Journal of Multidisciplinary Healthcare

Dovepress
Taylor & Francis Group

Open Access Full Text Article

ORIGINAL RESEARCH

Artificial Intelligence Based Clustering Algorithm for Pulse Diagnosis

Junsuk Kim[1], Won-Joon Koh[2], Heeyoung Moon[3], Su Hyun Lim[4], Minsoo Kim[4], HeeJung Kang[5], Hyeongsuk Ryu[1,6], In-Seon Lee[4]

[1]School of Information Convergence, Kwangwoon University, Seoul, Republic of Korea; [2]Department of Korean Medicine, Graduate School, Kyung Hee University, Seoul, Republic of Korea; [3]Department of Meridian and Acupoints, College of Korean Medicine, Semyung University, Jecheon, Republic of Korea; [4]Department of Meridian and Acupoints, College of Korean Medicine, Kyung Hee University, Seoul, Republic of Korea; [5]DAEYOMEDI Co. Ltd., Ansan, Republic of Korea; [6]Department of Neurology, Seoul National University Bundang Hospital, Seongnam, Republic of Korea

Correspondence: In-Seon Lee, Department of Meridian and Acupoints, College of Korean Medicine, Kyung Hee University, Dongdaemun-Gu, Seoul, 02447, Republic of Korea, Tel +82-2-961-2204, Email inseon.lee@khu.ac.kr

Background: In traditional medicine, pulse palpation is a unique diagnostic technique focusing on identifying patterns of symptoms through subjective assessment of bio-signals. However, its reliability and objectivity have been questioned. We developed an artificial intelligence-based algorithm for clustering doctors' diagnostic results using unsupervised clustering techniques on pulse waveform signals.

Methods: Raw pulse signals were recorded from both wrists of healthy individuals and were then analyzed, with diagnoses provided by a Korean Medicine doctor. To measure pairwise pulse similarity, Dynamic Time Warping (DTW) was used, and Multidimensional Scaling (MDS) was applied for dimensionality reduction, enabling the clustering and validation of data-driven diagnostic patterns.

Results: Our findings revealed discrepancies between traditional pulse diagnosis and automated diagnoses, yet the clustering algorithm showed high alignment between data-driven groupings and expert diagnoses. Notably, pulse signals from the left wrist had better alignment in several categories than those from the right wrist (cosine similarity: left hand 0.56 ± 0.13; right hand 0.54 ± 0.15). The "Floating-Sinking" pattern was particularly identifiable, achieving the highest Cosine similarity (0.83).

Conclusion: The results suggest significant alignment between data-driven pattern identification and expert diagnoses, especially for the "Floating-Sinking" pattern. Further refinement with diverse populations is necessary, but data-driven diagnostic tools hold potential for standardizing and quantifying traditional pulse diagnosis, moving it toward a scientifically robust practice.

Trial Registration: Clinical Research Information Service KCT0007655 (registered on 2024-02-29).

Keywords: pulse diagnosis, pulse waveforms, traditional medicine, artificial intelligence, pattern identification

Introduction

Diagnosis and prognosis are critical components of the medical process, as treatment and follow-up management strategies depend on the accurate diagnosis of a disease. In traditional Eastern Asia medicine, such as Traditional Chinese Medicine and Korean Medicine, the focus is on identifying patterns of symptoms based on overall health conditions, which include disease-related symptoms (eg, gastrointestinal symptoms, pain characteristics, etc.) and other lifestyle factors (eg, working hours, sleep patterns, constitution, etc.), as well as subjective experiences that may not be detected by diagnostic tools like endoscopy or blood tests. This approach is known as pattern identification, and in Korean medicine, for instance, the diagnoses process is conducted through four examinations: inspection (observation), listening and smelling, questioning, and palpation. However, diagnostic methods using subjective assessment like tongue diagnosis, pulse diagnosis, and abdominal diagnosis, lack standardization as diagnostic protocols in clinics still rely heavily on doctors' subjective feelings and interpretations. Among them, the pulse palpation is one of the most unique diagnostic techniques. It involves the subjective assessment of bio-signals and the interpretation of the sensations of the pulse and beats delivered to doctors' fingertips, based on traditional theories and empirical experiences. Pulse diagnosis,

Received: 2 July 2025
Accepted: 23 November 2025
Published: 3 December 2025

in particular, is fundamental in traditional medicine for identifying health conditions such as Deficiency-Excess (energy levels) and Cold-Heat patterns in patients. However, doctors depend significantly on their tactile perception for pulse diagnosis, and various medical sects advocate different methods for palpation and interpretation, resulting in variability and challenges in achieving objective assessments.[1,2]

Recent advances in the measurement and analysis methods of various bio-signals in medicine have led to the increased popularity and medical significance of interpreting them. For example, pulse wave signals, generated by radial artery pulsations, reflect hemodynamic changes and provide objective bio-signal data to researchers and clinicians. Technological advancements have led to the development of pulse diagnostic devices that analyze variables such as power spectrum, signal amplitude, frequency, regularity, and volume. In particular, the measurement of pulse signals and the analysis of pulse wave signals are increasingly being utilized for the diagnosis and monitoring of cardiovascular and system diseases like diabetes, thereby expanding their clinical applications.[3,4] In addition, recent studies have explored artificial intelligence (AI) techniques to analyze time-series data of pulse wave, aiming to extract clinically meaningful information and provide objective interpretations of traditional pulse patterns with significant prediction accuracy.[3–6]

To bridge the gap between traditional and modern diagnosis methods and explore the evolution of diagnostic techniques, we aimed to develop an AI-algorithm capable of clustering doctors' diagnostic results using unsupervised clustering techniques based on pulse waveform signals. Ultimately, the waveform that shows the highest degree of agreement among the ten types can be considered the most effective for predicting diagnoses, potentially allowing us to develop a traditional medicine-based medical health check-up program. To achieve this goal, we recorded raw pulse signals from both wrists of a healthy population, had a Korean Medicine doctor diagnose their pulse patterns, and developed and validated AI-algorithms using Dynamic Time Warping (DTW) and Multidimensional Scaling (MDS). DTW is an algorithm designed to measure the similarity between two time sequences that may vary in timing, characterized by its ability to flexibly align time-series data to capture intrinsic variations in pulse patterns.[7,8] In this study, DTW is used to evaluate the similarity between the pulse waveforms of two different participants. MDS is then applied to the DTW distance matrix to visualize the relational structure between participants in a reduced two-dimensional space.[9] The MDS algorithm seeks a configuration of points in two-dimensional space where the distances between points correspond closely to the original DTW distances between participants.

Methods

Recruitment

Nineteen healthy participants were recruited through Kyung Hee University's online community and promotional posters on campus. After confirming the inclusion and exclusion criteria via phone and email, participants were given a brief explanation of the study. Those who agreed to participate visited the Korean Medicine department at Kyung Hee University and all participants provided written consent prior to enrolling in the trial. To ensure the accuracy of the data collected during the experiment, participants were instructed to avoid overeating, excessive alcohol consumption, and medications that could affect pulse waves (eg, anticoagulants, vasodilators, antihypertensives, etc.) starting the day before their participation. This study was approved by the Kyung Hee University Institutional Review Board (KHSIRB-22-058) and was registered with the Clinical Research Information Service (CRIS number: KCT0007655; registered on 2024-02-29). All experiments were performed in accordance with Helsinki Declaration.

Inclusion criteria included healthy adults aged between 19 and 40 years. Exclusion criteria encompassed participants with a history of cardiovascular disorders, infectious diseases, diabetes, pain disorders, neurological disorders, psychiatric disorders, gynecological disorders, those taking medications that could affect the results of the experiment, individuals with skin diseases or sensory abnormalities at the pulse measurement site, and students, researchers, or anyone related to the principal investigator and researchers of this study.

Data Collection

The experiment consisted of two parts: 1) pulse diagnosis performed by a Korean Medicine doctor, and 2) pulse waveform signal recording using the DMP-Life device (DAEYOMEDI Co., Ltd., Ansan, South Korea). Participants were relaxed in a supine position, and the pulse data were recorded on both wrists, up to three times each in case of device malfunction, for 60 seconds. We also collected basic health data, including weight, height, and blood pressure, along with psychiatric status using questionnaires to confirm the participants' health conditions.

Questionnaires and Pulse Diagnosis

After measuring height, weight, and blood pressure, participants were asked to fill out the Korean versions of the State-Trait Anxiety Inventory (STAI),[10] Beck Depression Inventory-II (BDI-II),[11] 36-Item Short Form (SF-36),[12] and EuroQol-5D (EQ-5D).[13] Following the completion of the questionnaires, a Korean Medicine doctor with five years of clinical experience assessed the overall health status of the participants. The doctor conducted a detailed inquiry about the participants' basic symptoms and daily habits and performed pulse diagnosis, tongue diagnosis, and abdominal diagnosis. The pulse diagnosis protocol involves palpating the radial artery on both wrists to evaluate the strength, depth, speed, and smoothness of the pulse. The strength of the pulse was assessed by the intensity felt by the doctor's fingertips, the depth by the pressure required to detect the pulse, the speed by the pulse rate, and the smoothness by the evenness perceived by the doctor. Pulse characteristics were determined subjectively for each participant and were not based on objective measurements, and they include six diagnostic groupings: "Deficiency-Excess", "Cold-Heat", "Strong-Weak", "Floating-Sinking", "Slow-Rapid", "Slippery-Rough", each of which has three categories, including a "Normal" group. The diagnostic grouping results were utilized as predictive outcomes for the AI-algorithms. After completing the diagnostic process, the doctor performed syndrome differentiation. The doctor diagnosed excess or deficiency based on the participant's body type, strength of voice, digestive function, intensity of basic symptoms, chronicity of symptom onset, and pulse strength. In this paper, we only analyzed pulse diagnosis and pulse waveform data, and other results were published in our previous article.[14]

Pulse Waveform Measurement

Raw pulse waveform data from the left and right wrists of the participants were collected in 20 participants using the DMP-Life device (DAEYOMEDI Co., Ltd., Ansan, South Korea), a radial artery tonometry device. A bracelet equipped with a pressure sensor cartridge was placed on the participant's wrist over the radial artery. The sensor in the DMP-Life features a multichannel array with five piezoresistive semiconductor transducers. This setup enables the capture of pulse waveforms from five locations along and adjacent to the artery. Signal LEFT 1–5 was measured from the left wrist, while Signal RIGHT 1–5 was measured from the right wrist. The actuator applied pressure to the radial artery automatically, following a predefined algorithm to partially flatten the artery.[15] The device analyzed the pulse's strength, depth, speed, and smoothness, while also providing raw pulse signals. Participants rested for five minutes before the pulse signal measurement for stabilization, which then took an additional five minutes with them remaining comfortably in a supine position.

Analysis

Peak Detection and Normalization

To prepare the pulse signal data for analysis, several preprocessing steps were undertaken. First, the "scipy.signal.find_peaks" function from the SciPy library was utilized to identify peaks within each pulse waveform.[16] Total 100 peaks were extracted from each participant's waveform, while the time-series data lengths varied slightly among participants. To mitigate the impact of amplitude differences between participants, the pulse waveforms for each participant were then normalized using z-score transformation, rescaling the data to have a mean of zero and a standard deviation of one. Specifically, for each data point x_i, the normalized value z_i was calculated as: $z_i = (x_i - \mu)/\sigma$, where μ is the mean and σ is the standard deviation of the waveform data. All 10 pulse waveforms (five from each wrist) were processed separately to account for potential physiological differences.

Pairwise DTW Calculation

Pairwise DTW distances were computed between all participants for each waveform, resulting in 171 unique pairs (${}_{19}C_2$= 171). For example, from the time-series data of "waveform 1", we selected pairs of two participants and calculated the DTW distance, which represents the similarity between their "waveform 1" pulse waveforms. The DTW distance between two time series $X = [x_1, x_2, \ldots, x_N]$ and $Y = [y_1, y_2, \ldots, y_M]$ is calculated by finding the optimal alignment that minimizes the cumulative distance:

$$\mathrm{DTW}\,(X, Y) = min_{\pi}\left\{\sum_{(i,j)\in\pi} d\left(x_i, y_j\right)\right\} \tag{1}$$

where π is the warping path and $d(x_i,y_j)$ is the distance between points x_i and y_j. While the time-series data lengths varied slightly among participants, this was acceptable because the DTW algorithm is robust to temporal misalignments. By non-linearly warping the time axes, DTW enables accurate alignment of biological signals such as pulse waveforms, which naturally exhibit variations in timing and length. Unlike simpler measures like Euclidean distance, DTW allows flexible alignment of similar waveform features that may occur at slightly different time points, thereby improving the reliability of inter-participant similarity measurement.[7,17] The computed DTW distances were assembled into symmetric distance matrices, each with dimensions 19 by 19, where each element represents the DTW distance between a pair of participants for a given waveform. As the dataset included ten pulse waveforms, comprising five measurements from each wrist, a total of ten distance matrices were constructed to represent the pairwise similarities among the nineteen participants for each individual waveform.

Dimensionality Reduction and Diagnostic Grouping

MDS was utilized to project the DTW distance matrices onto a two-dimensional space.[9] Specifically, MDS seeks to position each participant as a point in a lower-dimensional space such that the Euclidean distances between points approximate the original DTW distances d_{ij} as closely as possible, thereby preserving the overall structure of pairwise dissimilarities in the data. This is achieved by minimizing the following stress function:

$$\text{Stress} = \sum_{i<j}(d_{ij} - \parallel y_i - y_j \parallel)^2 \tag{2}$$

where $\|y_i - y_j\|$ is the Euclidean distance between points y_i and y_j in the lower-dimensional space. We selected classical MDS for its ability to preserve global distance relationships and provide deterministic solutions without requiring initialization or tuning of learning rates. Compared to other nonlinear methods such as t-Distributed Stochastic Neighbor Embedding (t-SNE), MDS was preferred because it allows direct optimization of distance preservation between original DTW values and the projected coordinates. Given the modest number of participants ($n = 19$), the computational cost of MDS was minimal and scalability was not a concern. Clustering analysis was then performed using the K-means algorithm on these two-dimensional MDS coordinates for each waveform, allowing for visual assessment of clustering patterns and similarities based on their pulse waveforms. The K-means algorithm partitions the data into k clusters by minimizing the within-cluster sum of squares:

$$argmin_{(\mathrm{C})}\sum_{j=1}^{k}\sum_{x_i\in \mathrm{Cj}}\left|\left|x_i - \mu_j\right|\right|^2 \tag{3}$$

where C_j is the set of points in cluster j and μ_j is the centroid of cluster j. The number of clusters was set to three (ie, $k = 3$), based on prior knowledge from diagnostic groupings provided by the Korean Medicine doctor, which include six diagnostic groupings: "Deficiency-Excess", "Cold-Heat", "Strong-Weak", "Floating-Sinking", "Slow-Rapid", "Slippery-Rough", each of which has three categories, including a "Normal" group.

Clustering Evaluation via Cosine Similarity

To assess the effectiveness of the clustering results, the Cosine similarity metric was used to quantify the agreement between the K-means clustering results and the actual diagnostic groups assigned by the Korean Medicine doctor. We encoded the diagnostic group labels and cluster assignments as vectors and computed the Cosine similarity between them, a metric ranging from −1 to 1 where higher values indicate higher similarity. The Cosine similarity is calculated as:

$$cos(\theta) = \frac{u \cdot v}{\parallel u \parallel\parallel v \parallel} \tag{4}$$

where $u \cdot v$ is the dot product of the two vectors, and $\|u\|$ and $\|v\|$ are their magnitudes (Euclidean norms). Cosine similarity was selected as the evaluation metric due to its ability to quantify the angular similarity between two vectors independently of their magnitudes, making it suitable for comparing encoded categorical vectors such as cluster assignments and diagnostic group labels. In contrast to metrics like accuracy or the Adjusted Rand Index, which rely on exact label correspondence and may be sensitive to label distribution assumptions, Cosine similarity offers a continuous, geometry-based measure of alignment. This characteristic is advantageous in our setting, where class imbalance may exist. A higher Cosine similarity implies that the clustering based on pulse waveforms aligns well with the diagnostic groupings, suggesting that this waveform is effective in predicting diagnoses (Figure 1).[18]

Results

Demographic Characteristics of Participants

A total of 41 people participated in this experiment. Data from 40 participants were analyzed, excluding one participant, 24 year-old male, who showed BDI-II score over 25. Of the 40 participants, 19 were male (average age ± standard deviation: 25.26 ± 2.61 years) and 21 were female (22.62 ± 1.62 years) (Table 1). Raw pulse waveform data were collected from the left and right wrists of 20 out of 40 participants (10 male, aged 25.33 ± 5.21 years). In addition, data from one participant were excluded from the analysis due to low quality of the signal.

The SF-36 questionnaire produced scores for nine subcategories: physical functioning (mean ± standard deviation: 90.25 ± 17.46), role limitations due to physical health (90.47 ± 18.27), role limitations due to emotional problems (86.67 ± 21.31), energy/fatigue (55.94 ± 19.96), emotional well-being (75.13 ± 13.99), social functioning (86.88 ± 13.96), pain (81.73 ± 24.17), general health (66.00 ± 20.92), and health change (57.69 ± 22.75). The score for the EQ-5D questionnaire, which assesses quality of life, was 0.98 ± 0.04, with a score closer to 1 indicating better quality of life. The STAI scores were 37.08 ± 6.45 for trait anxiety and 36.67 ± 8.91 for state anxiety, indicating no participants had significantly high anxiety levels according to the questionnaire criteria (trait anxiety score ≥ 54, state anxiety score ≥ 52). The BDI-II score was 4.2 ± 3.4. The results suggest that the participants were suffering from fatigue and a moderate level of anxiety. However, their quality of life, pain, and depression levels were within a healthy range.

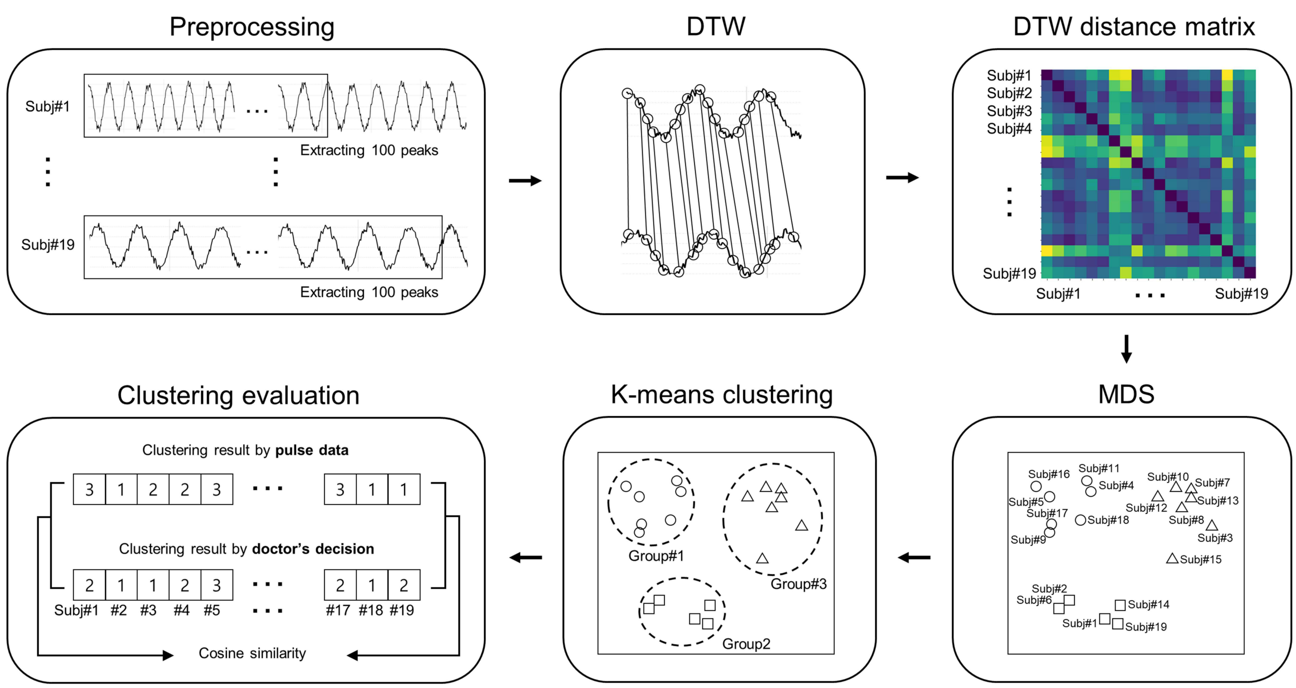

Figure 1 Workflow of pulse waveform analysis and clustering evaluation. This figure schematically outlines the entire analytical workflow, beginning with Preprocessing, which involves extracting 100 peaks and normalizing the data. Next, Dynamic Time Warping is applied to calculate pairwise distance matrices between participants, and the resultant matrix is projected into a two-dimensional space via Multidimensional Scaling (MDS) for visualization. K-means Clustering is then performed on the MDS coordinates to identify data-driven grouping patterns, with the number of clusters fixed at k = 3 based on the structure of the doctor's pulse diagnostic categories. Finally, the cluster assignments are assessed against the Korean Medicine doctor's diagnoses using Cosine Similarity to quantify the overall alignment.

Table 1 Demographic Characteristics of Participants

		Number or Mean ± Standard Deviation
Gender	Male	19
	Female	21
Age (years)	Male	25.26 ± 2.61
	Female	22.62 ± 1.62
Height (meters)	Male	1.76 ± 0.05
	Female	1.64 ± 0.04
Weight (kg)	Male	70.39 ± 9.58
	Female	56.6 ± 6.79
Blood pressure (mmHg)	Systolic	110.4 ± 12.04
	Diastolic	68.3 ± 9.46
SF-36	Physical function	90.25 ± 17.46
	Role limitations (physical)	90.47 ± 18.27
	Role limitations (emotional)	86.67 ± 21.31
	Energy/Fatigue	55.94 ± 19.96
	Emotional well-being	75.13 ± 13.99
	Social functioning	86.88 ± 13.96
	Pain	81.73 ± 24.17
	General health	66 ± 20.92
	Health change	57.69 ± 22.75
EQ-5D		0.98 ± 0.04
State-Trait Anxiety Inventory (Trait)		37.08 ± 6.45
State-Trait Anxiety Inventory (State)		36.67 ± 8.91
Beck Depression Inventory		4.2 ± 3.4

Abbreviations: EQ_5D, EuroQol-5D; SF-36, 36-Item Short Form.

Concordance Between Doctor and Device in Pulse Diagnosis

The doctor's pulse diagnosis results were consistent between the right and left hands of the patients. For pulse strength, 14 were diagnosed as normal, 17 as weak, and 9 as strong. For pulse depth, 1 was diagnosed as normal, 7 as floating, and 32 as sinking. For pulse speed, 21 were diagnosed as normal, 9 as rapid, and 10 as slow. The pulse diagnostic device showed differing results between the right and left hands of the patients. Combining the diagnoses from both hands, there were 35 strong pulses, 18 weak pulses, and 22 normal pulses. For pulse depth, there were 32 sinking pulses, 4 floating pulses, and 39 normal pulses. For pulse speed, there were no rapid pulses, 29 slow pulses, and 46 normal pulses. For pulse smoothness, there were 64 normal pulses, 7 rough pulses, and 4 slippery pulses. The diagnostic agreement of the pulse diagnostic device with the doctor's diagnosis for pulse strength was 30.77% for the right hand and 44.44% for the left hand, for pulse depth was 41.03% for the right hand and 36.11% for the left hand, for pulse speed was 46.15% for the right hand and 38.89% for the left hand, and for pulse smoothness was 51.28% for the right hand and 47.22% for the left hand.

Correspondence Between Clustering Results and Diagnostic Groups

The DTW distance matrices and MDS projections for the left and right wrists are presented in Figure 2. The results showed that the clustering patterns varied slightly between the left and right wrists, indicating potential physiological differences between the two. To evaluate the alignment between the data-driven clustering results and the diagnostic groupings assigned by the Korean Medicine doctor, Cosine similarity metrics were computed. These metrics quantify the degree of similarity, with higher values indicating stronger alignment. Table 2 presents the Cosine similarities between data-based groupings and expert diagnoses. The Cosine similarity values, ranging from 0.29 to 0.84, indicate variations in alignment across different waveforms. Specifically, the table compares the clustering results derived from ten separate pulse waveforms (five from the left wrist and five from the right wrist) against the six diagnostic categories assigned by the Korean Medicine doctor. Out of the 30 total paired comparisons (5 channels × 6 categories), the Left wrist demonstrated higher Cosine similarity than the corresponding Right wrist channel in 18 cases. Furthermore, the most significant difference in alignment between the wrists occurred in the "Strong-Weak" category for Channel 1, where LEFT 1 achieved a significantly higher Cosine similarity of 0.69 compared to RIGHT 1 at 0.39.

The evaluation of Cosine similarity metrics revealed differences in diagnostic alignment between pulse waveforms derived from the left and right wrists. For the left wrist, the diagnostic categories of "Strong-Weak", "Floating-Sinking", and "Slippery-Rough" demonstrated Cosine similarity values exceeding 0.5 across all five waveforms, suggesting that

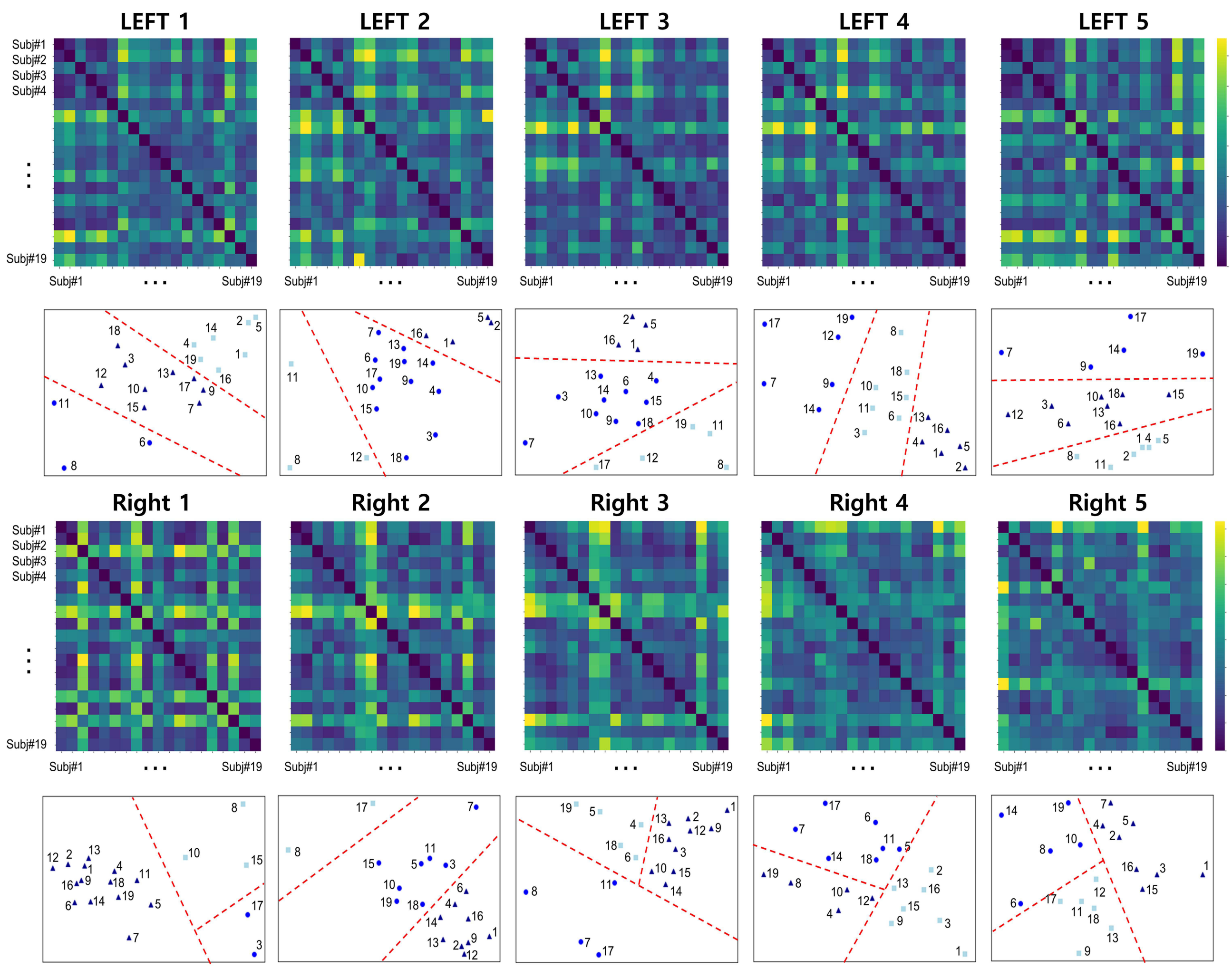

Figure 2 DTW distance matrices and MDS projections for left wrist and right wrist. Dynamic time warping (DTW) distance matrices from five pulse waveform measurements acquired at the left wrist (LEFT 1–5) and right wrist (RIGHT 1–5) are shown alongside their corresponding two-dimensional MDS projections with clustering results. Red dashed lines denote the boundaries separating the identified clusters.

Table 2 Cosine Similarity Values for Correspondence Between AI-Based Clustering Results and Doctor's Diagnostic Results

Doctor's Diagnosis Pattern or Pulse Diagnosis	Deficiency-Excess	Cold-Heat	Strong-Weak	Floating-Sinking	Slow-Rapid	Slippery-Rough
LEFT 1	0.55	0.40	0.69	0.66	0.52	0.54
LEFT 2	0.64	0.39	0.69	0.84	0.45	0.56
LEFT 3	0.51	0.49	0.53	0.55	0.40	0.59
LEFT 4	0.66	0.34	0.64	0.81	0.53	0.62
LEFT 5	0.43	0.46	0.75	0.65	0.37	0.53
RIGHT 1	0.48	0.53	0.39	0.50	0.29	0.29
RIGHT 2	0.60	0.39	0.59	0.61	0.47	0.46
RIGHT 3	0.67	0.65	0.59	0.78	0.53	0.49
RIGHT 4	0.59	0.35	0.77	0.84	0.58	0.73
RIGHT 5	0.62	0.32	0.48	0.72	0.47	0.33

Notes: Higher Cosine similarity values indicate stronger consistency between clustering-based groupings and Korean Medicine doctor's diagnoses. LEFT: clustering model based on the pulse signal measured from the left wrist; RIGHT: clustering model based on the pulse signal measured from the right wrist.

the clustering based on pulse waveforms measured from the left wrist aligns well with the diagnostic groupings (Cosine similarity for left wrist: 0.56 ± 0.13; right wrist: 0.54 ± 0.15). Additionally, "Deficiency-Excess" achieved similar values for four out of five waveforms. In contrast, the right wrist showed consistent alignment only with the "Floating-Sinking" category, achieving Cosine similarity values above 0.5 across all five waveforms.

Examining the results by waveform, LEFT 1 showed Cosine similarity values above 0.5 for all five diagnostic categories, including "Deficiency-Excess", "Strong-Weak", "Floating-Sinking", "Slow-Rapid", and "Slippery-Rough", indicating its broad agreement. Similarly, RIGHT 3 showed high alignment across five categories, encompassing "Deficiency-Excess", "Cold-Heat", "Strong-Weak", "Floating-Sinking", and "Slow-Rapid". Examining the results by category, "Floating-Sinking" consistently exhibited strong alignment, achieving Cosine similarity values above 0.5 across all ten waveforms.

The strongest correspondence between clustering results and expert diagnoses was observed in specific waveform-diagnostic pairs. RIGHT 4 with "Floating-Sinking" achieved the highest Cosine similarity value 0.83), followed by LEFT 2 with "Floating-Sinking" 0.838 and LEFT 4 with "Floating-Sinking" 0.814.

Discussion

In this study, we measured pulse waveform signals using a pulse diagnosis device and compared the results with pulse patterns identified by a trained Korean Medicine doctor. Additionally, we applied DTW and MDS to explore whether the raw pulse signals could be used to predict the pulse patterns identified by the doctor using an AI-based clustering algorithm. The results indicated that there were notable discrepancies between the doctor's pulse diagnosis and the device's readings, particularly in pulse strength, depth, and speed, with diagnostic agreement percentages ranging from 30.77% to 51.28% depending on the hand and pulse characteristic. Furthermore, the analysis of AI-based clustering results identified pulse signals that exhibited relatively high alignment between data-driven groupings and expert diagnoses. For instance, pulse signals from the left wrist demonstrated stronger alignment in several diagnostic categories compared to those from the right wrist. Moreover, the "Floating-Sinking" pattern emerged as the most classifiable using our algorithm, as indicated by higher Cosine similarity values.

Previous studies have successfully applied DTW and MDS to analyze physiological signals, demonstrating the effectiveness of these methods in extracting meaningful information from time-dependent biological signals.[19] For example, DTW has been used in photoplethysmography signals analysis for arrhythmia detection and classification.[20] Moreover, MDS has been utilized to visualize complex EEG data, aiding in the interpretation of brain activity patterns.[21] We found that the algorithm based on DTW and MDS methods could be effectively applied to pulse signals. Additionally, diagnostic pulse patterns traditionally used in medicine can be predicted and clustered by AI algorithms. However, there is still room for improvement, and there are many factors to consider. For example, it is notable that specific pulse characteristics (eg, Floating-Sinking) are better distinguished by AI algorithms compared to other categories. It seems that the most significant factor affecting AI performance might be an amplitude, while the awkwardness, similar to a slippery grip, might have been considered as noise. Additionally, patterns like "Slow-Rapid" may have lost their speed characteristics during the DTW process. However, in the case of "Slow-Rapid" since the pulse type can be relatively easily distinguished by calculating the pulse rate, such an AI-algorithm may not be necessary in clinics. Interestingly, in this study, it was found that the "Floating-Sinking" pattern showed a high Cosine similarity value, indicating that the DTW-MDS based algorithm effectively distinguished the pulse patterns like "Floating-Sinking". This suggests that in the future, using a pulse diagnosis device combined with AI-algorithms to differentiate pulse patterns like "Floating-Sinking" could enable health check-up functions that distinguish disease states and quantitatively demonstrate treatment effects.

While the overall Cosine similarity values suggested potential alignment, it is notable that the correspondence between the data-driven groupings and expert diagnoses showed considerable variability across the 10 different pulse waveforms and significant fluctuation among the 6 diagnostic categories. For instance, categories like "Cold-Heat" and "Slow-Rapid" often showed lower consistency (ranging down to 0.32 and 0.29, respectively) compared to the consistently high alignment of the "Floating-Sinking" pattern. This fluctuation indicates that the algorithm's effectiveness is highly dependent on the waveform source and the specific pattern being classified.

This study has a few limitations. It is often believed that pulse waves measured from the left, non-dominant wrist are more accurate, and indeed, in our study, the Cosine similarity value was higher when using pulse wave signals measured from the left wrist. However, deeper consideration of the physiological differences between left and right pulse wave signals is needed. Additionally, the algorithm should be further validated with a larger and more diverse population, including patient populations. While we present a novel approach, the findings must be interpreted cautiously due to the inherent subjectivity of the reference standard (ie, a single physician's pulse diagnosis) and the small sample size of 19 participants, which limits the statistical power and generalizability of the results. Lastly, the diagnosis made by a Korean Medicine doctor, which was used as the prediction outcome in this study, may not be sufficient to be considered the gold standard. In traditional medicine, the lack of a gold standard for pattern identification remains a concern, and it is unfortunate that the results of pattern identification can be subjective due to the reliance on the physician's manual skills in pulse diagnosis. However, this is precisely why we aim to develop an AI-algorithm, and we believe that the results of this study will be beneficial for future research, as a distinctive feature of this study is the use of the DTW algorithm, which can specify the correlation of time series data when comparing pulse waves. The DTW value quantifies the similarity between two time series values, and MDS analysis was conducted using this value. Thus, it is difficult to understand "why" the AI-algorithm was able to distinguish certain patterns and pulse waves effectively and not others. However, the advantage of DTW is that it can correct for differences in the periodic length of pulse wave characteristics that may vary among individuals. We believe that including additional information obtained from the extraction of features in the time or frequency domain (eg, average frequency, power, etc.) of the signal in the future study could improve the algorithm's performance.

In conclusion, by employing DTW and MDS, we demonstrated a significant alignment between AI-driven pattern identification of raw pulse signals and expert diagnoses, particularly for patterns like "Floating-Sinking". While the results are promising, the results also highlight the need for further refinement of the AI model, and the reliance on diagnoses from Korean Medicine doctors. Without a universally accepted gold standard, traditional diagnostic protocols would not survive. While our model offers a foundational step toward developing AI-assisted diagnostic tools, further validation with a larger and more diverse population, including clinical patient samples, is crucial before strong conclusions about the algorithm's clinical utility can be drawn. AI-based diagnostic tools could standardize and quantify traditional pulse diagnosis, moving us closer to transforming it into a robust, scientifically grounded practice.

Data Sharing Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Declaration and Consent to Participate

This study was approved by the Kyung Hee University Institutional Review Board (KHSIRB-22-058) and was registered with the Clinical Research Information Service (KCT0007655; registered on 2024-02-29). All participants provided written consent prior to enrolling in the trial.

Funding

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (RS-2023-00279315, RS-2025-22902971). This research was supported by a grant of the Korea Health Technology R&D Project through the Korea Health Industry Development Institute (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea (Grant Number: HI23C1283).

Disclosure

The authors declare that they have no competing interests in this work.

References

1. Bilton K, Zaslawski C. Reliability of manual pulse diagnosis methods in traditional East Asian medicine: a systematic narrative literature review. *J Altern Complement Med*. 2016;22(8):599–609. doi:10.1089/acm.2016.0056
2. Jacobson E, Conboy L, Tsering D, et al. Experimental studies of inter-rater agreement in Traditional Chinese Medicine: a systematic review. *J Altern Complement Med*. 2019;25(11):1085–1096. doi:10.1089/acm.2019.0197
3. Meng K, Xiao X, Wei W, et al. Wearable pressure sensors for pulse wave monitoring. *Adv Mater*. 2022;34(21):2109357.
4. Saugel B, Kouz K, Scheeren TW, et al. Cardiac output estimation using pulse wave analysis—physiology, algorithms, and technologies: a narrative review. *Br J Anaesth*. 2021;126(1):67–76. doi:10.1016/j.bja.2020.09.049
5. Tago K, Wang H, Jin Q. Classification of TCM pulse diagnoses based on pulse and periodic features from personal health data. Paper presented at: 2019 IEEE Global Communications Conference (GLOBECOM). 2019.
6. Guo C, Jiang Z, He H, Liao Y, Zhang D. Wrist pulse signal acquisition and analysis for disease diagnosis: a review. *Comput Biol Med*. 2022;143:105312. doi:10.1016/j.compbiomed.2022.105312
7. Salvador S, Chan P. Toward accurate dynamic time warping in linear time and space. *Intell Data Anal*. 2007;11(5):561–580. doi:10.3233/IDA-2007-11508
8. Senin P. Dynamic time warping algorithm review. *Inform Comput Sci Depart Univ Hawaii Manoa Honolulu USA*. 2008;855(1–23):40.
9. Kim J, Chung YG, Chung SC, Bulthoff HH, Kim SP. Neural categorization of vibrotactile frequency in flutter and vibration stimulations: an fMRI Study. *IEEE Trans Haptics*. 2016;9(4):455–464. doi:10.1109/TOH.2016.2593727
10. Kim JT. A study based on the standardization of the STAI for Korea. *New Med J*. 1978;21(11):69.
11. Lim S-Y, Lee E-J, Jeong S-W, et al. The validation study of beck depression scale 2 in Korean version. *Anxiety Mood*. 2011;7(1):48–53.
12. Kim SH, Jo M-W, Lee S. Psychometric properties of the Korean short form-36 health survey version 2 for assessing the general population. *Asian Nurs Res*. 2013;7(2):61–66. doi:10.1016/j.anr.2013.03.001
13. Jo M-W, Yun S-C, Lee S-I. Estimating quality weights for EQ-5D health states with the time trade-off method in South Korea. *Value Health*. 2008;11(7):1186–1189. doi:10.1111/j.1524-4733.2008.00348.x
14. Moon H, Kim M, Lim SH, Chae Y, Lee I-S. Observational clinical study on mibyeong based on Korean medicine diagnosis, questionnaire, and radial artery tonometry. *Kor J Acupunct*. 2023;40(2):44–53.
15. Zayat R, Drosos V, Schnoering H, et al. Radial artery tonometry to monitor blood pressure and hemodynamics in ambulatory left ventricular assist device patients in comparison with Doppler ultrasound and transthoracic echocardiography: a pilot study. *Artif Organs*. 2019;43(3):242–253. doi:10.1111/aor.13335
16. Virtanen P, Gommers R, Oliphant TE, et al. SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nature Methods*. 2020;17(3):261–272. doi:10.1038/s41592-019-0686-2
17. Janati H, Cuturi M, Gramfort A. Spatio-temporal alignments: optimal transport through space and time. Paper presented at: International conference on artificial intelligence and statistics. 2020.
18. Li G, Shen J, Dai C, Wu J, Becker SI. ShVEEGc: EEG clustering with improved cosine similarity-transformed Shapley value. *IEEE Trans Emerg Top Comput Intell*. 2022;7(1):222–236.
19. Zhang K, Lin S, Sun H, Ma L, Xu J. Dynamic time warping based clustering for time series analysis. In: *IoT and Big Data Technologies for Health Care*. Springer; 2021:376–385.
20. Neha, Sardana HK, Dogra N, Kanawade R. Dynamic time warping based arrhythmia detection using photoplethysmography signals. *Signal Image Video Process*. 2022;16(7):1925–1933. doi:10.2147/OPTH.S360719
21. Garima, Goel N, Rathee N. Modified multidimensional scaling on EEG signals for emotion classification. *Multimedia Tools Appl*. 2023;82(18):28547–28568.