Iterative Filtering Decomposition Based Early Dementia Diagnosis Using EEG With Cognitive Tests

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Abstract— *Objective*: There has been a constant increase in life expectancy with the advancement of modern medicine. Likewise, dementia has also increased and projected to elevate in the coming decades with the higher expenditure on healthcare. Consequently, it is essential to identify early dementia, e.g., a patient suffering from mild cognitive impairment who is highly vulnerable to developing dementia soon. *Methods*: Through this work, we brought forward an approach by fusing cognitive task and EEG signal processing. Continuous EEG of 16 dementia, 16 early dementia and 15 healthy subjects recorded under two resting states; eye open and eye closed, and two cognitive states; finger tapping test (FTT) and the continuous performance test (CPT). The present approach introduced iterative filtering (IF) as a decomposition technique for dementia diagnosis along with four significant EEG features power spectral density, variance, fractal dimension and Tsallis entropy. Multi-class classification conducted to compare the decision tree, k nearest neighbour (*k*NN), support vector machine, and ensemble classifiers. *Results*: The proposed approach deeply checked for their capability of prediction using cognitive scores and EEG measures. The highest accuracies obtained by *k*NN with 10-fold cross-validation for dementia, early dementia and healthy are 92.00%, 91.67% and 91.87%, respectively. *Conclusion*: The essential findings of this study are: 1) Experimental results indicate that *k*NN is superior over other classifier algorithms for dementia diagnosis. 2) CPT is the best predictor for healthy subjects. 3) FTT can be an essential test to diagnose significant dementia. *Significance*: IF decomposition technique enhances the diagnostic accuracy even with a limited dataset.

Index Terms— Early dementia, dementia diagnosis, iterative filtering decomposition, finger tapping test, continuous performance test.

I. Introduction

DEMENTIA is the umbrella term which describes and characterise several neurodegenerative disorders resulting from damage and death of neurons, presenting complaints of disturbance of cognitive and behavioural functions. This syndrome is described clinically as a group of symptoms that disrupts the functioning of the five cognitive domains (i.e., attention, memory, executive function, visual-spatial ability, and language) [1]. Dementia has different causes such as Alzheimer's disease (AD), vascular dementia (VD), Lewy body, frontotemporal dementia, and Parkinson's disease (PD) and others. Out of these, AD is the primary cause, accounting for about 50% to 70% of dementia cases worldwide, and the second-largest cause is VD. The common symptoms of AD are short-term memory loss and word-finding difficulties. In contrast, VD shows loss of executive functions. There were 46 million people had dementia worldwide in 2015. This number is predicted to increase to 131.5 million by the year 2050. It is indicated one new case appearing every 3.2 seconds and over 9.9 million new cases each year worldwide [2]. Early envisaging of dementia at right the stages is essential for improving treatment and therapy before brain damage ensues.

Recent studies have proved that the electroencephalography (EEG) complexity and frequency analysis could be addressed to diagnose AD and other types of dementia in the early stages [3]–[5]. EEG is a complicated and discontinuous time series, which is the sum over a large number of neuronal membrane potentials. The preferred mode of investigation for VD and AD patients is non-invasive. Thus, Magnetic Resonance Imaging (MRI) uses for image and EEG signal processing leading to the diagnosis of the two [6], [7]. In this project, we aimed to classify dementia, early dementia, and unaffected subjects in four varied situations, eye-open (EO), eye-close (EC), finger tapping test (FTT) and continuous performance test (CPT) by using iterative filtering decomposition (IFD). This work investigates four features of EEG: power spectral density (PSD), variance (Var), fractal dimension and Tsallis entropy (TE). EEG signals classified using four classifiers; decision tree (DT), k nearest neighbour (*k*NN), support vector machine (SVM), ensemble classifier based on these four features. The contributions of the proposed work are as follows:
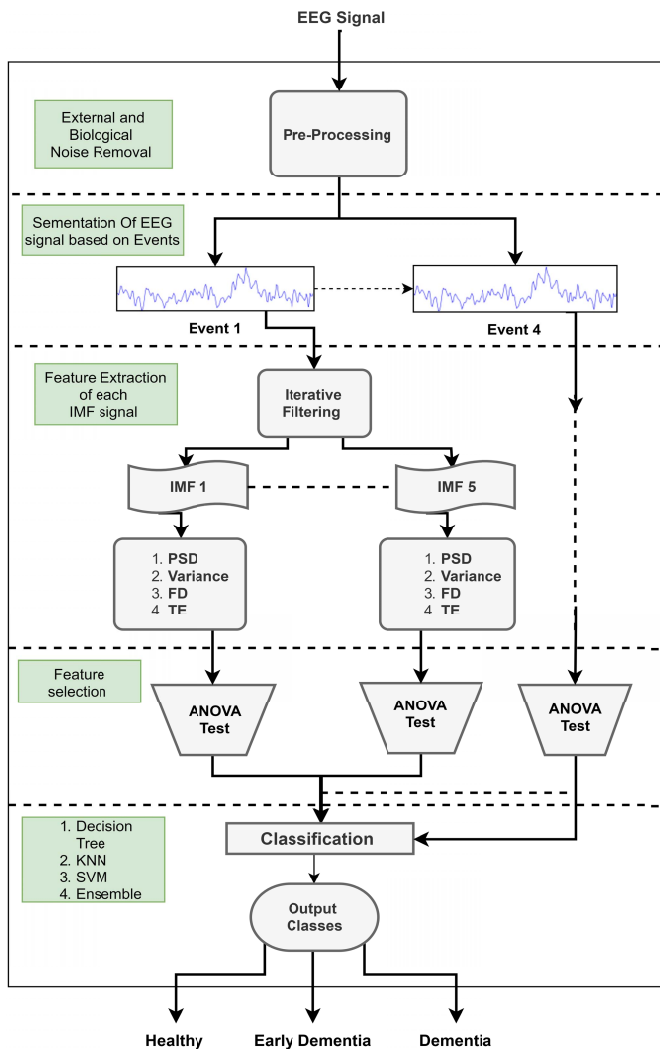
Fig. 1. Block diagram of the proposed approach.

- The Combination of the cognitive test (FTT and CPT) and EEG as a diagnostic tool for early dementia diagnosis in the clinical setting is introduced.
- CPT with EEG is the best test to differentiate early dementia from healthy subjects.
- FTT with EEG is the best test to diagnose dementia from the milder stage and healthy subjects.
- kNN classifier shows the best performance compare to SVM, DT and ensemble classifier.

II. PROPOSED APPROACH

The proposed approach is divided into four broad stages, as shown in Fig.1. The first step involves the acquisition of EEG in customised scenarios and preparing each signal for a further stage by removing external and biological noise. External noise includes the sinusoidal frequency from electricity fluctuations, electrical devices and fluorescent lights and other noise like unwanted frequency (above 65 Hz). Bandpass filter and frequency-domain regression technique removed the external noise from the EEG signal using CleanLine tool [8]. Biological noise such as eye blink, head jerk and

TABLE I
DEMOGRAPHIC DETAILS OF SUBJECTS

	Dementia	Early dementia	Healthy
Subject	16	16	15
Gender (Male: Female)	11:05	13:03	10:05
Age (years)	61.63±11.15	58.44±11.75	53.47±11.10
Education	6.81±6.20	7.19± 6.46	6.80±6.68
HMSE	12.56	22.19	27.27

ECG are removed by independent component analysis (ICA) using EEGLAB toolbox [9]. ICA decomposition is performed using the logistic infomax ICA algorithm. Wavelet-based denoising has been done to remove the white noise from the signal. The wavelet transform concentrates signal into a few large-magnitude wavelet coefficients. Wavelet coefficients which are small in value are typically noise, and those coefficients can be removed without affecting the signal quality. After eliminating those coefficients, the signal is reconstructed by using the inverse wavelet transform. ICA and wavelet denoising is the combination to eliminate artefact from EEG signal [10], [11]. The second stage encompasses the segmentation of continuous data into events; EO, EC, FTT and CPT.

Traditionally, Fourier spectral analysis has used to analysing signal [12], [13]. Another popular technique is the wavelet transform [14], [15]. These techniques are often effective, but these have few drawbacks. The main limitation is that these techniques are not data adaptive. Norden Huang et al., (1998) [16] proposed the empirical mode decomposition (EMD) technique for data analysis, which is a high data-adaptive compare to the Fourier and Wavelet transforms. Recently proposed IFD is advantageous over EMD technique. IFD is more stable than EMD under perturbations of a non-stationary signal like EEG [17], [18]. In the third stage, IFD is implemented on each segment of the segmented EEG signal, which decomposed the signal until six intrinsic mode functions (IMF). Sixth IMF has been discarded due to less information content. Further, four features; PSD, Var, FD and TE are extracted from each IMF. A total of 20 features (4 features × 5 IMF) are ready for the classification process.

III. MATERIAL

A. Subjects

EEG data acquired from 47 subjects. The study participants have been screened and classified by the clinical psychiatrists strictly based on the DSM-5 criteria and recruited for the study [1]. There sixteen subjects aged 61.63 ± 11.15 with dementia due to VD (56%), frontotemporal dementia (13%), unknown dementia (19%), AD (6%), PD (6%) diagnosed by the neurologist and psychiatrist of the AIIMS Patna Hospital. Sixteen aged subjects of mild cognitive impairments with age 58.44 ± 11.75 have been grouped in the early dementia group due to hypertension (6%), anxiety disorder (19%), sleep disorder (6%), mood disorder (6%), stress (19%) and combined causes (44%). The healthy group comprised fifteen subjects age 53.47 ± 11.10 with no previously noted disorders of neurology or psychiatry. All the subjects screened using the Hindi mini-mental state examination (HMSE) score [19]. Table I demonstrate demographic details of all groups which

show there is no significant difference in age and education of the subjects. All the subjects and their caregivers signed a consent form to involve in the study. The Ethics Committee of AIIMS Patna permitted the study following the set protocol.

B. Data Recording

Signals were obtained using a 21-channel EEG device. Thirteen minutes of activity was sampled at 256 Hz frequency from 21 following electrodes: $Fp1$, Fpz, $Fp2$, Fz, $F3$, $F4$, $F7$, $F8$, Cz, $C3$, $C4$, $T3$, $T4$, $T5$, $T6$, Pz, $P3$, $P4$, $O1$, Oz and $O2$. The present study followed the protocol mentioned in the paper [15], which has four events, EO, EC, FTT and CPT. FTT and CPT test performed on the CNS vital signs test battery [20].

FTT is a neuropsychological test which measures the motor speed of subjects. It does not require higher cognitive order. Its results are included in this study to support the EEG results of elder subjects. Subjects tapped the space-bar key of the keyboard of a laptop for 10 seconds thrice alternatively with the left and right index finger. Less score in the test demonstrates a decrease in motor speed. Usually, people perform better with their preferred hand, and all subjects in this study are right-handed.

CPT is a neuropsychological test used to estimate the span of attention over a while and impulsivity. The ability to sustain attention can understand as an essential cognitive skill which helps us to concentrate over a long period to finish tasks in the presence of other distracting stimuli. For an instant, few activities in our daily lives, such as reading newspapers take a long time to complete and require sustained attention. Sustained attention is an indication of the interaction of the cortical, sub-cortical and functional pathways between basal ganglia, thalamus and frontal lobes [21]. Impulsivity is a tendency to act on impulses fast without much focus on the response. The CPT test includes concentrating on a single stimulus for 5 minutes in the presence of 3-4 other distracting stimuli. The total of 40 responses shown to each subject.

IV. METHODS

A. Iterative Filtering Decomposition

The IF technique breaks up a given signal to a set number of IMF. The properties associated with the IMF are: first, the number of extrema is equivalent to zero-crossing, or their difference must be equal to 1. The second property is that the mean of the upper and lower envelopes, connecting all the local maxima and minima must be zero at any and every point [17]. Consider an EEG signal segment $S(n), n\epsilon\mathbb{R}$, let L be an operator which gives a moving average of the signal $S(n)$ by convolution with filter function w with a low pass filter, for instance, the double average filter $a(t)$

$$L.S(n) = \int_{-l}^{l} S(n+t)a(t)dt \tag{1}$$

If we define $S_1 = S$ and the operator Z detect the fluctuation of signal $S_m, m\epsilon\mathbb{N}$,

$$Z_{1,m} = S_m - L_m^1.S_m = S_{m+1}, \tag{2}$$

then the first IMF is given by

$$I_1 = \lim_{m\to\infty} Z_{1,m}.S_m, \tag{3}$$

where L_m^1 depends on the mask length l_m (the length of the filter at step m). Similarly, when applying Z operator on the remainder signal $S - I_1$, it provides the second IMF (I_2). By Iterating the process, k-th IMF as

$$I_k = \lim_{m\to\infty} Z_{1,m}.f_m) = f_{m+1}, \tag{4}$$

where $f_1 = f - I_1 - \ldots - I_{k-1}$. When $f = S - I_1 - \ldots - I_m, m\epsilon\mathbb{N}$, becomes a trend signal which means the remainder f has at most one local maximum or minimum. The IF process stops, and the signal decomposes as

$$S(n) = \sum_{j=1}^{m} I_j(n) + f(n) \tag{5}$$

Hence, the IF algorithm 1 has two nested loops. An inner loop calculates each single IMF, and an outer loop, to derive all the IMF [22]. Recently few studies have been reported in the field of the EEG signal processing i.e. epilepsy [18].

Algorithm 1: IMF

Result: $I_1, I_2 \ldots I_5$.
Initialize $\to S(n)$: EEG segment, m: An initial index,
K: Number of extreme points of $S_m(n)$,
N: The total number of sample point of $S_m(n)$,
v: 1.3,
while *the number of extrema for $f \geq 2$* **do**
   $S_1 = S$
   while *the stopping criteria is not satisfied* **do**
      Compute the filter length l_m for S_m
      $l_m := 2 \left\lfloor v \frac{N}{K} \right\rfloor$
      $S_{m+1}(n) = S_m(n) - \int_{-l_m}^{l_m} f(n+t)w_m(t)dt$
      $m = m + 1$
   end
   $IMF = IMF \cup S_m \quad S = S - S_m$
end
$IMF = IMF \cup S$

B. Extracted Features

1) Power Spectral Density: PSD is a significant parameter to estimate the slowing of EEG. Slowing of EEG refers to the reduction in PSD of higher frequencies more than 8 Hz and an increase in PSD of lower frequency bands (0-7 Hz). As per finding in [23], gamma-band PSD increased in the AD patient in comparison with the healthy group. PSD measures the average power distribution of the EEG signal at a specific frequency range [24]. Fourier Transform of IMF signal is calculated as

$$fft(x, y) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} S(n,m) \times e^{-i2\pi \times (x\frac{n}{N} + y\frac{m}{M})}, \tag{6}$$

where N and M are row and column of IMF. PSD is calculated by the squared magnitude of the Fourier transform of

IMF signal $S(n, m)$.

$$PSD = \frac{2}{N \times M} \times (fft(x, y))^2. \quad (7)$$

2) Variance: The variance is used as an important diagnostic feature for neurological disorders [25]. It measures the differences between each number in the dataset and the mean. Variance is calculated from IMF of EEG signal segments $S(n)$. Variance is empirically represented as:

$$\sigma^2 = \frac{\sum_{n=1}^{N}(S - \overline{S})}{N}. \quad (8)$$

where N is the total number of samples.

3) Katz Fractal Dimension: Fractal dimension is a ratio that measures the complexity. It compares different patterns of the signal segment with the scale called a fractal. The fractal specifies the correlation between different parts of the EEG signal segment in the time series. The low value of FD was reported in AD subject at parietal and temporal cortex as compared to healthy [26], [27]. Algorithm 2 is described KFD.

Algorithm 2: Katz Fractal Dimension

Result: KFD

Initialize $\rightarrow$ S : the EEG signal, n : an initial index, d : a delay constant N : The total length of the signal

for $K=1 : d_{max}$ **do**

Segment the signal $\rightarrow$
$S_n^d = s(n), s(n + d), \dots, s(n + \frac{N-n}{d})$

Average Length$(L_n^d) \rightarrow$

$(N - 1) \sum_{i=1}^{\frac{N-n}{d}} \frac{s(n+i*d)-s(n+(i-1)*d)}{\frac{N-n}{d} *K}$

Total Average Length$(L^d) \rightarrow \sum_{n=1}^{d} L_n^d$

Higuchi FD $\rightarrow \frac{\log_{10}(L)}{\log_{10}(d)}$

Normalizing with a;

Katz's FD $= \frac{\log_{10}(L/a)}{\log_{10}(d/a)}$;

$\implies \frac{\log_{10}(r)}{\log_{10}(d/L)+\log_{10}(r)}$ where $r = L/a$

end

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4) Tsallis Entropy: Entropy measures the uncertainty of information, and it has an extensive property which means its value depends on the initial condition of the source. Most systems behave independently of initial conditions. Similarly, the EEG signal has a non-extensive property, and its higher uncertainty correlates to the higher entropy and chaotic nature of the brain. Tsallis entropy is a non-extensive entropy proposed by Constantino Tsallis [28], which is a generalisation of the traditional Boltzmann-Gibbs entropy (BGS). The Tsallis entropy expresses as,

$$TE = k\frac{1}{q - 1}\left[1 - \sum_{i=1}^{w} p_i^q\right] \quad (9)$$

Where w is the total number of EEG states, $p = p_i$ is the probability each unique i^{th} EEG state, k is Boltzmann's constant, and q is an entropic index that characterises the

TABLE II
SELECTED FEATURES BASED ON P-VALUE (<0.05) OF THE ANOVA TEST

	Class 1	Class 2	EO	EC	FTT	CPT
PSD1	Healthy	ED	0.990	0.996	0.365	0.851
	Healthy	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
PSD2	Healthy	ED	0.122	**0.001**	**0.002**	0.114
	Healthy	Dementia	**0.000**	**0.000**	**0.001**	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.001**
PSD3	Healthy	ED	0.059	0.541	0.125	0.901
	Healthy	Dementia	**0.000**	**0.000**	0.055	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
PSD4	Healthy	ED	**0.017**	**0.021**	0.065	**0.004**
	Healthy	Dementia	**0.000**	**0.000**	0.471	**0.012**
	ED	Dementia	**0.000**	**0.000**	**0.001**	**0.000**
PSD5	Healthy	ED	**0.001**	**0.007**	0.114	0.077
	Healthy	Dementia	**0.000**	**0.000**	**0.022**	0.057
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
Variance1	Healthy	ED	0.990	0.978	0.310	0.787
	Healthy	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
Variance2	Healthy	ED	0.144	**0.001**	**0.004**	**0.042**
	Healthy	Dementia	**0.000**	**0.000**	**0.002**	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.011**
Variance3	Healthy	ED	0.066	0.608	0.177	0.771
	Healthy	Dementia	**0.000**	**0.000**	0.095	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
Variance4	Healthy	ED	**0.013**	**0.031**	0.064	**0.006**
	Healthy	Dementia	**0.000**	**0.000**	0.655	**0.024**
	ED	Dementia	**0.000**	**0.000**	**0.002**	**0.000**
Variance5	Healthy	ED	**0.001**	**0.018**	0.093	0.070
	Healthy	Dementia	**0.000**	**0.000**	**0.032**	0.141
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
FD1	Healthy	ED	0.914	0.988	**0.020**	**0.010**
	Healthy	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
FD2	Healthy	ED	**0.024**	**0.000**	**0.000**	0.257
	Healthy	Dementia	**0.000**	**0.000**	**0.002**	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
FD3	Healthy	ED	**0.000**	**0.000**	**0.000**	0.365
	Healthy	Dementia	**0.000**	**0.000**	0.378	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
FD4	Healthy	ED	**0.000**	**0.000**	**0.000**	**0.000**
	Healthy	Dementia	**0.000**	**0.000**	0.618	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
FD5	Healthy	ED	**0.000**	**0.000**	**0.000**	**0.002**
	Healthy	Dementia	**0.000**	**0.000**	0.091	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
Tsallis1	Healthy	ED	0.990	0.978	0.310	0.787
	Healthy	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
Tsallis2	Healthy	ED	0.144	**0.001**	**0.004**	**0.042**
	Healthy	Dementia	**0.000**	**0.000**	**0.002**	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.011**
Tsallis3	Healthy	ED	0.066	0.608	0.177	0.772
	Healthy	Dementia	**0.000**	**0.000**	0.096	**0.000**
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**
Tsallis4	Healthy	ED	**0.013**	**0.031**	0.064	**0.006**
	Healthy	Dementia	**0.000**	**0.000**	0.654	**0.024**
	ED	Dementia	**0.000**	**0.000**	**0.002**	**0.000**
Tsallis5	Healthy	ED	**0.001**	**0.018**	0.094	0.070
	Healthy	Dementia	**0.000**	**0.000**	**0.032**	0.141
	ED	Dementia	**0.000**	**0.000**	**0.000**	**0.000**

degree of non-extensivity. The results of TE is relative to the value of q, and its selection is crucial. The q-value varies from $1 < q < 2$ to enlarge the variations of the Tsallis super extensive entropy. However, a question arises: what is the precise q value for the EEG signal for dementia diagnosis? Recently few studies on AD diagnosis use q value range from 0.5 to 2 [29], [30]. The present work considered the entropic index q = 2.

C. Feature Selection

The ANOVA (analysis of variance) test implemented to select features for each event which act as input to the classifiers. Selection of features for events keenly leaned on
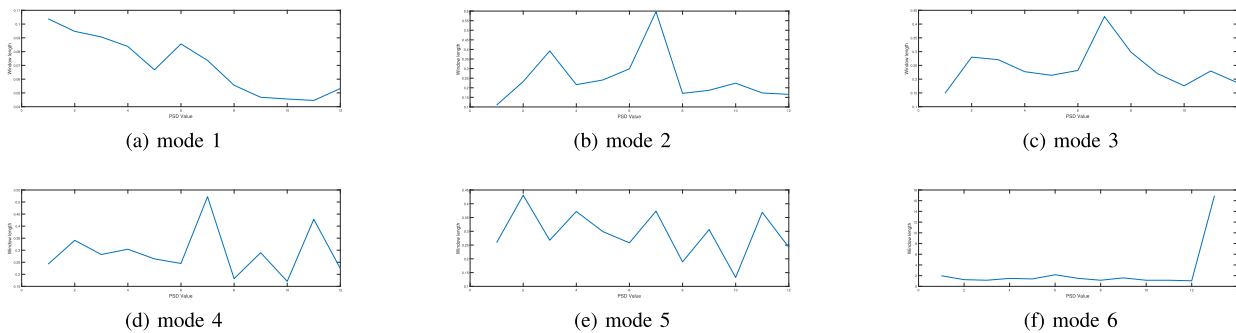
Fig. 2. PSD values of six IMF.

the significant p-value of EEG feature. Less than 0.05 p-values indicate the 95% significant difference among classes. Selected features based on P-value (<0.05) of the ANOVA test on the binary basis are shown in Table II. All significant p-values are shown in bold text. Apart from this, features also plotted to check the significant mode out of six IMF. Fig. 2 shows the PSD values of six IMF. Mode 6 shows the least significant information content. The Similar pattern was observed for other features also. Thus, we have considered the first five IMF.

D. Classification

The objective of the current work is to classify dementia, early dementia, and age-matched healthy subject with good accuracy to develop a diagnostic tool. In the present work, the one-versus-one approach used for multi-class classification. After training, we tested its performance on a testing set. 10-fold cross-validation used to reduce the risk of over-fitting and under-fitting of training and to obtain average prediction accuracy. A machine learning model is said to over-fit if the algorithm accuracy is more in fitting known data but less in predicting new data. Under-fitting occurs when the model fails to learn the training feature pattern. The classifier performs well in all k-fold iteration and so effective in identifying new data points. The total feature-length in this research work is 1816×20 for EO, 1824×20 for EC, 1300×20 for FTT, and 2803×20 for CPT. The feature vector size is well suited for efficient training and testing of the machine learning model. The whole dataset divided into 10 samples. One sample considered for testing and the remaining 9 samples considered as training sets. It continued 10 times, once for each testing sample. Like this, each sample acts as a testing sample. Four different classifiers are implemented to compare the classification performance. The classifiers are describing as follows:

1) Decision Tree: DT classification technique is selected when computational time is an issue. It represents a flowchart like a tree structure, which depicts the classification model. Classifier partition the instant space recursively, until all the data in a partition belong to the same class. A new node is appended to DT for each partition. The partition process stops after the data for partition have the same class and the corresponding leaf named as a class label. This classifier shows numerous merits over other learning methods, such as

robustness to noise and the low computational cost for the generation of the model. This classifier can automatically pick features and reduce complexity. We have used the fine tree preset with a hundred number of splits. Recently, DT has used in the area of AD diagnosis [33].

2) K Nearest Neighbour: The kNN algorithm is a non-parametric algorithm for classification, which classifies the data specified by local features. This classifier decides by analysing a new sample with the example data. One by one, each new data is compared with each example data. Those new data are chosen based on their distance from each example data. Mainly, the k different patterns with the least distance are selected. kNN is a supervised algorithm. The value of k is specified beforehand. By default, k is selected as 1. k is odd for two-class classification. The value of k can vary depending on the accuracy. In the present work, the k value selected as 10 with a weighted kernel in the classification. kNN classifier has the advantage of recognising linear and non-linear distributed data and has excellent performance with many data points. kNN has achieved good classification accuracy in MCI detection, the early AD diagnosis, and AD patient identification [33]–[35].

3) Support Vector Machine: The SVM classifier is the most widely used in medical imaging and signal processing [15], [36]. SVM divides the two-class with the hyperplane using kernels. The hyperplane is furthest away from the nearest points of different classes which maximises the margin of the classifier. It translates into a better generalisation performance. We have used fine radial basis kernel function, and kernel scale set to 1.1. SVM has a primary advantage; it performs great on data with many characteristics, instead of less training inputs. SVM has an excellent performance in many applications. However, it has the disadvantages of speed and size during the classification process [37].

4) Ensemble Classifier: Ensemble learning assembles a set of classifier models to enhance the classification output. It provides a more reliable predictive performance than one model. In an ensemble classifier, a weighted vote of each classifier considered for the classification process. Traditionally, ensemble classifier includes a Bayesian averaging method. At present, it involves error-correcting output coding, bagging and boosting [38]. In bagging, the items in the sampling of training data are chosen randomly from the training data with replacement as the data is unweighted. There are two types

TABLE III
PERFORMANCE COMPARISON OF DIFFERENT CLASSIFIERS (D-DEMENTIA, ED-EARLY DEMENTIA, H-HEALTHY)

Classifier	Events	Accuracy (%)			Precision (%)			Sensitivity (%)			Specificity (%)			F-measure (%)		
		H	ED	D	H	ED	D	H	ED	D	H	ED	D	H	ED	D
kNN	EO	90.36	**91.67**	91.41	**85.30**	**87.01**	87.56	83.33	**87.87**	**88.11**	**93.53**	93.54	93.20	84.30	**87.44**	87.83
	EC	89.58	**91.67**	**92.00**	82.26	**87.01**	**90.38**	85.14	**87.87**	86.77	91.61	**93.54**	**94.89**	83.68	**87.44**	**88.54**
	FTT	87.69	87.69	88.62	77.69	85.18	82.50	78.96	78.87	87.37	91.11	92.51	89.33	78.32	81.90	84.87
	CPT	**91.87**	88.80	89.44	84.93	84.11	86.24	**90.46**	83.94	81.03	92.52	91.42	93.60	**87.61**	84.03	83.56
Ensemble	EO	88.38	88.60	88.99	81.69	84.76	82.52	80.67	80.75	87.17	91.85	92.60	89.97	81.18	82.71	84.78
	EC	87.34	90.41	90.68	78.75	86.37	87.27	81.64	84.22	86.46	89.94	93.45	93.02	80.17	85.28	86.86
	FTT	86.15	84.85	87.92	75.41	80.05	81.93	75.41	76.03	85.89	90.36	89.66	89.09	75.41	77.99	83.86
	CPT	89.76	87.19	87.73	83.48	81.66	81.95	84.51	81.91	80.71	92.21	90.05	91.20	83.99	81.79	81.32
SVM	EO	88.05	88.66	88.27	80.28	84.91	82.27	81.56	80.75	84.98	90.97	92.68	90.06	80.91	82.78	83.60
	EC	87.61	91.06	89.42	79.73	89.41	83.36	81.12	82.72	87.85	90.58	95.17	90.29	80.42	85.94	85.54
	FTT	86.69	84.23	86.00	78.47	77.49	79.36	72.68	78.00	83.37	92.18	87.63	87.52	75.46	77.74	81.31
	CPT	89.94	88.33	87.69	85.20	85.13	79.06	82.72	80.89	85.45	93.31	92.36	88.80	83.94	82.96	82.13
DT	EO	82.05	81.94	81.61	71.79	75.31	71.57	69.50	69.17	79.19	87.70	88.45	82.92	70.63	72.11	75.19
	EC	80.70	83.72	83.39	68.52	75.63	77.32	71.15	74.75	75.54	85.06	88.13	87.73	69.81	75.19	76.42
	FTT	80.15	77.15	79.31	64.36	68.49	71.19	66.12	65.36	72.84	85.65	83.59	83.03	65.23	66.89	72.01
	CPT	82.27	82.05	83.59	71.09	76.75	74.12	74.52	70.12	77.48	85.88	88.51	86.61	72.77	73.29	75.76

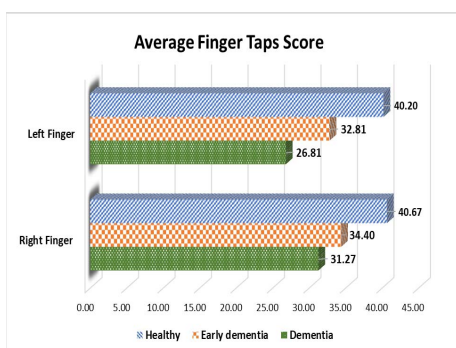
Fig. 3. Results of finger tapping test.

Fig. 4. Results of continuous performance test.

of algorithms, random forest and bagging meta-estimator. We used bagged tree preset with the DT type learner, which has a total of 30 learners to model the training data. Recently, ensemble classifier has been implemented in the area of dementia diagnosis, such as random forest used to differentiate Lewy bodies dementia and AD [39], and another voxel-based AD diagnosis study using MRI images [40].

V. RESULTS AND DISCUSSION

A. Cognitive Test Results

1) Finger Tapping Test: Fig. 3 showed that healthy subjects scored the highest motor speed (40.20 and 40.67) among all three group and dementia subject scored the least motor speed (26.81 and 31.27). Early dementia group scored 32.81 left finger and 34.40 right finger. These scores are comparable with dementia subjects but significantly different from healthy subjects. Thus, FTT is the best cognitive test which can screen the subject efficiently for further diagnostic analysis.

2) Continuous Performance Test: Fig. 4 shows the performance of subjects in the CPT task. The correct response (CR) is directly proportional to the good sustained attention and its reaction time estimate how fast subjects respond to CR. The healthy and early dementia group had higher CR than dementia. Omission error is when the subject did not press the space bar key on the target letter. It indicates the inattentive behaviour of subjects. Other hands, commission error, defined as how many times a subject responds to a stimulus letter
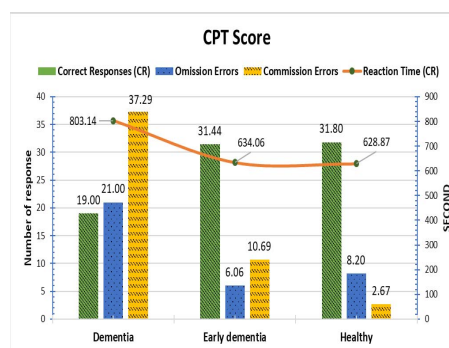
TABLE IV
OVERALL ACCURACY OF DIFFERENT CLASSIFIERS

Classifier/Event	EO	EC	FTT	CPT
kNN	**86.50**	**86.60**	**82.00**	85.10
Ensemble	83.00	84.20	79.50	82.30
SVM	82.50	84.00	78.50	83.00
DT	72.80	73.90	68.30	74.00

without the presence of a target stimulus. Usually, errors of commission increase with age, but still, healthy elder tends to do less of it in comparison to dementia and early dementia subjects. Fig. 4 shows the dementia group has high commission and omission error with slower reaction time which indicates inattention in subjects. The healthy and early dementia group shows fast reaction time with omission error and commission error which indicates the impulsivity issue in both groups. Early dementia group has higher commission error than omission error which might indicate the abnormality in interactive pathways of the cortex. The control group usually scored as per age norms. Therefore, CPT proof to be as a susceptible and specific cognitive test for dementia and early dementia detection. Trends of the cognitive test are similar to our previous work [15].

B. Classification Results

Four classifiers have been tested for this dataset. It is found that kNN classifier showed the best results among all

TABLE V
COMPARISON OF PROPOSED WORK WITH STATE-OF-THE-ART METHODS

State-of-the-art methods	Dataset	Extracted features	Classifier cross-validation	Event	Classes	Acc. (%)	Sen. (%)	Spe. (%)
Proposed Work	Subject=47 EEG=3 min (EC and EO), 2 min (FTT), 5 min (CPT)	PSD variance FD and TE using IFD	kNN, 10-fold	EC	Healthy	89.58	85.14	91.61
					ED	91.67	87.87	93.54
					Dementia	92.00	86.77	94.89
				EO	Healthy	90.36	83.33	93.53
					ED	91.67	87.87	93.54
					Dementia	91.41	88.11	93.20
				FTT	Healthy	87.69	78.96	91.11
					ED	87.69	78.87	92.51
					Dementia	88.62	87.37	89.33
				CPT	Healthy	91.87	90.46	92.52
					ED	88.80	83.94	91.42
					Dementia	89.44	81.03	93.60
Durongbhan et al., (2019) [14]	Subject=40 EEG=12 sec	Frequency bands, avg. magnitude using continuous wavelet transform (WT)	kNN 10-fold	EC	AD vs Healthy	83.41	73.80	86.89
				EO	AD vs Healthy	83.32	72.57	87.52
Sharma et al., (2019) [15]	Subject=44 EEG=3 min (EC and EO), 2 min(FTT), 5 min(CPT)	PSD, FD spectral entropy, linear features using WT	SVM 10-fold	EC	Healthy vs MCI	79.50	73.00	85.00
					Healthy vs Dementia	83.70	90.00	78.00
					MCI vs Dementia	86.60	86.00	88.00
				EO	Healthy vs MCI	84.10	86.00	81.00
					Healthy vs Dementia	82.00	82.00	82.00
					MCI vs Dementia	73.40	83.00	63.00
				FTT	Healthy vs MCI	89.80	84.00	94.00
					Healthy vs Dementia	83.80	85.00	83.00
					MCI vs Dementia	84.00	89.00	78.00
				CPT	Healthy vs MCI	73.90	63.00	82.00
					Healthy vs Dementia	87.90	88.00	88.00
					MCI vs Dementia	88.00	88.00	89.00
Wang et al., (2019) [31]	Subject=36 ERP=2.64 sec	Directed transfer function of power	SVM 10-fold	Visual oddball	VD vs Healthy	86.11	86.67	85.71
Al-Qazzaz et al., (2017) [32]	Subject=52, EEG=16 min (EC), 60 sec(task)	Relative powers, Permutation entropy and FD	SVM 10-fold	EC	AD vs Healthy	84.61	100.00	80.00
				Memory recall	AD vs Healthy	91.48	91.48	NA
McBride et al., (2014) [13]	Subject = 48 EEG = 10 min (EC and EO), 5 min (task)	Relative spectral power, Additional spectral features, Spectral power ratios, Entropy/complexity features, First derivative features	SVM leave-one-out	EC	multi-class	79.20	NA	NA
				EO	multi-class	83.30	NA	NA
				Counting with FTT	multi-class	85.40	NA	NA
Staudinger & Polikar,(2011) [26]	Subject =161 ERP = 30 min	FD, SE, spectral centroid, spectral roll-off,zero-crossing rate	SVM 6-fold	Auditory oddball	AD vs Healthy	77.61	NA	NA

classifiers. Detail performance of each class briefly discussed as follow:

1) Dementia Patient Classification: Table III showed the results of different classifiers for dementia patients. First observation, *k*NN come out as the best classifier for all the events with 91.99% to 88.61% accuracy. The second observation, EC showed the highest accuracy, precision, specificity and F-measure with all the classifiers. Table V focused on the results of *k*NN classifier with a few previous studies. EC was the best event for dementia diagnosis followed by EO, which showed the highest sensitivity with all the classifiers (88.10% to 81.03%) and the FTT event. The FTT event showed the least statistic except for the sensitivity (87.10%) in comparison to the CPT event (81.03%) which make it better diagnostic event based on F-measure (84.86%) than CPT. Thus, EC, EO and FTT come out to be the best test for diagnosing dementia.

2) Early Dementia Patient Classification: Table III showed the difference between performance for early dementia patients' classification. It is noticeable that *k*NN again came out superior among other classifiers with 91.66% to 88.79% accuracy in all four events. Table V showed the *k*NN results in comparison with other studies. EC and EO performed equally with 87.43% F-measure. EO and EC achieved the same accuracy 91.66% with *k*NN whereas EC event scored the highest with other classifiers, especially SVM with 85.93%

F-measure. Apart from this, CPT outperformed FTT with 84.02% F-measure, due to high sensitivity 83. 94%. Thus, the early dementia patient can be diagnosed using EO, EC and CPT test efficiently.

3) Healthy Subject Classification: Table III demonstrated the output of different classifier for four different events. *k*NN, SVM and ensemble showed comparative results still *k*NN outperformed in case of each event with 91.86% to 87.69% accuracy. Table V illustrated the results of *k*NN, which showed that CPT is the best event out of four events for the healthy subject classification with the F-measure of 87.60%. EO scored 90.36% accuracy and second-best F-measure 84.30% whereas EC scored the second-best sensitivity 85.13%. FTT event scored at least F-measure 78.31%, which make it less likely to choose for the healthy subject classification. It is a good test to differentiate dementia patients from healthy and early dementia. Unfortunately, it is not that good for classifying early-stage dementia from healthy subjects. Thus, CPT, EO and EC are the best tests for diagnosis of Healthy subject classification.

C. Overall Accuracy

Table IV demonstrates thorough differences among four events' overall accuracy with different classifiers. First observation, *k*NN classifier achieved the highest overall accuracy

among all the event ranged from 86.60% to 82%. Ensemble classifier scored 84.20% to 79.50%, and SVM achieved 83% to 78.50%, and DT scored least 72.80% to 68.3% overall in all the events. The second observation, ensemble and SVM classifiers achieved approximately similar accuracy in all the events. Third observation, EC event gets approximately the highest overall accuracy among all events. From Table IV, EC event scored the highest accuracy with the first three classifiers whereas CPT event scored the highest with DT classifier, which is approximately equal to EC. The fourth observation, CPT result shows the second-highest accuracy in case of three classifiers, except kNN. CPT scored with kNN was still higher than other classifiers' scores. The fifth observation, FTT event score least overall accuracy 82% to 68.3% among four classifiers. Last observation, the best events for cognitive impairment classification are EO with 86.50%, EC with 86.60% and CPT with 85.10% using kNN.

VI. CONCLUSION

Accurate classification of dementia and early-stage can delay the progression of cognitive impairment and can improve the quality of life of a patient. The proposed approach introduced IFD to enhance the classification accuracy in resting state and cognitive state EEG signal. EEG data have been acquired from 47 participants those were screened and classified by the clinical psychiatrists strictly on the basis of the DSM-5 criteria and recruited for the study. The proposed approach achieved up to 92%, 91.67% and 91.87% accuracies for dementia, early dementia and healthy classifications, respectively. The framework consists of multiple components, including cognitive tasks, IFD, various features, and multi-class classification. In the present study, kNN achieved good accuracy for many points in a low dimensional space. Therefore, it is the most effective classifier based on performance. We observed that the combination of FTT and CPT task with resting-state EEG improve the diagnostic measures of dementia and early dementia as CPT proved to be the best test to identify healthy from dementia and early dementia with 91.87% accuracy and 87.61% F-measure. The combination of FTT, along with EC and EO, can identify dementia patients efficiently. Eventually, dementia classification does not perform well on a small dataset, but designed protocol with the IFD technique and different features under cognitive tasks improved the average accuracy and F-measure. We plan to incorporate more features and subject in our future studies to improve dementia diagnosis. Early dementia patients' pathological details suggest that hypertension with other aetiologies might lead to dementia in the coming years. However, all early cognitive impairment does not develop dementia, and few patients recover their cognitive decline with time. Henceforth, this problem can be figured out more clearly during longitudinal studies of EEG with higher cognitive functions.

REFERENCES

[1] Diagnostic and Statistical Manual of Mental Disorders (DSM-5), Amer. Psychiatric Assoc., Washington, DC, USA, 2013.

[2] M. J. Prince, World Alzheimer Report 2015: The Global Impact of Dementia: An Analysis of Prevalence, Incidence, Cost and Trends. London, U.K.: Alzheimer's Disease International, 2015.

[3] R. Cassani, M. Estarellas, R. San-Martin, F. J. Fraga, and T. H. Falk, "Systematic review on resting-state EEG for Alzheimer's disease diagnosis and progression assessment," Disease Markers, vol. 2018, pp. 1–26, Oct. 2018.

[4] N. Sharma, M. H. Kolekar, and S. Chandra, "The role of EEG signal processing in detection of neurocognitive disorders," Int. J. Behavioural Healthcare Res., vol. 6, no. 1, pp. 15–27, 2016.

[5] N. Sharma and H. M. Kolekar, "Diagnosis of vascular cognitive impairment using EEG," Indian J. Public Health Res. Develop., vol. 8, no. 4, p. 947, 2017.

[6] S. Yang, J. M. S. Bornot, K. Wong-Lin, and G. Prasad, "M/EEG-based bio-markers to predict the MCI and Alzheimer's disease: A review from the ML perspective," IEEE Trans. Biomed. Eng., vol. 66, no. 10, pp. 2924–2935, Oct. 2019.

[7] A. Dragomir, A. G. Vrahatis, and A. Bezerianos, "A network-based perspective in Alzheimer's disease: Current state and an integrative framework," IEEE J. Biomed. Health Informat., vol. 23, no. 1, pp. 14–25, Jan. 2019.

[8] T. Mullen. (2012). NITRC: Cleanline: Tool/Resource Info. [Online]. Available: https://www.nitrc.org/projects/cleanline

[9] A. Delorme, A. Majumdar, S. Sivagnanam, R. Martinez-Cancino, K. Yoshimoto, and S. Makeig, "The open EEGLAB portal," in Proc. 9th Int. IEEE/EMBS Conf. Neural Eng. (NER), Mar. 2019, pp. 1142–1145.

[10] R. Mahajan and B. I. Morshed, "Unsupervised eye blink artifact denoising of EEG data with modified multiscale sample entropy, kurtosis, and wavelet-ICA," IEEE J. Biomed. Health Informat., vol. 19, no. 1, pp. 158–165, Jan. 2015.

[11] N. Al-Qazzaz, S. H. B. M. Ali, S. Ahmad, M. Islam, and J. Escudero, "Automatic artifact removal in EEG of normal and demented individuals using ICA–WT during working memory tasks," Sensors, vol. 17, no. 6, p. 1326, Jun. 2017.

[12] G. Fiscon et al., "Combining EEG signal processing with supervised methods for Alzheimer's patients classification," BMC Med. Informat. Decis. making, vol. 18, no. 1, p. 35, 2018.

[13] J. C. McBride et al., "Spectral and complexity analysis of scalp EEG characteristics for mild cognitive impairment and early Alzheimer's disease," Comput. Methods Programs Biomed., vol. 114, no. 2, pp. 153–163, Apr. 2014.

[14] P. Durongbhan et al., "A dementia classification framework using frequency and time-frequency features based on EEG signals," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 27, no. 5, pp. 826–835, May 2019.

[15] N. Sharma, M. H. Kolekar, K. Jha, and Y. Kumar, "EEG and cognitive biomarkers based mild cognitive impairment diagnosis," IRBM, vol. 40, no. 2, pp. 113–121, Mar. 2019.

[16] N. E. Huang et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," Proc. Roy. Soc. London A, Math., Phys. Eng. Sci., vol. 454, no. 1971, pp. 903–995, Mar. 1998.

[17] L. Lin, Y. Wang, and H. Zhou, "Iterative filtering as an alternative algorithm for empirical mode decomposition," Adv. Adapt. Data Anal., vol. 1, no. 4, pp. 543–560, Oct. 2009.

[18] D. P. Dash, M. H. Kolekar, and K. Jha, "Multi-channel EEG based automatic epileptic seizure detection using iterative filtering decomposition and hidden Markov model," Comput. Biol. Med., vol. 116, Jan. 2020, Art. no. 103571.

[19] M. Ganguli et al., "A hindi version of the MMSE: The development of a cognitive screening instrument for a largely illiterate rural elderly population in India," Int. J. Geriatric Psychiatry, vol. 10, no. 5, pp. 367–377, May 1995.

[20] C. Gualtieri and L. Johnson, "Reliability and validity of a computerized neurocognitive test battery, CNS vital signs," Arch. Clin. Neuropsychol., vol. 21, no. 7, pp. 623–643, Oct. 2006.

[21] C. Riccio, "The continuous performance test: A window on the neural substrates for attention?" Arch. Clin. Neuropsychol., vol. 17, no. 3, pp. 235–272, Apr. 2002.

[22] A. Cicone, J. Liu, and H. Zhou, "Adaptive local iterative filtering for signal decomposition and instantaneous frequency analysis," Appl. Comput. Harmon. Anal., vol. 41, no. 2, pp. 384–411, Sep. 2016.

[23] J. Jeong, "EEG dynamics in patients with Alzheimer's disease," Clin. Neurophysiol., vol. 115, no. 7, pp. 1490–1505, Jul. 2004.

[24] F. J. Simois and J. J. Murillo-Fuentes, "On the power spectral density applied to the analysis of old canvases," Signal Process., vol. 143, pp. 253–268, Feb. 2018.

[25] H. Zhang, Q. Meng, B. Meng, M. Liu, and Y. Li, "Epileptic seizure detection based on time domain features and weighted complex network," in *Proc. Int. Conf. Intell. Comput.*, 2018, pp. 483–492.

[26] T. Staudinger and R. Polikar, "Analysis of complexity based EEG features for the diagnosis of alzheimer's disease," in *Proc. 33rd Int. Conf. IEEE EMBC*, 2011, pp. 2033–2036.

[27] G. T. Henderson, E. C. Ifeachor, E. M. Allen, H. S. K. Wimalaratna, and N. R. Hudson, "Prospects for routine detection of dementia using the fractal dimension of the human electroencephalogram," *IEE Proc.—Sci., Meas. Technol.*, vol. 147, no. 6, pp. 321–326, Nov. 2000.

[28] C. Tsallis, "Possible generalization of Boltzmann-Gibbs statistics," *J. Stat. Phys.*, vol. 52, nos. 1–2, pp. 479–487, Jul. 1988.

[29] R. Sneddon, "The tsallis entropy of natural information," *Phys. A, Stat. Mech. Appl.*, vol. 386, no. 1, pp. 101–118, 2007.

[30] A. H. Al-nuaimi, E. Jammeh, L. Sun, and E. Ifeachor, "Tsallis entropy as a biomarker for detection of Alzheimer's disease," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 4166–4169.

[31] C. Wang, J. Xu, S. Zhao, and W. Lou, "Identification of early vascular dementia patients with EEG signal," *IEEE Access*, vol. 7, pp. 68618–68627, 2019.

[32] N. K. Al-Qazzaz, S. H. B. M. Ali, S. A. Ahmad, M. S. Islam, and J. Escudero, "Discrimination of stroke-related mild cognitive impairment and vascular dementia using EEG signal analysis," *Med. Biol. Eng. Comput.*, vol. 56, no. 1, pp. 137–157, Jan. 2018.

[33] H. Yu, X. Lei, Z. Song, C. Liu, and J. Wang, "Supervised network-based fuzzy learning of EEG signals for Alzheimer's disease identification," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 1, pp. 60–71, Jan. 2020.

[34] A. H. Al-Nuaimi, E. Jammeh, L. Sun, and E. Ifeachor, "Higuchi fractal dimension of the electroencephalogram as a biomarker for early detection of Alzheimer's disease," in *Proc. 39th Int. Conf. EMBC*, Jul. 2017, pp. 2320–2324.

[35] K. D. Tzimourta *et al.*, "EEG window length evaluation for the detection of Alzheimer's disease over different brain regions," *Brain Sci.*, vol. 9, no. 4, p. 81, Apr. 2019.

[36] M. H. Kolekar and D. P. Dash, "A nonlinear feature based epileptic seizure detection using least square support vector machine classifier," in *Proc. IEEE Region Conf. (TENCON)*, Nov. 2015, pp. 1–6.

[37] A. Mohammed, F. Al-Azzo, and M. Milanova, "Classification of Alzheimer disease based on normalized HU moment invariants and multiclassifier," *Int. J. Adv. Comput. Sci. Appl.*, vol. 8, no. 11, pp. 10–18, 2017.

[38] T. G. Dietterich, "Ensemble methods in machine learning," in *Proc. Int. Workshop Multiple Classifier Syst.*, 2000, pp. 1–15.

[39] M. Dauwan *et al.*, "Random forest to differentiate dementia with Lewy bodies from Alzheimer's disease," *Alzheimer's Dementia, Diagnosis, Assessment Disease Monitor.*, vol. 4, no. 1, pp. 99–106, Jan. 2016.

[40] R. Armananzas, M. Iglesias, D. A. Morales, and L. Alonso-Nanclares, "Voxel-based diagnosis of Alzheimer's disease using classifier ensembles," *IEEE J. Biomed. Health Informat.*, vol. 21, no. 3, pp. 778–784, May 2017.