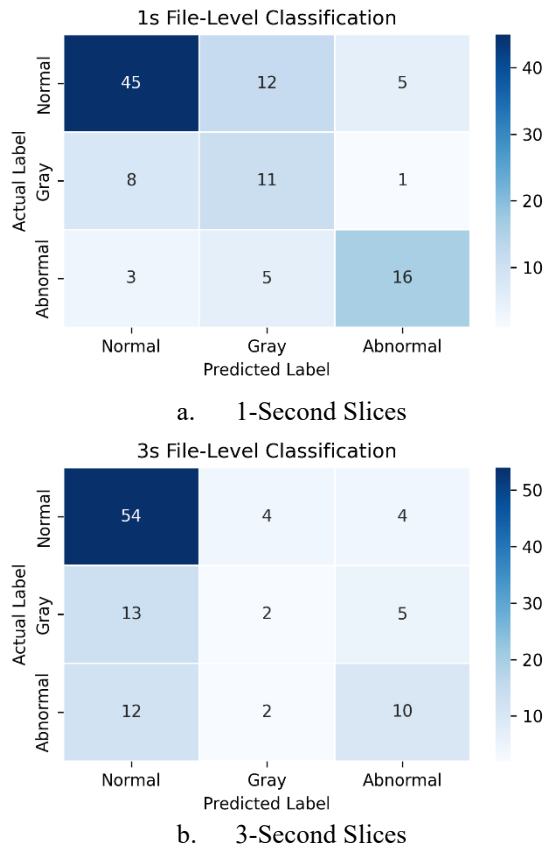


Figure 3 Confusion Matrix Comparison for the Proposed Two-Stage YOLOv4-Tiny Framework using 1-Second and 3-Second Spectrogram Slice Configurations

In contrast, the 3-second slices showed improved class separability between normal and non-normal classes during Stage 1 classification. Nevertheless, increased confusion was observed between the gray and abnormal classes in Stage 2. This indicates that longer temporal windows may capture broader acoustic variability while simultaneously introducing transitional sound characteristics that increase ambiguity in borderline cases. The findings highlight a compromise between classification robustness and sensitivity to temporal changes. The 1-second slices provided more stable classification performance, whereas the 3-second slices preserved broader temporal acoustic information.

Table 2 summarizes the classification performance of the proposed two-stage YOLOv4-Tiny framework for both the 1-second and 3-second slice configurations. For the 1-second slices, Stage 1 achieved an accuracy of 70.75%, while the final three-class classification achieved 67.92%. In comparison 3-second slice configuration yielded slightly lower performance, with accuracies of 68.87% and 65.09% for Stage 1 and the final classification stage, respectively.

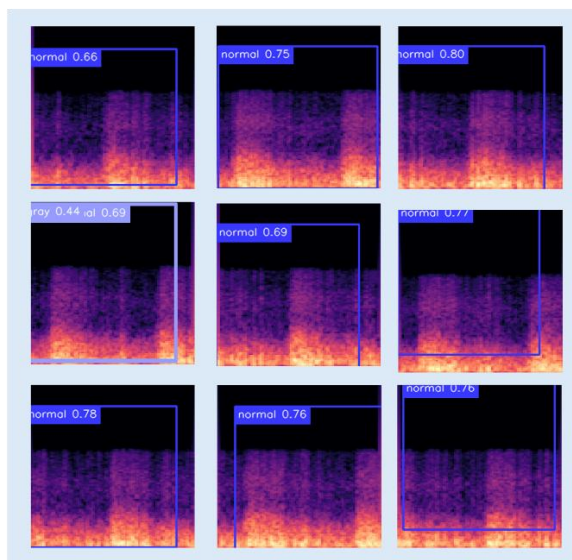
Class-wise evaluation further revealed that the 1-second configuration provided more balanced precision, recall, and F1-score across all classes. In particular, the gray class achieved a precision of 0.39, recall of 0.55, and F1-score of 0.46 for 1-second configuration. In contrast, although the 3-second configuration achieved a precision of 1.00 for gray class, its recall was only 0.10, resulting in an F1-score of 0.18. This indicate that the 3-second configuration was highly conservative in identifying gray cases and had limited sensitivity to clinically defined borderline stenosis conditions.

Table 2 Classification Performance Comparison for 1-Second and 3-Second Slice Configurations

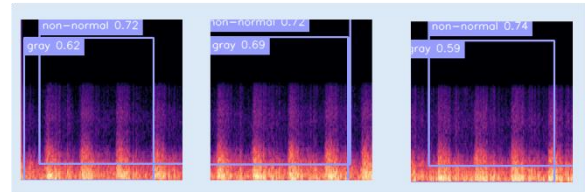
Method	Slice Duration	Stage-1 Accuracy	Final Accuracy	Class	Precision	Recall	F1-Score
YOLOv4-Tiny	1-second	-	61.32%	Normal	0.69	0.87	0.77
				Gray	0.00	0.00	0.00
				Abnormal	0.39	0.92	0.55
	3-second	-	60.38%	Normal	0.69	0.90	0.78
				Gray	0.00	0.00	0.00
				Abnormal	0.35	0.67	0.46
Two-Stage YOLOv4-Tiny	1-second	70.75%	67.92%	Normal	0.80	0.73	0.76
				Gray	0.39	0.55	0.46
				Abnormal	0.73	0.67	0.70
	3-second	68.87%	65.09%	Normal	0.67	0.90	0.77
				Gray	1.00	0.10	0.18
				Abnormal	0.52	0.46	0.49

For comparison, the single-stage YOLOv4-Tiny baseline achieved final three-class accuracies of 61.32% and 60.38% for the 1-second and 3-second configurations, respectively, and failed to identify the gray class, resulting in precision, recall, and F1-score of 0.00. In contrast, the proposed two-stage framework was able to identify gray cases, particularly with the 1-second configuration. These results support the effectiveness of the hierarchical classification strategy in improving discrimination of the clinically defined intermediate vascular stenosis conditions.

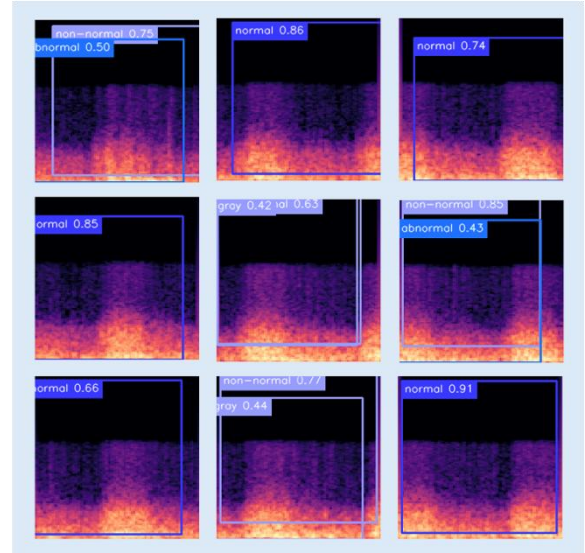
Figure 4 presents qualitative examples of classification behavior for the normal, gray, and abnormal classes using both slice configurations. Figure 4 (a) and 4(b) show examples of the normal class using 1-second and 3-second slices, respectively. The 1-second slices produced more stable predictions, whereas the corresponding 3-second slices occasionally generated gray-class classification for the same recording. Figure 4 (c) and 4(d) present representative examples of the gray-class using 1-second and 3-second slices, respectively. In both configurations, the slices exhibited mixed predictions among normal, gray, and abnormal outputs, reflecting the borderline characteristics of gray-class stenosis. Figure 4 (e) and 4(f) present examples of the abnormal class using 1-second and 3-second slices, respectively. In contrast, abnormal cases demonstrated relatively consistent abnormal classifications for both slice configurations, indicating that severe stenosis-related acoustic patterns were more robustly captured regardless of slice duration. These observations further support the influence of temporal window size on acoustic representation and classification behavior within the proposed framework.



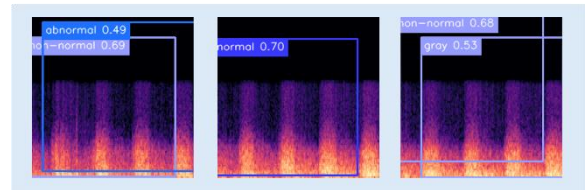
a. 1-Second Spectrogram Normal Class



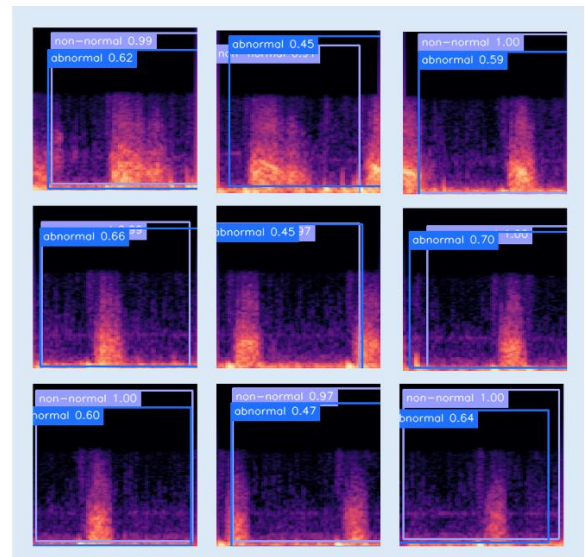
b. 3-Second Spectrogram Normal Class



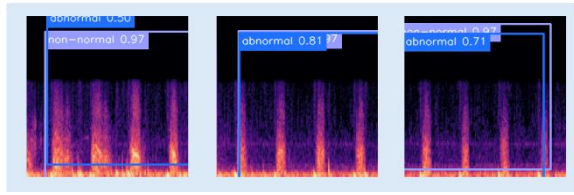
c. 1-Second Spectrogram Gray Class



d. 3-Second Spectrogram Gray Class



e. 1-Second Spectrogram Abnormal Class



f. 3-Second Spectrogram Abnormal Class

Figure 4 Qualitative Comparison of Classification Behavior using 1-Second and 3-Second Slice Configurations for Normal, Gray, and Abnormal AVF Shunt Sound Spectrograms

3.2. Confidence-based regression analysis

To investigate whether the confidence outputs generated by the proposed two-stage YOLOv4-tiny framework contain physiological information related to vascular stenosis severity, correlation analysis was conducted using confidence-derived features extracted from the classification results. The analysis focused on the relationship between YOLO confidence distributions and Doppler ultrasound parameters, including FV, PI, and RI.

Pearson correlation analysis revealed several moderate relationships between confidence-derived features and physiological vascular parameters, as illustrated in Figure 5. In particular, the abnormal and gray confidence features showed positive correlations with PI and RI, whereas the normal confidence feature exhibited negative correlations with these parameters. Conversely, FV demonstrated an opposite trend, showing positive correlations with normal confidence and negative correlations with abnormal and gray confidence.

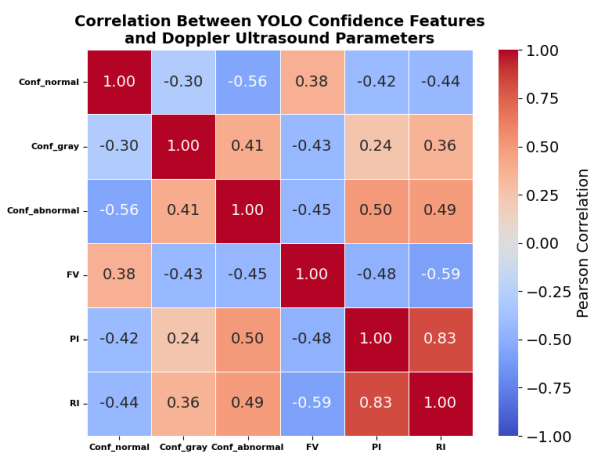


Figure 5 Pearson Correlation Heatmap between Confidence-Derived Features Generated by the Proposed Method and Doppler Ultrasound Parameters

4. Conclusion

The proposed hierarchical classification strategy enabled the differentiation of normal, gray, and abnormal vascular conditions while improving the handling of borderline stenosis cases. Comparative experiments using

1-second and 3-second spectrogram slice configurations demonstrated that slice duration influences classification behavior and acoustic representation. Overall, the 1-second slice configuration achieved more stable file-level classification performance and better generalization characteristics than the 3-second configuration. In addition to stenosis classification, confidence-derived feature analysis was conducted to investigate the physiological relevance of the YOLO confidence distributions. Pearson correlation analysis revealed moderate relationships between several confidence-derived features and Doppler ultrasound parameters, particularly for Flow Volume (FV), indicating that the proposed framework preserves partial hemodynamic information associated with vascular stenosis conditions. Overall, the proposed framework demonstrates the potential of combining lightweight deep learning and acoustic spectrogram analysis for non-invasive AVF stenosis screening and supplementary vascular assessment.

Acknowledgements

The authors gratefully acknowledge Togo Medikit Co., Ltd. for their technical support related to the electronic stethoscope used in this study.

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Authors Introduction

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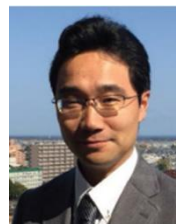
AI application as part of an industry-academia joint research team, including the University of Miyazaki.

Mr. Kazuya Kibune



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