Sensors and Materials, Vol. 37, No. 7 (2025) 3043–3050
MYU Tokyo

S & M 4101

Development of a Time-adaptive Ensemble Learning Algorithm for the Noninvasive Detection of Arteriovenous Fistula Occlusion in Hemodialysis Patients

Wen-Hsien Ho,[1,2,3,4†] Kao-Shing Hwang,[1,5†] Tian-Hsiang Huang,[6]
Yu-Jui Lien,[1] Yi-Wen Chiu,[7,8,9*] and Yenming J. Chen[1,10**]

[1]Department of Healthcare Administration and Medical Informatics, Kaohsiung Medical University, Kaohsiung 807378, Taiwan
[2]Department of Medical Research, Kaohsiung Medical University Hospital, Kaohsiung 807378, Taiwan
[3]Precision Sports Medicine and Health Promotion Center, Kaohsiung Medical University, Kaohsiung 807378, Taiwan
[4]College of Professional Studies, National Pingtung University of Science and Technology, Pingtung 912301, Taiwan
[5]Department of Electrical Engineering, National Sun Yat-Sen University, Kaohsiung 804201, Taiwan
[6]Department of Computer Science and Information Engineering, National Penghu University of Science and Technology, Penghu 880011, Taiwan
[7]Division of Nephrology, Department of Internal Medicine, Kaohsiung Medical University Hospital, Kaohsiung Medical University, Kaohsiung 807378, Taiwan
[8]Faculty of Medicine, College of Medicine, Kaohsiung Medical University, Kaohsiung 807378, Taiwan
[9]The Master Program of AI Application in Health Industry, Kaohsiung Medical University, Kaohsiung 807378, Taiwan
[10]Department of Information Management, National Kaohsiung University of Science and Technology, Kaohsiung 824005, Taiwan

(Received May 16, 2025; accepted June 30, 2025)

Keywords: hemodialysis, arteriovenous fistula (AVF), acoustic feature analysis, time-adaptive ensemble learning algorithm (TAELA)

Arteriovenous fistula (AVF) occlusion is a problem faced by all hemodialysis patients. However, current clinical methods for assessing the degree of AVF occlusion primarily rely on auscultation and palpation, which are subjective and relatively inaccurate methods. In this study, we developed a portable, noninvasive audio recording device for collecting vascular blood flow sounds and collected data from three patients who underwent two or more percutaneous transluminal angioplasty (PTA) procedures within 8 months. The data collection period was 4 months. By short-time Fourier transform, we extracted 25 signal features and 6 acoustic features from the recorded blood flow sounds. Moreover, we developed the time-adaptive ensemble learning algorithm (TAELA) to create an AI-based regression model for estimating the degree of AVF occlusion. This model can assist physicians in predicting the optimal timing for PTA procedures. Experimental results indicated that the TAELA outperformed adaptive and gradient boosting regression algorithms in terms of the coefficient of determination (R^2) and that the TAELA model did not exhibit overfitting. The developed audio recording device and TAELA

[*]Corresponding author: e-mail: chiuyiwen@gmail.com;
[**]Corresponding author: e-mail: yjjchen@nkust.edu.tw
[†]Equal contributors
https://doi.org/10.18494/SAM5825

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

enabled the effective and accurate identification of the degree of AVF occlusion in three hemodialysis patients. The overall system can serve as a portable, noninvasive, and user-friendly clinical diagnostic tool for assisting physicians in optimizing the interval between PTA procedures, thereby reducing surgical frequency for hemodialysis patients while ensuring that they do not experience complications associated with delayed dialysis.

1. Introduction

More than 90% of patients with end-stage renal disease require dialysis to sustain life, with hemodialysis being the predominant treatment modality. Before a patient undergoes hemodialysis, vascular access must be established, and this is commonly achieved by creating an arteriovenous fistula (AVF). However, dialysis treatment lasts a long time, and blood vessels often narrow over time, either from repeated needle punctures(1) or turbulent blood flow caused by high-velocity circulation.(2) The area around the AVF connection is thus prone to occlusion, necessitating the regular monitoring of the fistula's status. Currently, percutaneous transluminal angioplasty (PTA) is the main clinical intervention for AVF occlusion. This procedure involves inserting a catheter into the affected blood vessel, advancing a balloon to the site of the blockage, and inflating the balloon to dilate the narrowed region.(3)

Despite its effectiveness, PTA is an invasive procedure. Frequent PTA interventions can lead to the failure of the AVF, rendering it unusable. If the AVF becomes nonfunctional, the patient must undergo surgery to create a new fistula or rely on temporary vascular access for hemodialysis. However, delaying PTA procedures increases the risk of complications, such as acute arrhythmias, heart failure, and ischemic neuropathy,(4) posing severe threats to the patient's health and life. Therefore, a suitable clinical method for accurately predicting the degree of AVF occlusion should be developed. Such a method would help identify the optimal timing for PTA intervention, balancing the need to minimize surgical frequency while avoiding life-threatening complications.

Currently, the clinical assessment of AVF occlusion primarily relies on physical examination methods such as auscultation and palpation, which must be performed by healthcare professionals. These methods focus on evaluating the smoothness of blood flow vibration, assessing vascular pulsations, and detecting an elevated pulse rate.(5) However, such assessments are heavily dependent on the experience and expertise of medical staff. Accurately determining the degree of AVF occlusion by using the aforementioned empirical approaches is highly challenging, and the diagnostic accuracy is often low.

To determine the degree of AVF occlusion more accurately, advanced diagnostic methods—such as X-ray angiography, Doppler ultrasound, intravascular ultrasound imaging, and phonoangiography—are often required.(6,7) However, these methods require costly equipment and healthcare professionals trained to operate such equipment. Consequently, the aforementioned precise diagnostic techniques are unsuitable for the routine and real-time monitoring of AVF occlusion in hemodialysis patients.

Many researchers have explored the use of fistula blood flow sounds combined with machine learning for assessing the degree of AVF occlusion.(8,9) For instance, Wang(10) employed an electronic stethoscope to collect blood flow sounds, after which sound features were extracted and input to k-nearest neighbors and support vector machine (SVM) machine learning models, which then evaluated occlusion levels. These models achieved accuracies of 90.9 and 85.7%, respectively. Similarly, Higashi *et al.*(9) used features such as the frequency power ratio, mel-frequency cepstrum, and normalized cross-correlation coefficient in an SVM model for classifying fistula stenosis. They used the resistance index values obtained from ultrasound equipment as class labels and achieved a classification accuracy of 82.6%. Vesquez *et al.*(11) proposed the use of wavelet transform coefficients from different frequency bands as input features in the classification of blood flow sounds. Their results indicated that SVM exhibited excellent classification performance. The aforementioned studies have classified fistula occlusion levels; however, in clinical settings, predicting the percentage of occlusion, which is a continuous value, is more crucial. Classification models cannot complete this task; therefore, a suitable and robust regression model must be developed.

In response to the aforementioned requirement, we developed a handheld, noninvasive acoustic device for collecting blood flow sounds from hemodialysis patients and investigated the roles of acoustic features in assessing the degree of AVF occlusion. Moreover, a time-adaptive ensemble learning algorithm (TAELA) was designed to create an AI-based regression model for predicting the degree of AVF occlusion. Given the clinical understanding that AVF occlusion gradually worsens over time, in this study, we assumed a linear increase in the degree of AVF occlusion over time. The experimental results of this study indicated that the created model accurately predicted the degree of AVF occlusion. Thus, this model can assist healthcare professionals in making more informed decisions regarding the interval between PTA procedures.

2. Materials and Methods

We conducted the long-term monitoring of three hemodialysis patients prone to AVF occlusion. During the period from post-PTA surgery to complete occlusion, weekly blood flow sound recordings were collected prior to each dialysis session to assess the level of AVF occlusion for each patient.(9) According to Sato *et al.*, the optimal recording site for blood flow sounds is the arteriovenous anastomosis, which is also the most common site of AVF occlusion.(12) AVF occlusion is generally understood to progress gradually over time; therefore, we assumed a linear progression of occlusion. The blood flow sounds recorded immediately after PTA surgery were labeled as 0% occlusion, whereas those recorded immediately before PTA surgery were labeled as 100% occlusion. Intermediate recordings were assigned occlusion percentages linearly between these two values. A total of 9, 11, and 13 recordings were collected for Patients A, B, and C, respectively. This study was approved by the Institutional Review Board of Kaohsiung Medical University Hospital (IRB number: KMUHIRB-E(I)-20200423).

We developed a recording device for collecting blood flow sounds. This device consisted of a mobile power supply, a high-sensitivity contact microphone, a Raspberry Pi module (model: Pi4d+), and headphones (Fig. 1). The contact microphone had a sound sensitivity of −70 dB, allowing it to capture faint sounds that are inaudible to the human ear. Data collection began

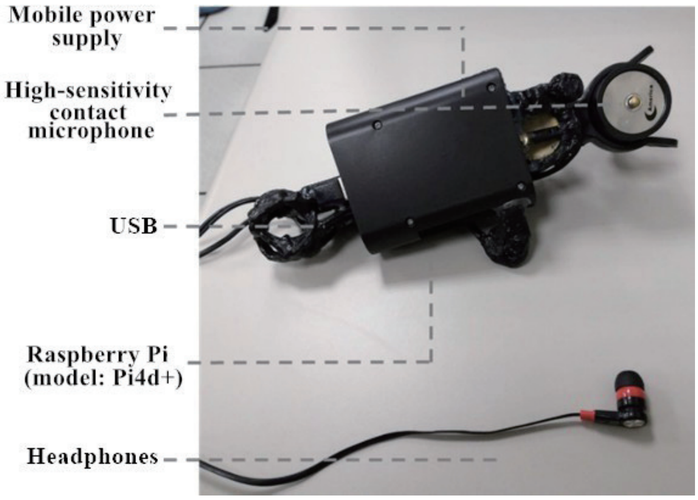

Fig. 1. (Color online) Image of the developed recording device.

after the recording device was applied to a patient's skin at the designated recording site, and the recording status was confirmed through the headphones. Once the recording was complete, the device transmitted the collected sound data to a computer through Wi-Fi for storage. Subsequently, sound features were extracted, with the recorded sounds converted into acoustic signal features that served as input for machine learning models. The operational process of the developed recording device is depicted in Fig. 2.

Araya-Salas and Smith-Vidaurre(13) identified 25 acoustic signal features that can be extracted from sound. These features are listed as follows.

1. Mean frequency: average signal frequency
2. Standard deviation of frequency: variability in frequency
3. Median frequency: middle value of the frequency distribution
4. First frequency quartile: 25th percentile of frequency values
5. Third frequency quartile: 75th percentile of frequency values
6. Interquartile frequency range: range between the first and third frequency quartiles
7. Median time: time corresponding to the median frequency
8. First quartile time: time corresponding to the first frequency quartile
9. Third quartile time: time corresponding to the third frequency quartile
10. Interquartile time range: range between the first and third quartile times
11. Skewness: asymmetry of the frequency distribution
12. Kurtosis: sharpness of the peak of the frequency distribution
13. Spectral entropy: measure of the disorder or randomness in the frequency spectrum
14. Temporary entropy: entropy calculated over temporal window
15. Entropy: overall randomness of the acoustic signal
16. Spectral flatness: measure indicating the extent to which the spectrum resembles noise
17. Average dominant frequency across the spectrogram: mean of dominant frequencies

Fig. 2. (Color online) Operational process of the developed recording device.

18. Minimum dominant frequency across the spectrogram: lowest dominant frequency
19. Maximum dominant frequency across the spectrogram: highest dominant frequency
20. Range of dominant frequencies across the acoustic signal: difference between the maximum and minimum dominant frequencies
21. Modulation index: amplitude variation of the signal
22. Dominant frequency at the start of the signal: dominant frequency at the beginning of the signal (measured on the spectrogram)
23. Dominant frequency at the end of the signal: dominant frequency at the termination of the signal (measured on the spectrogram)
24. Slope of change in dominant frequency over time: rate of change in dominant frequency over time
25. Mean peak frequency: average peak frequency of the signal

The aforementioned features are essential for characterizing and analyzing acoustic signals in various applications, including biomedical signal analysis and machine learning.

In this study, we developed a TAELA-based regression model that predicts the degree of AVF occlusion and can thus assist physicians in determining the optimal time for patients to undergo PTA. Adaptive boosting (AdaBoost) regression(14) and gradient boosting regression(15) algorithms exhibit good fitting performance; thus, these algorithms were combined to develop the TAELA. The TAELA operates as follows. The AdaBoost and gradient boosting regression algorithms are used to process the first and second parts of the recorded audio, respectively, to assess the degrees of AVF occlusion corresponding to these parts. Thus, the developed TAELA leverages the strengths of the AdaBoost and gradient boosting regression algorithms at different time intervals to enhance its prediction accuracy.

3. Results and Discussion

Four evaluation metrics were employed to assess the performance of the developed regression model: the mean square error (*MSE*),[16,17] mean absolute error (*MAE*),[18,19] root mean square error (*RMSE*),[18,19] and coefficient of determination (R^2).[20–23] The R^2 value of a model should be as high as possible, whereas its *MSE*, *MAE*, and *RMSE* values should be as low as possible. A total of 80% and 20% of the collected acoustic feature dataset were used for training and testing, respectively. This dataset contained data on 25 features extracted from the audio recordings of the three patients involved in this research. Python (version 3.9.12) was the primary programming language used in this study.

The evaluation results of the developed TAELA for the three patients are presented in Table 1 and shown in Fig. 3. The experimental results indicated that the R^2 values of the TAELA for

```
Algorithm: Time-adaptive ensemble learning algorithm
Input: Recorded acoustic signal features
Output: Degree of AVF occlusion
1. sound(t): Signal features recorded at week i
2. t: Number of weeks after PTA
3. adaboost: AdaBoost regression model
4. gradientboost: Gradient boosting regression model
if (t ≥ 0.5) then
    adaboost(sound(t))
    return adaboost(sound(t))
else
    gradientboost(sound(t))
    return gradientboost(sound(t))
end if
```

Table 1
Evaluation results of different regression models for Patients A, B, and C.

Patient	Regression model	*MSE*	*RMSE*	*MAE*	R^2
A	AdaBoost	0.05	0.21	0.18	0.59
	Gradient Boost	0.05	0.22	0.16	0.56
	TAELA	0.02	0.14	0.08	0.82
B	AdaBoost	0.05	0.23	0.19	0.40
	Gradient Boost	0.05	0.23	0.17	0.42
	TAELA	0.01	0.11	0.06	0.88
C	AdaBoost	0.02	0.15	0.09	0.79
	Gradient Boost	0.02	0.13	0.08	0.85
	TAELA	0.01	0.10	0.05	0.91

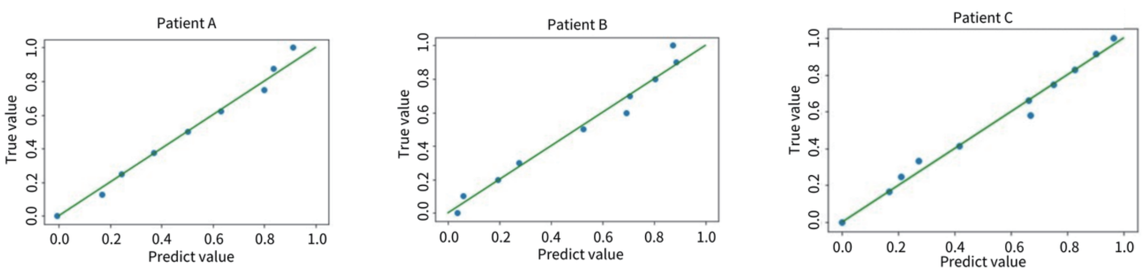

Fig. 3. (Color online) Predictions of TAELA for Patients A ($R^2 = 0.82$), B ($R^2 = 0.88$), and C ($R^2 = 0.91$).

Patients A, B, and C were 0.82, 0.88, and 0.91, respectively. These values were higher than those achieved using the AdaBoost regression algorithm alone (R^2 values of 0.59, 0.40, and 0.79 for Patients A–C, respectively) and the gradient boosting regression algorithm alone (R^2 values of 0.56, 0.42, and 0.85 for Patients A–C, respectively). Moreover, the developed algorithm did not exhibit overfitting. The aforementioned results indicated that the TAELA accurately determined the degree of AVF occlusion from the blood flow sounds recorded by the developed device. Thus, the combination of the developed device and TAELA serves as a practical clinical system for the accurate estimation of the degree of AVF occlusion in hemodialysis patients.

4. Conclusions

In this study, we developed a device for recording blood flow sounds in AVFs in hemodialysis patients. This device was used to record blood flow sounds from three hemodialysis patients before and after PTA. Subsequently, the TAELA was developed and used to process the data recorded by the developed device to predict the degree of AVF occlusion. The results of this study indicated that the R^2 values of the TAELA exceeded those of the AdaBoost and gradient boosting regression algorithms. Thus, the proposed TAELA can accurately predict the level of AVF occlusion at the time of recording blood flow sounds. The combination of the developed device and TAELA enables the portable, noninvasive, and accurate determination of the level of AVF occlusion. Clinicians can use the determined AVF occlusion to identify suitable timings of PTA interventions for hemodialysis patients, thereby minimizing surgical frequency for these patients while ensuring that they avoid the complications associated with delayed dialysis treatment.

Acknowledgments

This work was supported by the National Science and Technology Council, Taiwan, under Grant nos. MOST 110-2221-E-037-005 and NSTC 112-2221-E-037-004-MY3. The authors also thank the NKUST-KMU joint research project (Grant no. NKUSTKMU-112-KK-009), the NSYSU-KMU joint research project (Grant no. NSYSU-KMU-114-P06), and KMU-TC114A06-1.

References

1 T. Lee, J. Barker, and M. Allon: Am. J. Kidney Diseases **47** (2006) 1020. https://doi.org/10.1053/j.ajkd.2006.02.181
2 A. Brahmbhatt, A. Remuzzi, M. Franzoni, and S. Misra: Kidney Int. **89** (2016) 303. https://doi.org/10.1016/j.kint.2015.12.019
3 J. Schmidli, M. K. Widmer, C. Basile, G. de Donato, M. Gallieni, C. P. Gibbons, P. Haage, G. Hamilton, U. Hedin, and L. Kamper: Eur. J. Vasc. Endovasc. Surg. **55** (2018) 757. https://doi.org/10.1016/j.ejvs.2018.02.001
4 R. Stolic: Med. Princ. Pract. **22** (2013) 220. https://doi.org/10.1159/000343669
5 L. Salman and G. Beathard: Clin. J. Am. Soc. Nephrol. **8** (2013) 1220. https://doi.org/10.2215/CJN.00740113
6 A. Asif, F. N. Gadalean, D. Merrill, G. Cherla, C. D. Cipleu, D. L. Epstein, and D. Roth: Kidney Int. **67** (2005) 1986. https://doi.org/10.1111/j.1523-1755.2005.00299.x
7 J. Gilmore: Nephrol. Nurs. J. **33** (2006) 487.
8 W.-L. Chen, C.-H. Lin, and C.-D. Kan: Adv. Technol. Innovation **2** (2017) 46.

9 D. Higashi, K. Tanaka, S. Shin, K. Nishijima, and K. I. Furuya: Proc. of the 12th Int. Conf. Complex, Intelligent, and Software Intensive Systems (CISIS-2018) (2019) 884. https://doi.org/10.1007/978-3-319-93659-8_81
10 Y. Y. Wang, Application of Empirical Mode Decomposition and Machine Learning to Arteriovenous Graft Occlusion Analysis for Hemodialysis Patients (National Cheng Kung University, Tainan City, Taiwan, 2018).
11 P. O. Vesquez, M. M. Marco, and B. Mandersson: 2009 Annual Int. Conf. IEEE Engineering in Medicine and Biology Society (2009) 1298. https://doi.org/10.1109/IEMBS.2009.5332592
12 T. Sato, K. Tsuji, N. Kawashima, T. Agishi, and H. Toma: J. Artif. Organs **9** (2006) 97. https://doi.org/10.1007/s10047-005-0327-7
13 M. Araya-Salas and G. Smith-Vidaurre: Methods Ecol. Evol. **8** (2017) 184. https://doi.org/10.1111/2041-210X.12624
14 L. Gao, F. Gao, X. Guan, D. Zhou, and J. Li: 6th World Congr. Intelligent Control and Automation (2006) 4400. https://doi.org/10.1109/WCICA.2006.1713209
15 D. A. Otchere, T. O. A. Ganat, J. O. Ojero, B. N. Tackie-Otoo, and M. Y. Taki: J. Pet. Sci. Eng. **208** (2022) 109244. https://doi.org/10.1016/j.petrol.2021.109244
16 O. Köksoy: Appl. Math. Comput. **175** (2006) 1715. https://doi.org/10.1016/j.amc.2005.09.016
17 Timothy O. Hodson, Thomas M. Over, and S. S. Foks: J. Adv. Model. Earth Syst. **13** (2021) e2021MS002681. https://doi.org/10.1029/2021MS002681
18 T. Chai and R. R. Draxler: Geosci. Model Dev. **7** (2014) 1247. https://doi.org/10.5194/gmd-7-1247-2014
19 T. O. Hodson: Geosci. Model Dev. **15** (2022) 5481. https://doi.org/10.5194/gmd-15-5481-2022
20 O. Renaud and M.-P. Victoria-Feser: J. Stat. Plann. Inference **140** (2010) 1852. https://doi.org/10.1016/j.jspi.2010.01.008
21 D. Zhang: Am. Stat. **71** (2017) 310. https://doi.org/10.1080/00031305.2016.1256839
22 L. Sun, Z. Yang, N. Pan, S. Chen, Y. He, and J. Yang: Int. J. Eng. Technol. Innovation **14** (2024) 451. https://doi.org/10.46604/ijeti.2024.13621
23 W. Wang, S. S. Ngu, M. Xin, R. Liu, Q. Wang, M. Qiu, and S. Zhang: Int. J. Eng. Technol. Innovation **14** (2024) 271. https://doi.org/10.46604/ijeti.2024.13387