RESEARCH ARTICLE

High-Dimensional Feature Space for Diabetes Diagnosis and Identification of Diabetic-Sensitive Features in Ayurvedic Nadi Signals

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Abstract: Nadi-based disease diagnosis is a traditional art in Ayurvedic medicine that is an inquisitive yet not widely comprehended subject. A collection of higher dimensional features from a preprocessed Nadi dataset was extracted and analyzed to diagnose diabetes. The t-distributed Stochastic Neighbor Embedding was used to visualize the higher dimensional feature space in 2-D. The linear dimensionality reduction method of Principal Component Analysis and several linear and nonlinear classifiers were tested on the reduced feature space in identifying diabetes. The key outcomes of this paper are the ability to reduce the feature space by 73.33% while retaining a classification accuracy of 95.4%, identifying age as a compounding factor in diagnosis, and extracting the diabetes-sensitive features with eigenvalue loading.

Keywords: Nadi, higher-dimensional features, t-SNE, PCA, diabetes diagnosis, wearable sensors

1 Introduction

Nadi is the collective term for three distinct pulses known as Vata, Pita, and Kapha, felt at the wrist (on the radial artery) of a person with the index, middle, and ring fingers of an experienced physician in Ayurvedic medicine. These pulses are regarded as the individual's psychophysiology and a flow of consciousness [1]. Though it is an empirical study subjective to both physician and patient, it is also a versatile source of information reflecting a person's physical and mental conditions [1]. In a pragmatic context, the nuanced distinctions in pulses distinguished by Nadi practitioners with their experience are critical for accurate diagnosis. Thus, a scientific study based on Nadi and its informative features vital for practitioners in disease diagnosis can be an efficacious study for the medical field. We hope this study can establish a scientific basis for Nadi for future studies and allow Nadi to be an established disease diagnosis method rather than divulging it as an enigmatic method found in folk medicine known by a handful.

The art of reading pulse for diagnosis exists in several medical practices, such as Traditional Chinese Medicine (TCM) [2], Greek/Yunani, Ayurvedic Medicine [3], and similar oriental medical practices. Each practice may have fine distinctions in finger placement, pressure application, and related diagnostics. This research is based on the Ayurvedic and orthodox Nadi practices found in Sri Lanka.

Within this scope, the authors conducted a study on Ayurvedic Nadi signals to investigate the possibility of information extraction from Nadi and then apply it to diagnose diabetes. In this paper, authors present their work on feature extraction and classification of Nadi signals to improve diabetes diagnosis accuracy and to identify diabetic-sensitive feature clusters in the feature space extracted from Nadi.

Establishing recognition for Nadi as a disease diagnosis method requires the initial steps of acquiring the Nadi signals reliably and recognizing the parameters the practitioner perceives by feeling the Nadi of a patient. Hence, signal acquisition, preprocessing, and feature extraction are crucial steps for Nadi as well as any signal-based classification. There have been several studies to identify suitable sensor and data collection devices with pressure sensors [4–6], piezoelectric sensors [4], optical sensors [5], and condenser microphones [2]. Signal preprocessing steps such as adaptive techniques [9, 10], and filter-based methods [11, 12] for noise removal, along with denoising and baseline wander removal, have been commonly utilized. Similar to other pulse signals, Nadi pulse segmenting [11, 13] and outlier removal steps maximize the information extraction from the collected data.

Feature extraction and classification are crucial aspects of Nadi signal analysis. Different researchers have used a variety of approaches in extracting features and classification, where some methods are highly dependent on the signal extraction method or the sensors they have used. Spatial features found in pulses and power spectral density were used to distinguish pulse patterns before and after lunch as well as after exercise [6]. A time-domain pulse-based features were tested to identify cardiovascular diseases [7]. A set of time and frequency data was analyzed with Independent Component Analysis(ICA), concluding it has the potential to be used as a classification method for diseases [8]. A two-dimensional feature extraction method that included the within-class information giving periodic and non-periodic features has been tested for diabetic diagnosis [9]. The authors have used a set of ratio-based features in both the time and frequency domains [18, 19] for diabetes diagnosis as well.

A variety of classification methods such as Support Vector Machine (SVM), Wavelet transforms, Autoregressive models, Artificial Neural Networks (ANN) [20,21], and Convolution Neural Networks (CNN) [10] have been used in the diagnosis of conditions such as liver problems [11], diabetes [17, 20, 21] and pregnancy [9] detection with pulse gathered according to different oriental medicine based pulse acquisition techniques.

In the following parts of this paper, the methodology of feature extraction, extracted features, applied effective dimension reduction technique, and identified diabetes-sensitive features are detailed with the classification results followed by the discussion and conclusion.

2 Methodology

2.1 Nadi Acquisition Device

The database for this experiment was collected using a non-invasive device designed by the authors with three practitioner-wearable piezoelectric sensors and three similar lowpass filter and amplifier circuits for Nadi acquisition described elsewhere [12]. These signals were fed to a PC using a data acquisition card (NI USB6009 DAQ) with a 1kHz sampling frequency and were monitored in real-time using a customized LabVIEW virtual interface. The device and the finger placement with wearable sensors are shown in Figure 1. Signal processing and classification were done using MATLAB© R2020a software (Mathworks, Inc).

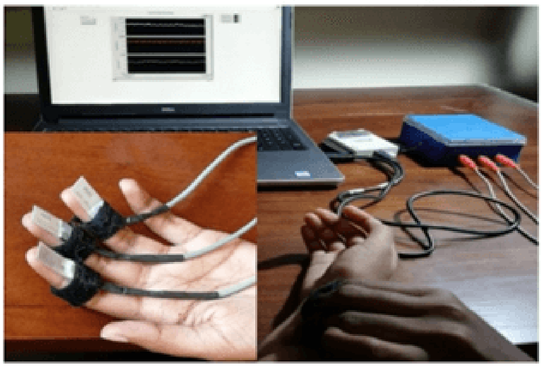

Figure 1 Sensor clad fingers that are placed on the wrist of the subject (left) and the device with the monitoring interface (right)

Data was collected from consented volunteers. They were asked to sit and relax for ten minutes before recording Nadi from their resting right hand. Their medical history of diabetes was noted as 'diabetic' based on having high blood glucose levels over the past few months in their recorded blood tests and have been identified as diabetic by a physician while as 'non-diabetic' if there were no indication of higher blood glucose levels than the reference range in their past blood tests or have never been identified as diabetic by a physician.

2.2 Nadi Database

The collected dataset consists of 47 non-diabetic subjects and 18 subjects with a medical history of diabetes, adding up to 65 volunteer subjects. Age distribution for non-diabetes subjects has a mean of 37 years with a standard deviation of 13.9 for 25 females and a mean of 38.9 years and a standard deviation of 17.9 for 22 male subjects. The age distribution for diabetes subjects has a mean of 59 years and a 2.3 standard deviation for 9 females, while the mean and standard deviation were 60 years and 10.7, respectively, for 9 males. However, it is worth mentioning that all the volunteers with diabetes were above 50 and had no subjects under 50 years suffering from diabetes in the database we assessed. The impact of age and gender that could reflect on the diabetes diagnosis with the acquired dataset was also tested and is described in the results section. Moreover, during the time of data collection, relaxing time

(10 minutes seated while right hand relaxing on a table) and recording the history of diabetes were the controls, while the time of the day, diet [6], and sleep pattern [1] were not controlled during this study which could be confounding factors to the obtained accuracy.

The database was constructed with 25 seconds of Nadi readings from each subject in the database, with 3 Nadi signals per subject (Vata, Pita, and Kapha) recorded and saved prior to feature extraction. Then, the 5-stage preprocessing method [13] was applied to this dataset which denoised, removed baseline wandering, segmented the signal into pulses, normalized (resampled) the pulses to their mode pulse length, and removed outliers resulting in an ensemble of pulses that gave averaged pulses, as shown in Figure 2, that were used in the following feature extraction process.

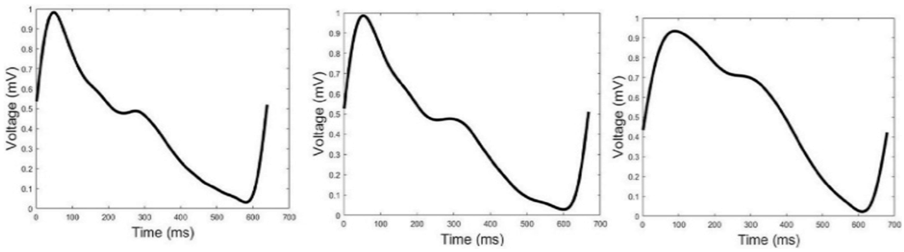

Figure 2 (a) Vata, (b) Pita, and (c) Kapha ensemble averaged signals for a single subject after the preprocessing

2.3 Feature Space

Following are the features obtained from both time and frequency domains of Nadi signals for the dataset to be used in diabetes classification, resulting in 75 features.

I. Power Spectral Density Ratio (PSD Ratio): The PSD ratio is calculated using the Welch power spectral density estimation method. Here, the signal was binned with a Hamming window with a 50% overlap in the time domain, and the power spectral estimate of each bin was found using a periodogram method. The ratio between the power of fundamental (f_0) and second harmonic ($2f_0$) [12] was taken as the PSD ratio.

$$Ratio_{PSD} = \frac{PSD\ of\ f_0}{PSD\ of\ 2f_0} \tag{1}$$

II. Crest Factor (CF): It is the ratio between the peak value of the ensemble-averaged Nadi pulse signal and its root mean square (RMS) value. The Crest Factor indicated the signal peaks of Nadi signals that can be compared with each other [12].

$$CF = \frac{V_{peak}}{V_{RMS}} \tag{2}$$

III. Pulse Period (P): The period of the ensemble-averaged signals, which is the mode pulse length of the segmented Nadi pulses.

IV. Intra-class distance: Nadi pulses of each subject have individual-dependent and disease-dependent pulse spaces, which are superimposed on the Nadi signals. The individual-dependent space F is obtained from the ensemble average, which is assumed to be the periodic part of the pulse, while the disease-sensitive part, D, is assumed to be in the non-periodic dimensions, which was obtained using equation 3 [9]. Information from D was extracted using the intra-class distance method, and the first six eigenvalues with maximum energies were taken as the distances in these orthogonal non-periodic directions.

$$D = X - F \tag{3}$$

$$F = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{4}$$

$$DD^T = \sum_{i=1}^{N} (X_i - F)(X_i - F)^T \tag{5}$$

D - disease-sensitive non-periodic orthogonal directions
X - Pulses extracted from each subject
F - Individual-dependent periodic space(ensemble average)
N - number of segments used in ensemble averaging

V. Gaussian fitting parameters: These parameters show the goodness of fit of the final distribution obtained with a combination of Gaussian distribution models that can closely predict the shape of the Nadi pulse signal. The coefficients a, b, and c in equation 6 change according to the fitting model.

$$f(x) = \sum_{i=1}^{n} a_i e^{-\left(\frac{x-b_i}{c_i}\right)^2} \tag{6}$$

n - number of Gaussian distributions used

The goodness of fit was measured using the curve fitting tool in MATLAB, which uses equation 6 [9], and the obtained parameters were sum-square error (SSE), R-square, and Root Mean Square Error (RMSE). Fitting parameters from 2 to 8 Gaussian models were obtained, and their mean, standard deviation(std), and inter-quantile region (IQR) were compared to obtain the best fit for each ensemble averaged signal. Lower SSE, R-square, and RMSE values indicate a better-fitting Gaussian model for the Nadi pulses. For Vata and Pita, the model fitted with 7 Gaussians gave the best results, while for Kapha, it was a model with 8 Gaussians. Corresponding SSE, R-square, and RMSE values were used as the Gaussian fitting parameters in the feature space.

VI. Approximate Entropy (ApEn): ApEn is the unpredictability of fluctuating time series signals. The higher the repetitive pattern, the lower the ApEn [14]. It was found by generating a lagging signal with dimensions m and lag r (in our case, it is the successive pulse in the recorded train of Nadi pulse signals). Then, (7) calculates the number of points (N) inside the range where point i with 1 as the indicator function and R as the similarity radius where y_i and y_k are points on the signal and its lagging signal, respectively. Finally, the approximate entropy is calculated with (8) and (9), indicating how likely each pulse pattern is to be repeated.

$$N_i = \sum_{i=1, i\neq k}^{n} 1(\|y_i - y_k\|_\infty < R) \tag{7}$$

$$ApEn = \phi_m - \phi_{m+1} \tag{8}$$

$$\phi_m = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} \log N_i \tag{9}$$

VII. Hilbert Huang Transform(HHT): HHT is a signal processing technique applicable to non-stationary and nonlinear signals. It has two steps: applying Empirical mode decomposition (EMD) to get Intrinsic Mode Functions (IMF) and applying Hilbert transform to IMFs. The most prominent four IMFs $(IMF_n(t))$ with corresponding instantaneous amplitude $a_n(t)$ and instantaneous frequency $(f_n(t))$ were used in equations 10, 11, and 12 to find the average instantaneous amplitude (h_n), average instantaneous frequency (ω_n), and instantaneous power (P_n), respectively [14], resulting in 12 features per each Nadi signal – Vata, Pita, and Kapha adding 36 features to the high-dimensional feature space.

$$h_n = \frac{\sum_{t=1}^{l} a_n(t)}{l} \tag{10}$$

$$\omega_n = \frac{\sum_{t=1}^{l} a_n(t)\, f_n(t)}{\sum_{t=1}^{l} a_n(t)} \tag{11}$$

$$P_n = \frac{\sum_{t=1}^{l} |IMF_n(t)|^2}{\sqrt{\sum_{n=1}^{N} \sum_{t=1}^{l} |IMF_n(t)|^2}} \tag{12}$$

Each Nadi(Vata, Pita and Kapha) signal contributed 25 features to the feature space with PSD ratio, CF, P, six intra-class distances, three Gaussian fitting parameters, ApEn, and twelve HHT features resulting in a total of 75 features.

2.4 Classification of Diabetes Diagnosis

As a high-dimensional data set was used, visualizing the features in 2-D or 3-D space, taking 2 or 3 features at a time, is a tedious task. Instead, dimension reduction techniques that map the dataset of a higher dimension to a lower dimension while preserving its most important information have been incorporated. For the visualization, we have used t-distributed Stochastic Neighbor Embedding(t-SNE), and for dimension reduction prior to the classification, we embraced Principal Component Analysis (PCA). Using such methods, we expected to preserve the critical information of higher dimensions in the lower dimensional representation as much as possible by increasing the interpretability of such derived lower dimensional data while minimizing the information loss. Also, our attempt to interpret highly correlated features with diabetes is described.

2.5 t-Distributed Stochastic Neighbor Embedding (t-SNE) for High-Dimensional Data Visualization

t-SNE is an unsupervised method with the purpose of visualization using a random algorithm to reduce the dimensionality non-linearly while focusing on the preservation of the local structure of the data. It uses the student t-distribution to derive similarity between two points in the reduced feature space instead of Gaussian distribution, which aids in mitigating crowding and optimization issues. One significant advantage of t-SNE is the immunity to outliers in the dataset. However, the major downside of this method is the inability to be used as a classification technique, as the embedding is relative to the available data. Hence, this method cannot classify any new data points added to the data set with respect to the already embedded data points.

Figure 3 shows the 2-D embedding of t-SNE with the 'Barnes-Hut' algorithm with 'Hamming' distance metrics with a perplexity of 15, where the visualization implicates the possibility of separating diabetic and healthy subjects with the available features.

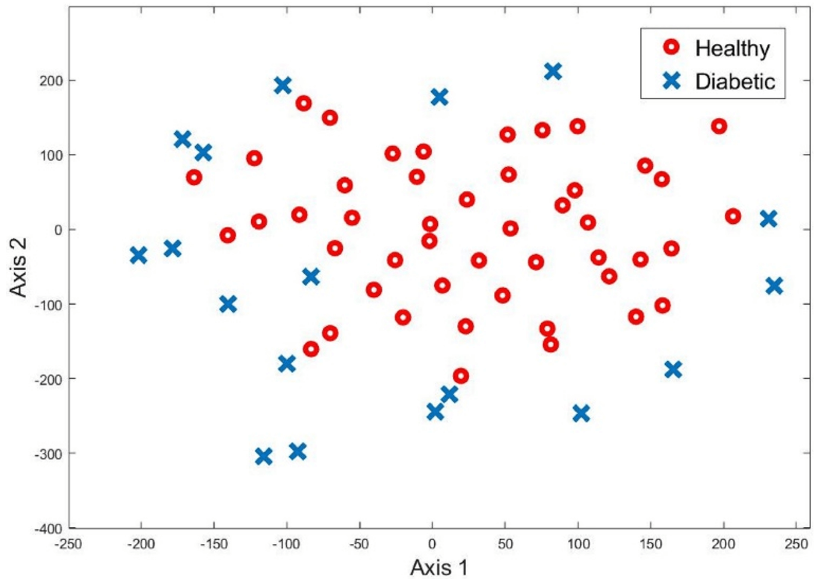

Figure 3 2-D embedding with Barnes-hut algorithm, Hamming distance metric, and perplexity of 15 using t-SNE, which indicates the separability of diabetic and non-diabetic classes with the extracted feature space of Nadi.

2.6 Dimension Reduction With PCA

PCA is a linear method used in dimension reduction while preserving the global structure of the data using a deterministic algorithm that preserves the variance of the data governed by the eigenvalues. In our research, we have obtained a total of seventy-five features from the extracted Nadi pulses. A scree plot was used to determine the minimum number of principal components that should be retained to preserve the information in the Nadi, shown in Figure 4.

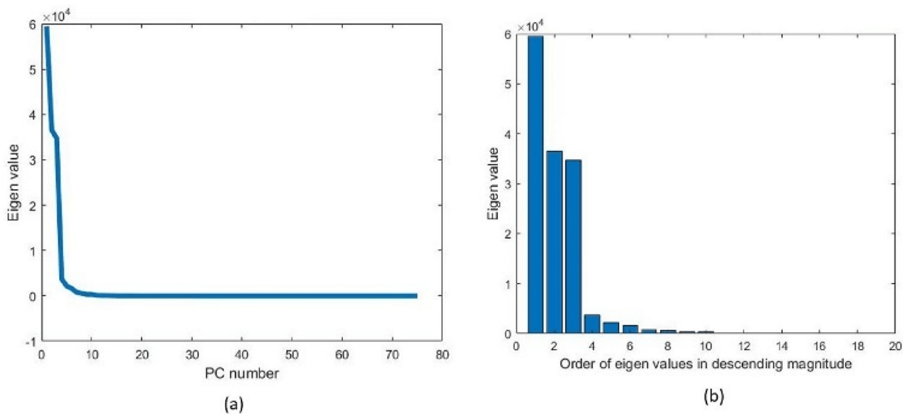

Figure 4 (a) The scree plot for 75 eigenvalues of the feature matrix where the knee is at 4 pcs, and (b) the bar plot showing the first 20 pcs in descending order.

The scree plot also showed the dominance of principal components(PC) in the feature space and can be used to decide the number of PCs that can reduce dimensions with minimum data loss. Figure 4 provides evidence of the first 4 PCs covering 95.5% of the data variance, while the first ten eigenvalues cover up to 99.6% of the variance in feature space, and 20 PCs cover up to 99.98%. (*i.e.*, can ignore the rest of the PCs if compactness or memory saving is needed without missing critical data spread dimensions). Based on the above analysis, it is evident that we can reduce the high-dimensional data into an information-dense low-dimensional dataset and save the computational and memory power that is required otherwise.

The new dimension-reduced dataset was then classified with several techniques such as SVM, Decision tree, Naïve Bayes, and K-Nearest Neighbors (K-NN). Moreover, a neural network(NN) with 2-hidden layers was used to classify the diabetes patients with the high dimensional feature space of Nadi. Different reduced feature sets were tested to identify the optimal feature reduction possible and the best neural network to identify diabetes effectively. The accuracy of these tests is included in the results section.

2.7 Finding Diabetes-Sensitive Features with Eigen Loading

Eigen loading was used to find the diabetes-sensitive features in the dataset that correlate the eigenvectors and the used features. It is used to find the highly correlated features in the used feature space, making separation possible for the healthy and diabetic classes. Eigen loading is defined in equation 13, where L is the Loading with V denoting eigenvectors and E being eigenvalues. Table 1 shows the features of the Nadi database with the PCs (*i.e.*, eigenvectors) they maximally correlate.

$$L = V.\sqrt{E} \tag{13}$$

Table 1 Features highly correlating with each eigenvector

PC / eigenvectors in descending order	Feature Number	The feature that correlated the highest
1	10	Intra-class distance 1- Vata
2	16	Intra-class distance 1- Pita
3	22	Intra-class distance 1- Kapha
4	17	Intra-class distance 2- Pita
5	23	Intra-class distance 2- Kapha
6	11	Intra-class distance 2- Vata
7	72	Power of IMF 1 (HHT) - Kapha
8	72	Power of IMF 1 (HHT) - Kapha
9	12	Intra-class distance 3- Vata
10	19	Intra-class distance 4- Pita

3 Results

By transforming all the data onto the principal axes given by the PCA, different numbers of PCs were used to identify the optimal number of features that can be retained for the classification. The transformed dataset was then used in several classification algorithms with five-fold cross-validation to overcome the overfitting due to a limited database. The classification results are shown in Table 2, along with the accuracy of each method. The second column of Table 2 is the classification of high dimensional data set without reducing features.

Table 2 Transformed dataset classification with different methods for different numbers of PCs with prediction results

Classifier	Accuracy (%)				
	With 75 features	With 43 features	With 20 features	With 10 features	With 4 features
The cumulative sum of the variance (%)	100	100	99.98	99.60	95.50
SVM(Linear)	72.30	100	89.20	67.70	72.30
SVM (Fine Gaussian)	69.20	96.90	72.30	72.30	70.80
Fine Tree	58.50	100	83.10	63.10	49.20
Gaussian Naïve Bayes	66.20	98.50	87.70	69.20	56.90
K-NN (Fine KNN)	55.40	98.50	89.20	64.60	61.50
A 2-hidden layered Neural Network	84.6	81.5	95.4	78.5	72.3

Based on the results in Table 2, the authors decided that having 20 features in the dimension-reduced transformed dataset would be a reasonable compromise in terms of cumulative variance while retaining a higher accuracy compared to the different dimensions analyzed. Two-hidden layer neural network trained with the dataset gave the highest accuracy among the tested classifiers. Figure 5 conveys the confusion matrix of the applied neural network after five-fold cross-validation. A comparison of accuracies and used methods to classify diabetes using Nadi pulses and other pulse-based methods is given in Table 3.

Table 3 comparison of Classification method and features used along with accuracy for diabetes diagnosis

Classification method	Features	Accuracy %
Fuzzy C-means classifier	Gaussian Model [15]	85.9
Two-Category Classifier	Wavelet feature [16]	85.6
Neural Network	Ratio method [12]	85.7
SVM with RBF kernel	Fusion features [9]	91.6
3- hidden layer NN	Fusion Features [13]	88.9
2-hidden layer NN	The proposed method	95.4

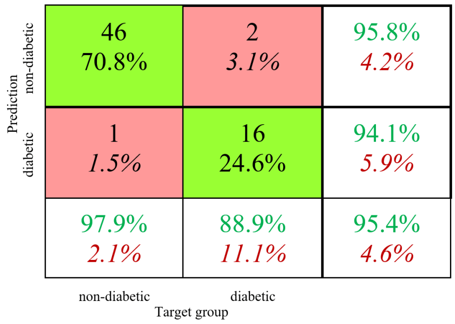

Figure 5 Confusion matrix for the 2-hidden layer neural network trained and tested for the reduced dataset

Age and gender influence Nadi [1]. To verify the parameters (out of age and gender) that could affect the diagnosis, the authors performed a Chi-squared test on independence. It resulted in 5×10^{-2} with 1 Degree of Freedom (DF) with a p-value of 0.82 for testing independence between gender and diabetes diagnosis, while 20.05 with 1 DF resulted in a p-value of 8×10^{-6} for the independence test between age and diabetes diagnosis. The Chi-squared tests suggest that there is no significant evidence to associate gender with the diagnosis of diabetes, while age can have a statistically significant impact on diabetes diagnosis.

4 Discussion

In this study, the authors present a diabetes diagnosis method based on Nadi signals acquired according to Ayurvedic practice found in Sri Lanka with an accuracy of 95.4%. The collected Nadi database was carefully processed and extracted 75 high-dimensional fusion feature space that was effectively reduced by 73.3% to 20 orthogonal features using PCA and was used in the classification. Furthermore, the authors identified the intra-class space as the diabetes-sensitive feature space using eigen loading.

Table 2 indicates that the number of features does not guarantee better accuracy, while the disease-dependent features that have captured the variance are what matters. Hence, it is possible to reduce the Nadi dataset to 43 and obtain near-perfect classification with a linear SVM classifier, reducing the feature space by 42.67%, yet it is reasonable to assume some overfitting of the data due to higher feature dimensions. However, if database reduction with higher accuracy is the primary goal, it is reasonable to use higher variant 20 features which can diagnose diabetes with up to 95.4% accuracy depending on the method we use and obtain a database truncation of 73.3%.

The approach taken by the authors compared to other similar pulse-based (Ayurvedic Nadi and TCM) diabetes diagnosis techniques, as given in Table 3, indicates that the time and frequency domain fusion features [17, 18] (last three rows in Table 3) have better diagnosis accuracy concerning extracted features. Rather than 75 features, with highly effective 20 features, it is possible to achieve above accuracy with a 2-layer NN. It is a considerable development given the previous work by the authors and some other studies, as listed in Table 3. Table 1 enumerates eight out of the ten highest correlated features to be in the intra-class distance space, which was hypothesized as the disease-sensitive feature space by the authors, and it aligns well with the work by Wang, Zhang, and Lu [9].

While accuracy could have been improved by the wearable sensor-based Nadi sensing method, the robustness of the preprocessing framework, and the classification method adopted, the authors suspect some compounding factors that may adversely affect the findings reported here. Human error due to the sensor wearer, lack of better control in the collected database other than for a ten-minute resting period, and having no validation of the blood glucose level during the data collection are some identified drawbacks. Though the database was limited, it was used with five-fold cross-validation to avoid overfitting in classification.

The age and gender variation of healthy and diabetic subjects is another parameter that was suspected to impact the diagnosis. The Chi-squared tests indicate a significant impact of age on diabetes diagnosis, while no such significance is conveyed for gender. The above statistical results suggest an impact of age on diabetes prediction, which is also intuitive based on the high susceptibility to diabetes in older adults [26]. However, the high accuracy of the presented method is not solely due to the age distribution present in the database. It includes the interplay of carefully extracted features and signal processing embodied in the diagnosis process. Age dependency could be verified and eliminated with further studies with a controlled database. Further studies with a controlled database could help verify and eliminate any age dependency.

The overall results suggest that the primary goal of the study of identifying the potential of Ayurvedic Nadi as a diabetes diagnosis method can be accomplished with the proposed feature space reduction and classification method for the collected and preprocessed data the authors have used here. The derived feature space substitution for the raw feature space in the classification is also a novel improvement in effectively reducing feature space to our best knowledge. Identifying intra-class space to have more disease-sensitive features is a valuable milestone for future researchers in exploring the relationship between the disease-sensitive features in Nadi and detecting not just diabetes but a plethora of other diseases. The findings of this research implicate the possibility of establishing Nadi as a non-invasive primary disease diagnosis method that could be incorporated into a groundbreaking point-of-care diagnostic device acclaimed by the medical community with the aid of rigorous clinical trials that further validate the efficacy.

5 Conclusion

The Nadi pulse gathered at the wrist from a cohort of volunteered subjects was used in diagnosing diabetes after extracting features from them. They were visualized with t-SNE to verify the possibility of diabetes identification. Then, with PCA, the feature space was reduced to obtain a trade-off between accuracy and size of the feature space. The authors identified an age dependency of diabetes diagnosis for the used database. The analysis also found non-periodic Nadi space to be particularly sensitive to diabetes through the correlation of eigenvalue loading.

Conflict of Interest

The authors declare no conflict of interest in the material included in this paper.

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