Low Cost Parkinson's Disease Early Detection and Classification Based on Voice and Electromyography Signal

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Abstract Parkinson's disease (PD) is one of the health problems concerning for elderly population. Manageable symptom is an important thing for Parkinson's sufferer in order to be independent enough to do daily activities. As a solution to Parkinson's early detection method, this research purpose is to develop a low cost diagnostic tool for PD which inexpensive yet accurate and easy to use by neurologist, enriching and giving new insight for neurologist about voice and electromyography (EMG) signal analysis result. It can be very useful for PD clinical evaluation and spreading awareness about PD as well as the important of early diagnose to citizen. Parkinson's detection method in this research uses pattern recognition method, the first step is initiated with voice and EMG data acquisition. Second step is feature extraction using five features for voice and EMG signal. The last step is classification using Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural network (ANN) methods. The pattern recognition of PD is divided in two sections, the first is for two class classification, and the second is four stage classification based on Hughes Scale which commonly used in Indonesia as PD diagnose guideline. Based on the results, voice method classification has higher accuracy than EMG classification because the feature for voice is a good feature which can well classified the voice data. Voice data sampling rate is higher than EMG data sampling rate which means voice data

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recording has more data each second than EMG data. Two class classification has higher accuracy than four class classification both in ANN and ANFIS. Based on the four class classification results in both of voice and EMG signals using ANN and ANFIS, the probable class has the lowest accuracy of all classes.

Keywords Parkinson's disease · Pattern recognition · Voice · EMG · ANN ANFIS

1 Introduction

1.1 Parkinson's Disease (PD)

Parkinson's Disease (PD) was first described by Dr. James Parkinson in a book entitled "An Essay on the Shaking Palsy" published in 1817. For several centuries later known as shaking palsy and in the medical terms known by the name of paralysis agitans. Along with its development later called Parkinson's Disease to commemorate the services of Dr. James Parkinson as the first person to explain the disease [1].

Many studies have been done by experts related to PD but until now not yet known exactly what causes of PD. The Parkinson's Institute team in California, USA conducted a study by interviewing 519 PD patients and 511 healthy people associated with occupational history and exposure to toxins experienced including pesticides and solvent fluids [2]. The results show that those who work in education, agriculture, health workers and welders are not directly related to PD. Researchers found 8.5 percent of PD patients are people who are often exposed to pesticides. The results of this study proves that there is a relationship between pesticides with PD, not just fertilizers but other chemicals [2]. The National Institute of Neurological Disorders and Stroke (NINDS) identifies several possible causes of PD, among others [3]:

- Premature aging, premature aging of brain cells (neurons) allows one of the causes of PD
- Oxidative damage, free radicals are very unstable and potentially damaging molecules produced through normal chemical reactions in the body
- Environmental toxins, both external and internal toxins that can damage the cells (neurons) of the body
- Genetic influence, 10 to 15 percent of PD patients have close relatives who also experience PD symptoms

PD shows some symptoms in patients, among others as follows [3, 4]:

- Tremor at rest
  Tremor at rest is one of the typical symptoms of PD so that PD is often called shaking palsy. The shaking that occurs during this break can be seen on the hands,

arms, legs, jaws and faces. Tremor generally begins from the hand and for the early stages of tremor occurs on one side of the body only.

- Rigidity
  Rigidity is the stiffness that occurs in the limbs. The human muscle basically has opposite muscle sections. The basic principle of movement is when one muscle is activated and the opposite muscle is relaxed. Rigidity will occur when the muscles are moving and the opposite muscles are both in active state because the signals from the brain are disrupted.
- Bradykinesia
  Bradykinesia is taken from the Greek word meaning "slow motion". Bradykinesia can be seen from facial expressions such as masks (hypomimia) and decreased frequency of eye blinks, delay in moving and decreased fine motor coordination such as not being able to button clothes or cut meat.
- Gait (walking posture)
  The running posture will be slightly disturbed at the beginning. Disturbed walking posture can be seen from the arm that does not move when the patient is walking. When walking will experience freezing (silent in place) for a few moments.
- The problem of balance and posture instability
  Instability posture makes PD patients have a hunched posture. Impaired balance and coordination cause PD patients to fall easily and injury.

1.2 Classification of Parkinson's Disease (PD)

Parkinson's disease has a stage of development of symptoms. Each stage is measured on a widely used scale. Several common scales are used to determine the stage of PD development in patients. UPDRS (Unified Parkinson's Disease Rating Score), Hoehn and Yahr Scales, and Schwab and England of Daily Living Scales are the most commonly used scales in PD staging. Each scale reflects the burden of PD disease and how far the impact of symptoms on the patient. This scale is particularly useful for defining disease progression as well as appropriate treatments for patients.

The UPDRS scale is the most widely used scale for determining PD stadium in patients. The UPDRS consists of 44 sections where each section has an assessment of 0–4. The number 0 indicates that the patient is a healthy person and the number 4 indicates the patient has symptoms of PD [5, 6].

Schwab and England of Daily Living Scales is one of the scales to assess PD stadium. The scale consists of 100% which patients completely independent and able to perform all tasks without obstacles, difficulties and slowness. Basically normal to 0% which patients depends entirely [7].

Hoehn and Yahr Scales consists of two, namely Hoehn and Yahr Scales and Modified Hoehn and Yahr Scales. Hoehn and Yahr Scales are used as guidelines in determining the stages of PD patients. Hoehn and Yahr Scales consists of stage 1 to stage 5. Stage 1 is when only the one side of the body affected and Stage 5 when the patients lying in bed and or wheelchair unless assisted [7]. While Modified Hoehn and Yahr Scales consists of Stage 0 to Stage 5 where Stage 0 means there is no sign of disease and Stage 5 means the patients lying in bed and or wheelchair unless assisted [7].

PD examination in Indonesia is conducted clinically. Dr. Kariadi General Hospital distinguishes PD into three criteria according to Hughes criteria, as follows [8]:

- Possible
  Expressed as possible if there is one of the main symptoms of tremor at rest, rigidity, bradykinesia and failure of postural reflexes.
- Probable
  It is stated probable when there is a combination of two main symptoms (including postural reflex failure) or alternatively asymmetric rigidity or asymmetric bradykinesia.
- Definite
  It states defitinite if there is a combination of three of the four symptoms or two symptoms with one symmetrical symptom.

2 Data Acquisition

The first method in pattern recognition is data acquisition. Data acquisition can be described as the process of physical phenomenon using sensors and computer. This pattern recognition application on PD detection use two kinds of data acquisition: voice and Electromyography (EMG) data acquisition. The data acquisition process is conducted in two group of research participants, healthy participants and PD participants. There are some regulations associated with human data collection. Ethical clearance and informed consent must be fulfilled before data acquisition is conducted. Ethical clearance is an ethical appropriation given by research ethic committee for a research which involving human and animals. Ethical clearance approval for this research is obtained from Medical faculty, Diponegoro University in Semarang, Indonesia

2.1 Voice

Voice data acquisition process begins with the recording equipment preparation. Unidirectional microphone is chosen as part of recording device. Unidirectional microphone is a microphone which receives voice from one direction. Unidirectional type microphone selection aims to minimize noise from the environment. The selected recording device is Yamada multifunctional microphone DM-Q6000 and it can save the voice recorded in mp3 format through external storage like a flash disk. Figure 1 shows used unidirectional microphone and Yamada multifunctional recording device. The selected sample rate in this voice acquisition is 44 kHz.

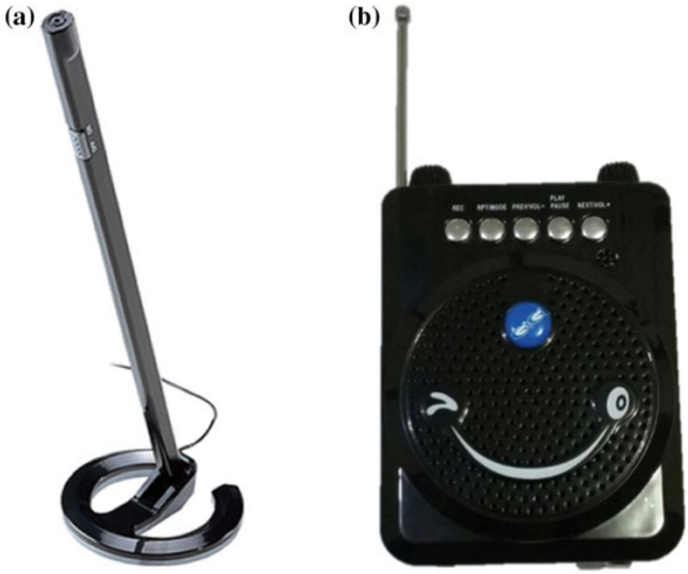

Fig. 1 Voice recording data acquisition tool. **a** Unidirectional microphone, and **b** Yamada multi-functional microphone DM-Q6000

Parkinson's patients have distinctive symptoms that are different from healthy people. In patients with Parkinson's there is a change of voice that comes out of the larynx. The change is the hoarseness of the vocal letters [5]. Based on these considerations, then the procedure data retrieval is done by recording the patient's vocal voice and healthy participants [5, 9, 10]. Voice data acquisition procedure is taken as follows:

- Research participants speak "aaaa ……" with a stable pitch for about 10 s [5, 9, 10]. When talking try positioning the mouth close to the microphone.
- Data retrieval is conducted in six times.

Figure 2 below is a picture of the process of taking voice signals in Parkinson's patients and healthy people. The voice signal is saved in .mp3 format. The format is selected because it can store the voice signal for 44 kHz with less byte and the .mp3 format also can be operated easily in MATLAB environment. Images will be blurred to protect privacy and patient confidentiality. The example of acquired voice signal from healthy and study participant with PD can be shown in Fig. 3.

Fig. 2 Participants voice data acquisition process, **a** Healthy participant, **b** Participant with PD

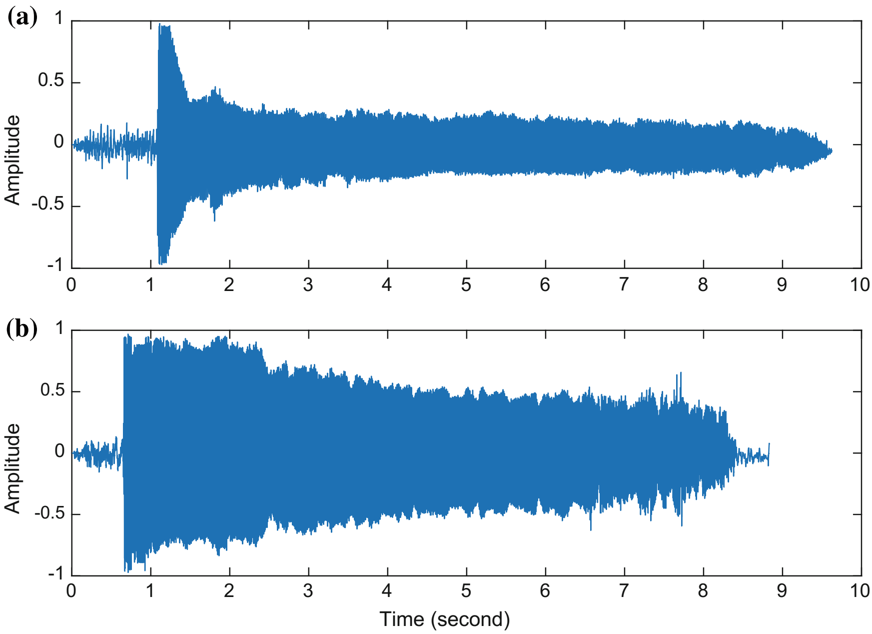

Fig. 3 Participant's voice signals, **a** Healthy Participant, **b** Participant with PD

2.2 Electromyography (EMG)

Gait data acquisition is conducted using BITalino EMG sensor. Figure 4 shows the BITalino plugged kit sensor. BITaino plugged kit consists of data acquisition component as main board, sensors consisting of EMG sensors, ECG (electrocardiography), EDA (electrodermal activity), accelerometer and LUX sensor (luminous sensor), 500

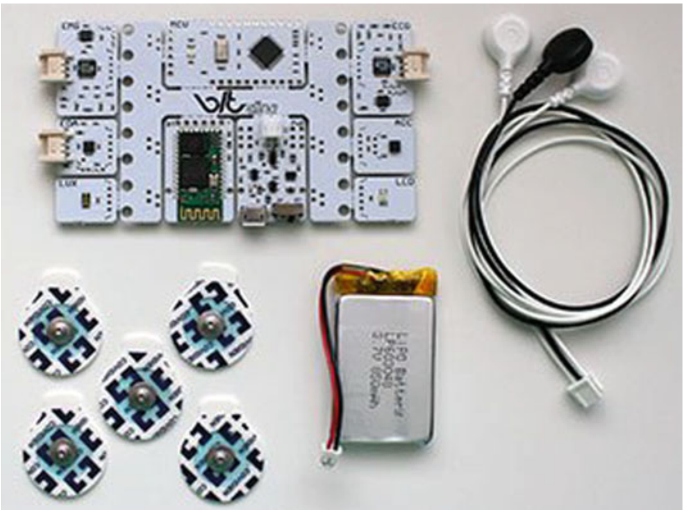

Fig. 4 BITalino plugged kit

mAh battery, main connection cable, cable pad for EMG sensor and cable pad for ECG and EDA sensors. The sample rate on BITalino plugged kit that can be selected is 1, 10, 100 and 1000 Hz.

BITalino plugged kit uses bluetooth 3.0 as wireless interface with a computer and a maximum capture distance of 10 m. The selected sample rate is 1000 Hz. BITalino can connect with MATLAB software and open access software: OpenSignals as data acquisition tool. This study uses OpenSignals as a software for storing the gait signal data. The most noticeable symptoms in Parkinson's patients are tremor and stiffening of the muscles of the limbs. With these considerations then gait signal data acquisition is conducted as follows [11]:

- The EMG sensor is mounted on the *Tibialis Anterior*, *Gastrocnemius Medialis,* and *Gastrocnemius Lateralis*. Installation EMG sensor is based on SENIAM guidelines [11, 12]. Figure 5 shows the EMG sensor position attachment.
- First data collection task is the study participants sat down and tapped the fingertips and heels on the floor alternately for 20 s. Data recording is conducted 3 times.
- Second data collection task is participants sitting and raising feet approximately 10 cm from the floor and twisted the ankle for 20 s. Data recording is conducted 3 times.

Figure 6 shows gait data recording with EMG sensors on the study participants. For the sake of privacy and the participant's secrecy, the face part is intentionally not shown. The example of acquired gait signal using EMG signal for healthy and study participant with PD can be shown in Fig. 7.

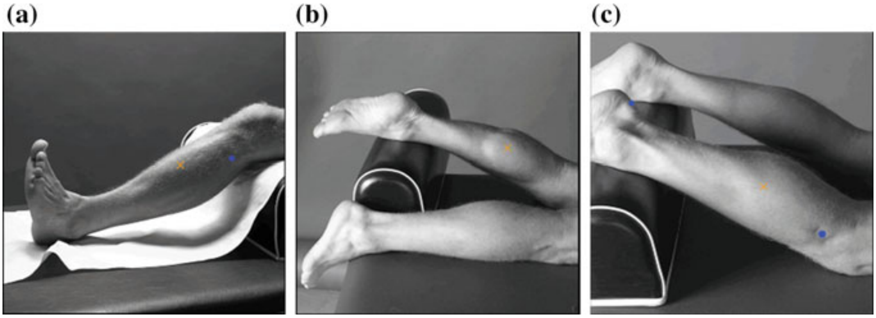

Fig. 5 EMG sensor attachment on *Tibialis Anterior* (**a**), *Gastrocnemius Medialis* (**b**) and *Gastrocnemius Lateralis* (**c**) [12]

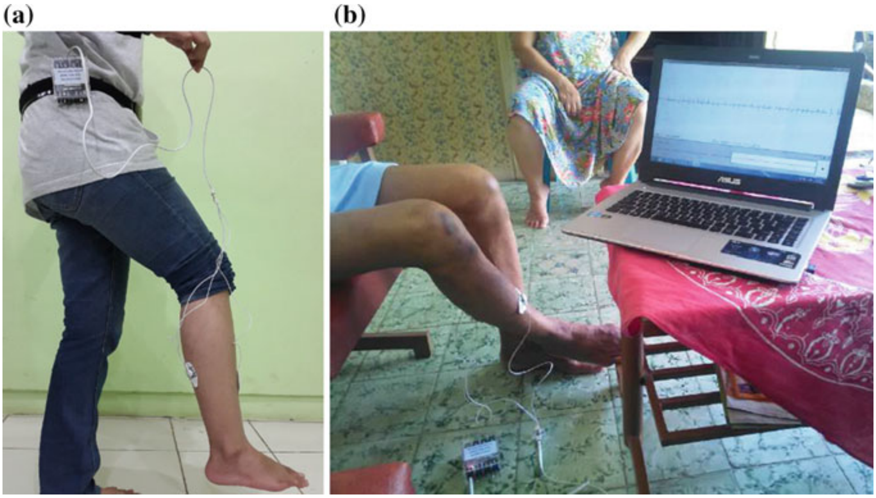

Fig. 6 Participants gait data acquisition process, **a** Healthy Participant, **b** Study participant with PD

3 Feature Calculation

In this study, the pattern recognition in PD staging is conducted using voice and EMG signal. The previous study [5, 13, 14] used 22 voice features. In this study, 22 voice features are selected into five features as presented in Sect. 3.1. All of the voice features are calculated in frequency domain. EMG signals use five selected features as discussed in Sect. 3.2. The EMG features consist of three features in time domain and two features in frequency domain. In the previous study, the five features of EMG have high accuracy on finger motion classification in five class pattern recognition [15].

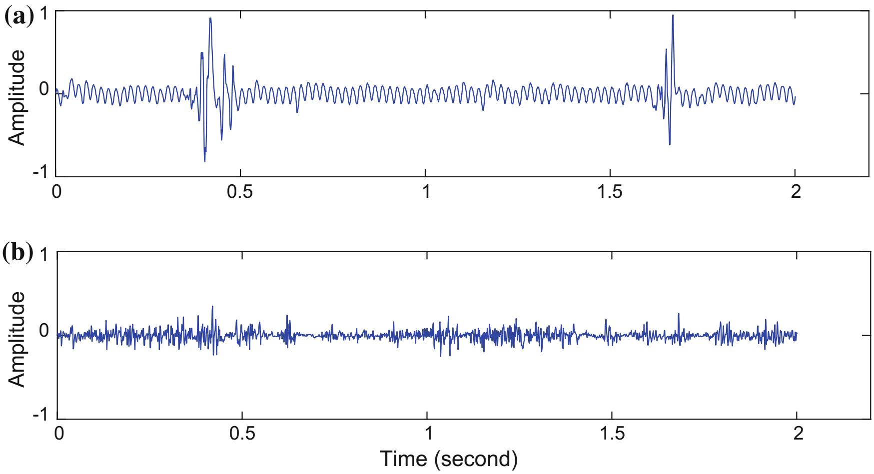

Fig. 7 Participant's gait signals using EMG, **a** Healthy Participant, **b** Participant with PD

3.1 Voice Features

a. Multi-Dimensional Voice Program/MDVP (F0)

F0 is the average value of the fundamental frequency. F0 estimation is important for voice signal characterization. Gender and age affect estimated value F0. In addition to gender and the estimated age of F0 as well influenced by emotional state while speaking, while talking through phone, incoming voice interference as background and indication when the speaker is in a state of alcohol. But the factors is only small and negligible [4]. Some researchers develop algorithms for value estimation F0 which is called Pitch Detection Algorithm (PDA). Generally the PDA has three stages of preprocessing, identification possible values of F0 and post-processing [4]. Identification of the algorithm include DYPSA (Dynamic Programming Projected Phase-Slope Algorithm), PRAAT, SHRP and SWIPE (Sawtooth Waveform Inspired Pitch Estimator) [4].

b. Local Jitter

Jitter serves to identify disorders and small irregularities which occurs in the period from cycle to cycle [4]. Equation (1) is the equation for local jitter [16].

$$Jitter\ local = \frac{jitter\ \text{(second)}}{mean\ period} \tag{1}$$

where:

$$Mean\ period = \sum\nolimits_{i=1}^{N} \frac{T_i}{N}\ \ \text{(second)} \tag{2}$$

$$Jitter\ second = \frac{\sum_{i=2}^{N} |T_i - T_{i-1}|}{(N-1)} \text{ (second)} \tag{3}$$

$T_i =$ Period interval-i (second)
$N =$ Sum of interval period

c. Period Perturbation Quotient 5 (PPQ5)

PPQ5 is the average value of the difference between the periods at a given interval with the four closest periods divided by the average period value [16]. Equation (4) is used to calculate PPQ5 [16].

$$PPQ5 = \frac{Absolute\ PPQ5 \text{ (second)}}{Mean\ period \text{ (second)}} \tag{4}$$

where:

$$Absolute\ PPQ5 = \frac{\sum_{i=3}^{N-2} |T_i - (T_{i-2} + T_{i-1} + T_i + T_{i+1} + T_{i+2})/5|}{N-4} \tag{5}$$

$$mean\ period = \sum_{i=1}^{N} \frac{T_i}{N} \tag{6}$$

d. Recurrence Period Density Entropy (RPDE)

RPDE is a feature that can be used to determine the period deviation on a repeating signal [4]. The vocal cords have the ability to maintain vocal stability while oscillating. In patients with PD there is a larger period deviation than healthy people when the vocal cords oscillate. The following Eq. (7) is the equation for RPDE.

$$RPDE = \frac{\sum_{i}^{T\max} p(i) \ln(p(i))}{\ln(T\max)} \tag{7}$$

e. Pitch Period Entropy (PPE)

PPE is a value that describes the subject's deviation or incompetence in maintaining the stability of the voice tone. PPE is a feature developed by a professor from MIT named Max A. Little [5].

3.2 EMG Features

a. Integrated EMG (IEMG)
IEMG is one of the EMG signal features that belong to the time domain feature. IEMG is commonly used as early detection of EMG signal interpretation for clinical areas [17, 18]. The following Eq. (8) is an equation for the IEMG feature.

$$IEMG = \sum_{i=1}^{N} |x_i| \tag{8}$$

where:

$N =$ number of EMG data
$i =$ ith EMG data
$x_i =$ raw ith of EMG data

b. Mean Absolute Value (MAV)
MAV is one of the EMG signal features that is included in the time domain feature. MAV is often used to interpret EMG signals. The following Eq. (9) is the equation for MAV.

$$MAV = \frac{1}{N} \sum_{i=1}^{N} |x_i| \tag{9}$$

c. Variance of EMG (VAR)
VAR is one of the EMG signal features that is included in the time domain feature. VAR is defined as the mean value of the square of the deviation value for the EMG signal. The following Eq. (10) is the equation for VAR [19].

$$VAR = \frac{1}{N-1} \sum_{i=1}^{N} x_i^2 \tag{10}$$

d. Mean Frequency (MNF)
Mean frequency (MNF) is an average frequency which is computed as sum of product of the signal power spectrum and the frequency divided by total sum of the spectrum intensity [20]. It can be calculated as expressed in (11).

$$MNF = \frac{\sum_{j=1}^{M} f_i P_j}{\sum_{j=1}^{M} P_j} \tag{11}$$

where f_j is spectrum frequency at frequency bin j, P_j is the signal power spectrum at frequency bin j, and M is length of the frequency.

e. Mean Power *(MNP)*
Mean power is defined as the average value of EMG signal in frequency domain. It can be expressed as in Eq. (12).

$$MNP = \frac{\sum_{j=1}^{M} P_j}{M} \tag{12}$$

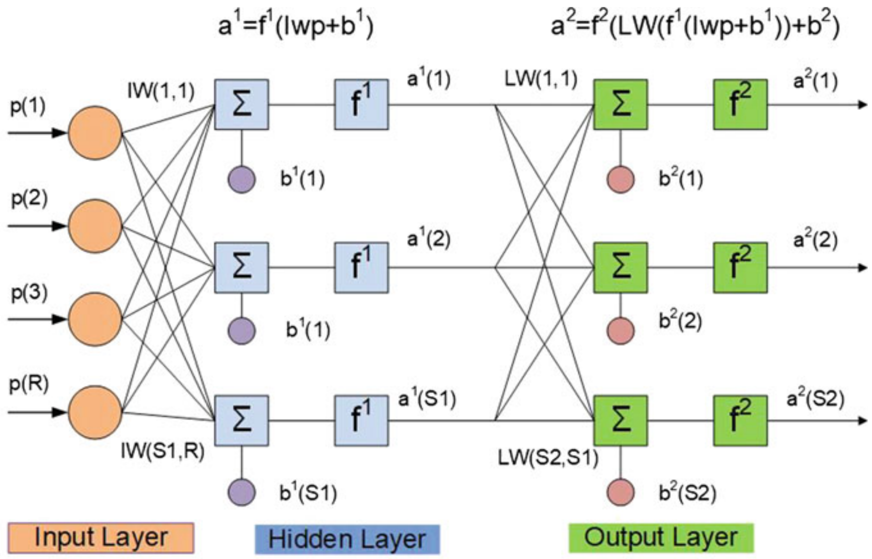

Fig. 8 Commonly used neural network structure

4 Pattern Recognition

4.1 Artificial Neural Network

In this section, the pattern recognition for voice and EMG features is classified using the neural network as can be shown in Fig. 8. The standard network that is used for pattern recognition method consists of input layer, hidden layer, and output layer. The first output neuron in the hidden layer can be expressed as in (13).

$$a^1 = f^1(IWp + b^1) \tag{13}$$

where a^1 is output vector in hidden layer, p is an n-length input vector, IW is input weight matrix, f^1 is transfer function of hidden layer, and b^1 is the bias vector of hidden layer. In the Fig. 8, R indicates the number of elements in input vector, while S1 and S2 denote the number of neuron in hidden layer and output layer respectively.

The first output neuron in the output layer as expressed in (14)

$$a^2 = f^2(LW(f^1(IWp + b^1)) + b^2) \tag{14}$$

where a^2 is output vector in output layer, LW is output layer weight matrix, f^2 is transfer function of the output layer, and b^2 is the bias vector of the output layer.

The Levenberg-Marquardt training algorithm is used in this study. It was designed to approach second-order training speed without having to compute the Hessian matrix. As typical training feedforward networks, the performance function of this training algorithm has the form of a sum of squares, and the Hessian matrix can be approximated using Eq. (15).

$$H = J^T J \tag{15}$$

and the gradient can be calculated as

$$g = J^T e \tag{16}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors.

The Levenberg-Marquardt training algorithm uses Eq. (17) to approximate the Hessian matrix

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{17}$$

When the scalar μ is zero, the Eq. (17) uses the approximated Hessian matrix. When μ is large, this becomes gradient descent with a small step size.

In this research study, Mean Square Error (MSE) is utilized in ANN for classification. The MSE measures the magnitude of the forecast errors as shown in (18). Better model will show the smaller values of MSE.

$$mse_{error} = \frac{\sum (y_1 - y_2)^2}{m} \tag{18}$$

where y_1 is the real output in classification, y_2 is the output from ANN classification, and m is the total number of samples in the classification.

In two class classification of PD, the used ANN has five input features and has two class classification results for healthy and PD. While In four class classification of PD, the ANN has five input features and four class classification results using Hughes scale for healthy, possible, probable, and definite. The training algorithm employs Levenberg-Marquardt training algorithm. The neural network has one hidden layer and 25 neurons in hidden layer both in two class and four class classifications. Finally, the proposed ANN's structure can be presented in Fig. 9. Hyperbolic tangent sigmoid transfer function is used in hidden layer and soft max transfer function is employed in output layer.

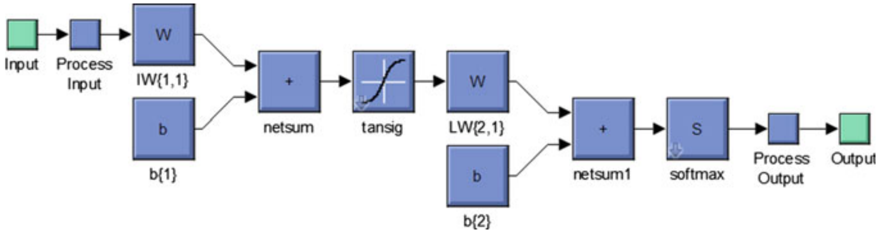

Fig. 9 Utilized ANN input and output for PD pattern recognition

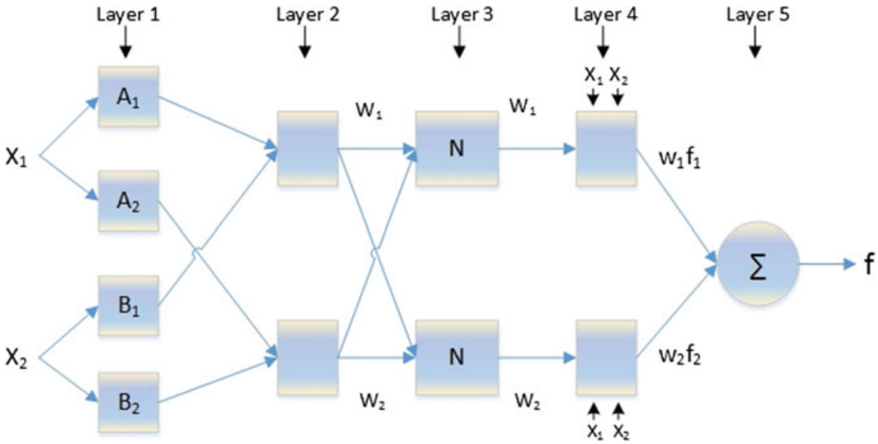

Fig. 10 Typical ANFIS architecture with first-order Sugeno fuzzy model

4.2 *Adaptive Neuro Fuzzy Inference System*

The adaptive neuro-fuzzy inference system (ANFIS) is a kind of neuro-fuzzy classifier method which integrates the neural network's adaptive capability and the fuzzy logic qualitative approach [21]. The common rule set with two fuzzy if-then rules for a first-order Sugeno fuzzy model can be written as follows

Rule 1: If x is A1 and y is B1, then f1 = p1x + q1y + r1;
Rule 2: If x is A2 and y is B2, then f2 = p2x + q2y + r2;

where p1, p2, q1, q2, r1 and r2 are linear parameters, and A1, A2, B1 and B2 are nonlinear parameters.

The ANFIS architecture consists of five layers as depicted in Fig. 10. The layers in ANFIS can be described as follows

Layer 1: All the nodes are adaptive nodes. The output of the *i*th node in layer 1 is denoted as $O_{l,i}$. The outputs of this layer are the fuzzy membership function of the inputs that can be expressed as in Eqs. (19) and (20)

$$O_{1,i} = \mu_{Ai}(x), \quad for\, i = 1, 2 \tag{19}$$

$$O_{1,i} = \mu_{Bi}(y), \quad for\, i = 3, 4 \tag{20}$$

where x (or y) is the input to nodes i and Ai (or Bi–2) generating a linguistic label coupled with the node. In this study, the membership function for A (or B) can be any parameterized as a gaussian membership function as written in (21)

$$\mu A_i(x) = \exp\left\{-\frac{1}{2}\frac{(x - c_i)^2}{\sigma_i^2}\right\} \tag{21}$$

where (c_i, σ_i) are the parameter set.

Layer 2: This layer perform as a simple multiplier. Each node in this layer calculates the firing strengths of each rule via multiplying the incoming signals and sends the product out. The outputs of this layer can be expressed as in (22)

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y), \quad i = 3, 4 \tag{22}$$

Layer 3: The nodes are also fixed nodes, indicate a normalization role to the firing strengths from the previous layer. The ith node of this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths as in (23)

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_{i=1}^{2} w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \tag{23}$$

Layer 4: This nodes are adaptive nodes. Parameters in layer 4 will be referred to as consequent parameters. The output of each node in this layer is the product of the normalized firing strength and a first order polynomial. The output of this layer can be express in (24)

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \tag{24}$$

where $\bar{w}_i$ is a normalized firing strength from layer 3.

Layer 5: There is only single fixed node. This node performs the summation of all incoming signals from layer 4. The output of layer 5 is summarized as in (25)

$$O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{25}$$

In this study, the utilized ANFIS structure can be seen in Fig. 11. The structure has 243 rules. The layer 1 uses gaussian membership function. Each of input has three gaussian membership functions. The layer 4 uses linear output function. For the training algorithm, hybrid learning is selected. The used Fuzzy operators are product

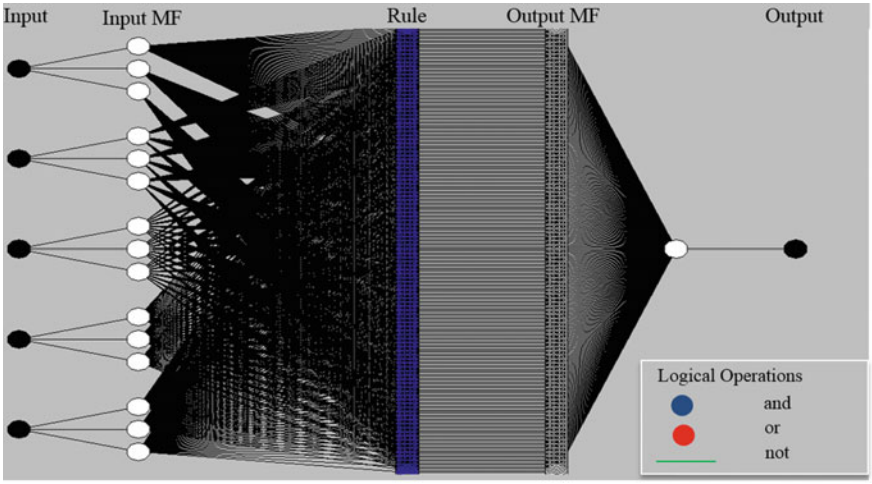

Fig. 11 Proposed ANFIS architecture with first-order Sugeno fuzzy model for PD classification

for And method and probabilistic OR for Or method. The selected implication and aggregation method are minimum and maximum method. Weighted average of all rule outputs method is used for defuzzification process.

5 Result

All of the involved study participants are PD patients from dr. Kariadi general hospital in Semarang. Eight healthy participants and 15 study participants with PD are involved in this study. Table 1 shows the list of study participants. There are 23 study participants who join in the research, 15 participants with PD both male and female with age range from 39 years old to 80 years old, and 8 healthy participants both male and female with age range from 52 years old to 75 years old. Classification process in this research used total 126 data for voice signals and 69 data for EMG signals. Voice and EMG signal data have been collected from 8 healthy participant and 15 people with PD participants. Healthy participants recorded their voice six times per person. Voice signal have been collected from PD patients consist of 10 patients with six time recording each, 3 patients with four recording each and 2 patients with 3 recording each. There are different data recording for PD patients because some of patients struggling to produce their voice to be recorded. EMG signals have been collected three times each for both healthy and PD participants.

For the convenience and confidentiality of the study participants, the participant name's identity is kept secret. Unfortunately, the data acquisition for EMG signals is less than the data from voice signals because of the condition on the study participants with PD. Few PD participants can be acquired using EMG signals depending

Table 1 List of data capturing study participants

Parkinson participants				Healthy participants		
Study participants	Sex	Age (years old)	Status	Study participants	Sex	Age (years old)
S 1	Male	68	Definite	S 16	Female	71
S 2	Male	53	Possible	S 17	Female	53
S 3	Male	59	Possible	S 18	Female	75
S 4	Female	79	Definite	S 19	Male	70
S 5	Female	66	Definite	S 20	Female	55
S 6	Female	39	Probable	S 21	Female	70
S 7	Female	58	Possible	S 22	Male	52
S 8	Female	54	Probable	S 23	Male	60
S 9	Male	66	Probable			
S 10	Male	80	Probable			
S 11	Male	76	Probable			
S 12	Male	70	Definite			
S 13	Male	68	Probable			
S 14	Male	68	Definite			
S 15	Male	72	Definite			

on his/her health condition. The classification results are presented in performance measures i.e. accuracy, precision, recall, F1 score, and Cohen's kappa. The resulted value of Kappa is characterized based on the reference [22].

5.1 Classification Result of Artificial Neural Network Method

Classification using ANN method recognizes the terms of training and testing. Training in ANN is a dataset that serves to adjust the weighting and biases in the ANN method. Testing in ANN is a dataset that serves to test the final solution to confirm the strength and toughness of the ANN classifier. The dataset selected for training and testing process is randomly assigned by the ANN. The dataset is selected based on a percentage of 70% of the data for training, and 30% for testing. The ANN classification results for this study consist of training and testing results for two class classification using voice signals, four class classification using voice signals, two class classification using EMG signals and four class classification using EMG signals.

Table 2 Accuracy of voice signals for two classes using ANN in testing

Actual class	Classification result	
	Healthy	PD
Healthy	12	5
PD	0	21
Accuracy (%)	70.59	100
Total accuracy (%)	86.84	

Table 3 Performance measures of voice signals for two classes using ANN in testing

Performance	Values
Accuracy	0.8684
Precision	1
Recall (Sensitivity)	0.7059
F1 score	0.8276
Kappa	0.7262

5.1.1 Classification Results of Voice Signals for Two Classes

The data for training and testing consists of 126 voice record data from healthy and participants with PD. The data are divided into two sets, 88 for training and 38 for testing. The data for training and testing are selected randomly. For training data, the data are divided in two sets i.e. 31 for healthy class and 57 for participants with PD.

Table 2 shows the accuracy of the testing result with the ANN of the voice signal for two classes. The dataset included in the first and second class is class with healthy and participants with PD randomly selected 17 and 21 data respectively. Accuracy testing for healthy and PD is 70.59 and 100%. The overall testing accuracy for the two classes is 86.84%. The performance measures of the classification results can be summarized in Table 3. Based on the Table 3, F1 score and Kappa are 0.8276 and 0.7262. Based on the Kappa value, the classifier has substantial agreement.

Table 4 shows the overall accuracy (training and testing) of the ANN classifier for two classes. The target for the first class of healthy class shows an accuracy of 89.58%. The target class for the second class is the participants with PD showing an accuracy of 100%. The overall accuracy result is 96.03%. The performance measures of the overall classification can be summarized as in Table 5. It indicates that the ANN classifier has both high precision and high recall. The resulted Kappa shows that the classifier has almost perfect agreement.

5.1.2 Classification Results of Voice Signals for Four Classes

In four class classification, the data for training and testing consists of 126 voice record data from 48 healthy and 78 PD. The overall data are divided into two sets, 88 for training and 38 for testing. For training data, the data is divided in four sets

Table 4 Accuracy of voice signals for two classes using ANN in overall

Target class	Classification result	
	Healthy	PD
Healthy	43	5
PD	0	78
Accuracy (%)	89.58	100
Total accuracy (%)	96.03	

Table 5 Performance measures of voice signals for two classes using ANN in overall

Performance	Values
Accuracy	0.9603
Precision	1
Recall (Sensitivity)	0.8958
F1 score	0.9451
Kappa	0.9141

Table 6 Accuracy of voice signals for four classes using ANN in testing

Actual class	Classification Result			
	Healthy	Possible	Probable	Definite
Healthy	9	1	3	1
Possible	0	1	0	3
Probable	1	4	4	1
Definite	0	3	2	5
Accuracy (%)	64.29	25	40	50
Total accuracy (%)	50			

i.e. 34 for healthy, 11 for possible, 20 for probable, and 23 for definite. The data for training and testing are selected randomly.

Table 6 shows the ANN test results for four class classification of voice signals. The dataset for testing is divided in four sets i.e. healthy, possible, probable, and definite randomly selected from 14, 4, 10, and 10 data respectively. The accuracy of each class is 64.29% for healthy, 25% for possible, 40% for probable, and 50% for definite. The overall testing accuracy for the four classes is 50%. The performance measures of classifier in overall can be summarized in Table 7. Based on the resulted Kappa, the classification result has fair agreement.

Table 8 reveals the ANN classification overall (training and testing) results for four class classification of voice signals. The overall accuracy of each class is 87.5% for healthy, 80% for possible, 70% for probable, and 84.85% for definite. The overall accuracy for the four classes is 81.75%.

The performance measures of the overall classification for four class classification are summarized as in Table 9. Based on the resulted Kappa, it shows that the classifier has moderate agreement. Healthy class has the highest accuracy of all classes.

Table 7 Performance measures of voice signals for four classes using ANN in testing

Performance	Healthy	Possible	Probable	Definite	Total
Accuracy	0.6429	0.2500	0.4000	0.5000	0.5000
Precision	0.9	0.1111	0.4444	0.5000	0.4889
Recall (Sensitivity)	0.6429	0.2500	0.4000	0.5000	0.4482
F1 score	0.7500	0.1538	0.4211	0.5000	0.4562
Kappa	0.4265	0.6999	0.5805	0.5534	0.2500

Table 8 Accuracy of voice signals for four classes using ANN in overall

Target class	Classification result			
	Healthy	Possible	Probable	Definite
Healthy	42	1	4	1
Possible	0	12	0	3
Probable	2	5	21	2
Definite	0	3	2	28
Accuracy (%)	87.5	80	70	84.85
Total accuracy (%)	81.75			

Table 9 Performance measures of voice signals for four classes using ANN in overall

Performance	Healthy	Possible	Probable	Definite	Total
Accuracy	0.8750	0.8000	0.7000	0.8485	0.8175
Precision	0.9546	0.5714	0.7778	0.8235	0.7818
Recall (Sensitivity)	0.8750	0.8000	0.7000	0.8485	0.8059
F1 score	0.9130	0.6667	0.7368	0.8358	0.7881
Kappa	0.3039	0.7281	0.5796	0.4981	0.5132

5.1.3 Classification Results of EMG Signals for Two Classes

The data for training and testing consists of 69 EMG signal record data from healthy and participants with PD. The data are divided into two sets, 48 for training and 21 for testing. The data for training and testing are selected randomly in EMG signal classification. For training data, the data is divided in two sets i.e. 16 for healthy class and 32 for participants with PD.

Table 10 shows the accuracy of the testing result of the EMG signal for two classes. The dataset in the first and second class is a class with healthy and participants with PD randomly selected 8 and 13 data respectively from testing data. Accuracy testing for healthy and PD is 87.5% and 84.62%. The overall testing accuracy for the two classes using EMG signals is 85.71%. The performance measures of the classification

Table 10 Accuracy of EMG signals for two classes using ANN in testing

Actual class	Classification result	
	Healthy	PD
Healthy	7	1
PD	2	11
Accuracy (%)	87.5	84.62
Total accuracy (%)	85.71	

Table 11 Performance measures of EMG signals for two classes using ANN in testing

Performance	Values
Accuracy	0.8571
Precision	0.7778
Recall (Sensitivity)	0.8750
F1 score	0.8235
Kappa	0.7042

Table 12 Accuracy of EMG signals for two classes using ANN in overall

Target class	Classification result	
	Healthy	PD
Healthy	22	2
PD	3	42
Accuracy (%)	91.67	93.33
Total accuracy (%)	92.75	

Table 13 Performance measures of EMG signals for two classes using ANN in overall

Performance	Values
Accuracy	0.9275
Precision	0.8800
Recall (Sensitivity)	0.9167
F1 score	0.8980
Kappa	0.8418

results in two class classification can be shown in Table 11. Based on the Kappa value in Table 11, the classifier has substantial agreement.

The overall accuracy (training and testing) of the ANN for two classes can be shown in Table 12. The overall accuracy for healthy class and participants with PD is 91.67 and 93.33% respectively. The overall accuracy result is 92.75%. The performance measures of the overall classification can be summarized in Table 13. Based on F1 Score, It indicates that the classifier has both high precision and high recall. The resulted Kappa in overall classification result shows that the classifier has almost perfect agreement.

Table 14 Accuracy of EMG signals for four classes using ANN in testing

Target class	Classification result			
	Healthy	Possible	Probable	Definite
Healthy	3	1	1	3
Possible	1	1	0	1
Probable	1	1	0	2
Definite	1	0	1	4
Accuracy (%)	37.5	33.33	0	66.67
Total accuracy (%)	38.1			

Table 15 Performance measures of EMG signals for four classes using ANN in testing

Performance	Healthy	Possible	Probable	Definite	Total
Accuracy	0.3750	0.3333	0	0.6667	0.3810
Precision	0.5000	0.3333	0	0.4000	0.3083
Recall (Sensitivity)	0.3750	0.3333	0	0.6667	0.3438
F1 score	0.4286	0.3333	NaN	0.5000	NaN
Kappa	0.4762	0.7429	0.7506	0.3950	0.3942

5.1.4 Classification Results of EMG Signals for Four Classes

In four class classification using EMG signals, the data for training and testing consists of 69 voice record data from 24 healthy and 45 participants with PD. The data are divided into two sets, 48 for training and 21 for testing. For training data, the data are divided in four sets i.e. 16 for healthy, 6 for possible, 11 for probable, and 15 for definite. The data for training and testing are selected randomly.

Table 14 shows the ANN classification testing results for four class classification of EMG signals. The dataset for testing is divided in four sets i.e. healthy, possible, probable, and definite randomly selected from 8, 3, 4, and 6 data respectively. The testing accuracy of each class is 37.5% for healthy, 33.33% for possible, 0% for probable, and 66.67% for definite. The overall testing accuracy for the four classes is 38.1%. The performance measures of classifier in testing are presented in Table 15. F1 Score has the value of NaN (Not a Number). It indicates that the classifier has poor precision and poor recall. Based on the resulted Kappa, the classification result has fair agreement.

The overall accuracy result of the EMG signal classification is shown in Table 16. The overall accuracy result for the ANN classification is 76.81%. The lowest accuracy is probable class. The performance measures of classifier in overall are presented in Table 17. Based on the resulted Kappa, the overall classification result has fair agreement in four class classification using EMG signals.

Table 16 Accuracy of EMG signals for four classes using ANN in overall

Target class	Classification result			
	Healthy	Possible	Probable	Definite
Healthy	19	1	1	3
Possible	1	6	0	2
Probable	1	2	9	3
Definite	1	0	1	19
Accuracy (%)	79.17	66.67	60	90.48
Total accuracy (%)	76.81			

Table 17 Performance measures of EMG signals for four classes using ANN in overall

Performance	Healthy	Possible	Probable	Definite	Total
Accuracy	0.7917	0.6667	0.6000	0.9047	0.7681
Precision	0.8636	0.6667	0.8182	0.7037	0.7630
Recall (Sensitivity)	0.7917	0.6667	0.6000	0.9048	0.7408
F1 score	0.8261	0.6667	0.6923	0.7917	0.7442
Kappa	0.3861	0.7516	0.6464	0.3687	0.3816

5.2 *Classification Result of Adaptive Neuro-Fuzzy Inference System (ANFIS)*

The dataset selected for the training and testing process is randomly assigned. The dataset is selected based on a percentage of about 70% of the data for training, and about 30% for the testing. ANFIS classification results consist of training and testing results for two class classification using voice signals, four class classification using voice signals, two class classification using EMG signals and four class classification using EMG signals.

5.2.1 Classification Results of Voice Signals for Two Classes

The data for training and testing consists of 126 voice record data from 48 healthy and 78 with PD. The data are divided into two sets, 88 for training and 38 for testing. The data for training and testing are selected randomly. For training data, the data are divided in two sets i.e. 29 for healthy class and 59 for PD. Table 18 shows the accuracy of the testing result of voice signal for two classes. The dataset in the first and second class is a class with healthy and participants with PD randomly selected 19 and 19 data respectively. Accuracy testing for healthy and PD is 100% and 100% respectively. The overall testing accuracy is 100%. The performance measures of the classification results can be summarized in Table 19. Based on the Table 19, F1 score

Table 18 Accuracy of voice signals for two classes using ANFIS in testing

Actual class	Classification result	
	Healthy	PD
Healthy	19	0
PD	0	19
Accuracy (%)	100	100
Total accuracy (%)	100	

Table 19 Performance of voice signals for two classes using ANFIS in testing

Performance	Values
Accuracy	1
Precision	1
Recall (Sensitivity)	1
F1 score	1
Kappa	1

Table 20 Accuracy of voice signals for two classes using ANFIS in overall

Actual class	Classification result	
	Healthy	PD
Healthy	48	0
PD	0	78
Accuracy (%)	100	100
Total accuracy (%)	100	

Table 21 Performance measures of voice signals for two classes using ANFIS in overall

Performance	Values
Accuracy	1
Precision	1
Recall (Sensitivity)	1
F1 score	1
Kappa	1

and Kappa are 1 and 1. It indicates that the classification results has best precision and best recall. Based on the Kappa value, the classifier has perfect agreement.

Table 20 shows the overall accuracy (training and testing) of the ANFIS for two classes. The overall accuracy of both healthy and PD class is 100%. The overall accuracy result is 100%. The performance measures of the overall classification can be summarized as in Table 21. It indicates that the classifier has both best precision and best recall. The resulted Kappa show that the classifier has perfect agreement in overall two class classification using voice signals.

Table 22 Accuracy of voice signals for four classes using ANFIS in testing

Actual class	Classification result			
	Healthy	Possible	Probable	Definite
Healthy	15	0	0	0
Possible	0	1	1	3
Probable	2	2	1	3
Definite	0	0	1	8
Accuracy (%)	100	20	12.5	88.89
Total accuracy (%)	67.57			

Table 23 Performance measures of voice signals for four classes using ANFIS in testing

Performance	Healthy	Possible	Probable	Definite	Total
Accuracy	1	0.200	0.125	0.8889	0.6757
Precision	0.8824	0.3333	0.33	0.5714	0.5301
Recall (Sensitivity)	1	0.2000	0.125	0.8889	0.5535
F1 score	0.9375	0.2500	0.1818	0.6957	0.5162
Kappa	0.1720	0.8003	0.7305	0.4418	0.1351

5.2.2 Classification Results of Voice Signals for Four Classes

In four class classification using ANFIS, the data for training and testing consist of 126 voice record data from 48 healthy and 78 PD. The data are divided into two sets, 89 for training and 37 for testing. For training data, the data are divided in four sets i.e. 33 for healthy, 10 for possible, 22 for probable, and 24 for definite. The data for training and testing are selected randomly.

The classification test result for four class classification using ANFIS of EMG signals is presented in Table 22. The dataset for testing is divided in four sets i.e. healthy, possible, probable, and definite randomly selected from 15, 5, 8, and 9 data respectively. The testing accuracy of each class is 100% for healthy, 20% for possible, 12.5% for probable, and 88.89% for definite. The overall testing accuracy for the four classes is 67.57%. The performance measures of classifier in testing can be summarized in Table 23. Based on the resulted Kappa, the classification result has slight agreement.

Table 24 reveals the classification results in overall (training and testing) for four class classification of voice signals. The overall accuracy of each class is 100% for healthy, 73.33% for possible, 76.67% for probable, and 96.97% for definite. The overall accuracy for the four classes is 90.48%. The performance measures of the overall classification for four classes can be presented in Table 25. Based on the resulted Kappa, it shows that the classifier has substantial agreement.

Table 24 Accuracy of voice signals for four classes using ANFIS in overall

Actual class	Classification result			
	Healthy	Possible	Probable	Definite
Healthy	48	0	0	0
Possible	0	11	1	3
Probable	2	2	23	3
Definite	0	0	1	32
Accuracy (%)	100	73.33	76.67	96.97
Total accuracy (%)	90.48			

Table 25 Performance measures of voice signals for four classes using ANFIS in overall

Performance	Healthy	Possible	Probable	Definite	Total
Accuracy	1	0.7333	0.7667	0.9697	0.9048
Precision	0.9600	0.8462	0.9200	0.8421	0.8921
Recall (Sensitivity)	1	0.7333	0.7667	0.9697	0.8674
F1 score	0.9796	0.7857	0.8364	0.9014	0.8758
Kappa	0.2320	0.7834	0.5816	0.4564	0.7460

Table 26 Accuracy of EMG signals for two classes using ANFIS in overall

Actual class	Classification result	
	Healthy	PD
Healthy	2	4
PD	3	10
Accuracy (%)	33.33	76.92
Total accuracy (%)	63.16	

5.2.3 Classification Results of EMG Signals for Two Classes

The training and testing data consist of 69 EMG signal data from healthy and PD. The data are divided into two sets, 50 for training and 19 for testing. For training data, the data is divided in two sets i.e. 18 for healthy class and 32 for participants with PD. Table 26 shows the accuracy of testing result of the EMG signals for two classes. The dataset in the first and second class are a class with healthy and participants with PD randomly selected 6 and 13 data respectively from testing data. The overall testing accuracy for the two classes is 63.16%. The performance measures can be shown in Table 27. Based on the Kappa value, the classifier has slight agreement in testing.

The overall accuracy for two classes is presented in Table 28. The overall accuracy for healthy class and participants with PD class is 70.83% and 91.11% respectively. The overall accuracy result is 84.06%. The performance measures of the overall classification can be summarized in Table 29. The resulted Kappa on overall classification result shows that the classifier has substantial agreement.

Table 27 Performance measures of EMG signals for two classes using ANFIS in testing

Performance	Values
Accuracy	0.6316
Precision	0.4000
Recall (Sensitivity)	0.3333
F1 score	0.3636
Kappa	0.1074

Table 28 Accuracy of EMG signals for two classes using ANFIS in overall

Actual class	Classification result	
	Healthy	PD
Healthy	17	7
PD	4	41
Accuracy (%)	70.83	91.11
Total accuracy (%)	84.06	

Table 29 Performance measures of EMG signals for two classes using ANFIS in overall

Performance	Values
Accuracy	0.8406
Precision	0.8095
Recall (Sensitivity)	0.7083
F1 score	0.7556
Kappa	0.6381

5.2.4 Classification Results of EMG Signals for Four Classes

The training and testing data consist of 69 voice record data from 24 healthy and 45 PD. The data are divided into two sets, 47 for training and 22 for testing. For training data, the data are divided in four sets i.e. 16 for healthy, 6 for possible, 10 for probable, and 15 for definite. Table 30 shows the accuracy of test results for four class classification of EMG signals. The dataset for testing is divided in four sets i.e. healthy, possible, probable, and definite randomly selected from 8, 3, 5, and 6 data respectively. The overall testing accuracy for the four classes is 31.82%. The performance measures of classifier in testing are shown in Table 31. F1 score has the value of NaN (Not a Number). It indicates that the classifier has poor precision and poor recall. Based on the Kappa value, the classification result has moderate agreement.

The overall accuracy result of the EMG signal classification using ANFIS is presented in Table 32. The overall accuracy result for the ANFIS is 75% for healthy, 66.67% for possible, 40% for probable, and 61.91% for definite. The lowest accuracy is probable class. The performance measures of classifier in overall can be presented in Table 33. Based on the Kappa value, the overall classification result has slight agreement in four class classification using EMG signals.

Table 30 Accuracy of EMG signals for four classes using ANFIS in testing

Actual class	Classification result			
	Healthy	Possible	Probable	Definite
Healthy	4	1	0	3
Possible	0	2	1	0
Probable	4	0	0	1
Definite	2	3	0	1
Accuracy (%)	50	66.67	0	16.67
Total accuracy (%)	31.82			

Table 31 Performance measures of EMG signals for four classes using ANFIS in testing

Performance	Healthy	Possible	Probable	Definite	Total
Accuracy	0.5000	0.6667	0	0.1667	0.3182
Precision	0.4000	0.3333	0	0.2000	0.2333
Recall (Sensitivity)	0.5714	0.7895	0.9412	0.7500	0.3333
F1 score	0.4444	0.4444	NaN	0.1818	NaN
Kappa	0.4040	0.6318	0.7479	0.6061	0.4500

Table 32 Accuracy of EMG signals for four classes using ANFIS in overall

Actual class	Classification result			
	Healthy	Possible	Probable	Definite
Healthy	18	1	2	3
Possible	0	6	2	1
Probable	6	2	6	1
Definite	2	6	0	13
Accuracy (%)	75	66.67	40	61.91
Total accuracy (%)	62.32			

Table 33 Performance measures of EMG signals for four classes using ANFIS in overall

Performance	Healthy	Possible	Probable	Definite	Total
Accuracy	0.7500	0.6667	0.4000	0.6191	0.6232
Precision	0.6923	0.4000	0.6000	0.7222	0.6036
Recall (Sensitivity)	0.7500	0.6667	0.4000	0.6191	0.6089
F1 score	0.7200	0.5000	0.4800	0.6667	0.5917
Kappa	0.3743	0.6812	0.6722	0.4992	0.0048

6 Conclusion and Future Works

There are some conclusions that can be concluded from the research:

- Two class classification has higher accuracy than four class classification both in neural network and adaptive fuzzy-inference system.
- Voice method classification has higher accuracy than EMG classification because the feature for voice is a good feature which can well classified the voice data. Voice data sampling rate is higher than EMG data sampling rate which means voice data recording has more data each second than EMG data.
- EMG signal classification has less accuracy because there is a lot of noise in the EMG Sensor and it has one channel with low sampling rate i.e. 1000 Hz.
- Based on the four class classification results in both of voice and EMG signals using ANN and ANFIS, the probable class has the lowest accuracy of all.

To increase the accuracy of pattern recognition method, it can be conducted by using higher sampling rate up to 100 kHz and more channel in EMG sensor. The low accuracy in four class classifications especially in testing can caused by wrong staging PD of patient. For example when the PD study participants met the neurologist, he/she has been diagnosed with staging possible, but when the researcher met the study participant, the staging of PD become probable or definite when his/her healthy condition become worse. When this study participant's signal is used, it can give miss classification and decrease the accuracy in PD pattern recognition.

Future research can be conducted by adding a new method for PD detection: hand tremor method. Based on the research, almost all PD participants have a tremor in their hands as sign of PD symptom. With hand tremor detection method, there is a hope that this PD detection tool will be very accurate. The accuracy result between voice, gait EMG and hand tremor can be combined in order to achieve higher accuracy.

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