



# Analysis of EEG signals with the use of wavelet transform for accurate classification of Alzheimer Disease, Frontotemporal Dementia and healthy subjects using Machine Learning Models

Akanksha Parihar<sup>\*1</sup>, Preety D Swami<sup>2</sup>

<sup>1,2</sup>Department of Electronics and Communication, UIT-RGPV, Bhopal, India  
Emails: [akanksha14parihar@gmail.com](mailto:akanksha14parihar@gmail.com); [preetydswami@rgpv.ac.in](mailto:preetydswami@rgpv.ac.in)

## Abstract

Dementia is a brain disorder, if not prevented; takes the form of various types of diseases that have no cure yet. Accurate classification of multiple types of dementia diseases is required to provide proper medication to the patient so that growth of that disease can be delayed. This study analyzes EEG signal for the classification of multiple dementia diseases such as Alzheimer's disease (AD), Fronto-temporal dementia (FTD) and control normal (CN) subjects using machine learning (ML) algorithms. Each of the 19 channels of EEG dataset is analyzed separately in this work to perform the classification. Combination of parameters like Hjorth Activity, Mobility and Complexity along with kurtosis value of the data has been extracted in time-frequency domain for each EEG frequency band (Delta, Theta, Alpha, Beta and Gamma) is applied to the machine learning algorithms. This research is focused on classification of multiple dementia classes (ADvsFTD) as well as three-way (ADvsFTDvsCN) classification. This research is validated using public EEG dataset with 23 participants of each category. Best classification result is achieved using random forest classifier and leave-one-subject-out (LOSO) cross validation method. The three-way classification i.e., ADvsCNvsFTD achieved best accuracy of 75.29%, whereas binary classifications i.e. ADvsCN, ADvsFTD and CNvsFTD achieved best accuracy of 88.90%, 88.44% and 84.10% respectively. The proposed framework shows better results than existing work on dementia classification using machine learning. The results obtained from proposed framework showed that combination of EEG frequency band features can be utilized for the classification of multiple dementia diseases with greater accuracy.

**Keywords:** Alzheimers Disease; Frontotemporal Dementia; EEG; Continuous Wavelet Transform; Time-frequency domain analysis; Feature extraction; Classification; Machine Learning; Cross Validation.

## 1. Introduction

Dementia is a brain disorder which is caused due to the death of brain cells and hence leads to cognitive impairment in a person [1,2]. A significant obstacle in dementia analysis is to achieve a precise and timely detection [3] so that progression of any disorder can be prevented by providing proper medication to the patient. There are various types of dementia diseases, two of them are dementia due to Alzheimer's and the second one is Frontotemporal Dementia (FTD). These neurodegenerative diseases are major cause of dementia [4] for which no cure is known yet [1]. AD influences the neurons inside the brain by affecting the neurotransmitters that works for the tasks of memory storage and transmits information to brain whereas; FTD causes localized deterioration in the frontal and temporal lobe of the brain [5]. AD and FTD are most widely spread forms of dementia, with different, but somewhat similar symptoms and brain responses. Jee Bang et. al. [6] describes some variations between AD and FTD effects on human brain. AD patients suffer from visuospatial impairment/visual memory impairments whereas FTD patients suffers from recurring and critical behavioural changes [4,5,6]. The number of patients suffering from Alzheimer's disease is directly proportional to the age of

population [7], hence patients having age over 65, AD is more prevalent than FTD. However, in the patients belonging to 45 to 65 years of age group, FTD is as prevalent as AD [4]. Due to the presence of behavioural changes and cognitive deficits in both diseases, it becomes difficult to discriminate between the two diseases [5]. Accurate detection and classification of these diseases is essential to manage a patient's daily living tasks and for the execution of proper medical treatment.

## 2. Related Work

Currently, anatomical imaging methods are mostly used for the detection of neurodegenerative diseases that focus on the classification of a particular disease but hardly on their diagnostic differentiation (ADvsFTD) [4].

There is a requirement of an accurate tool that should be dedicated to this diagnostic challenge. Automated or semiautomated algorithms have recently been added to clinical research, showing potential for computer assisted dementia diagnosis as they are less prone to human errors. Automated systems show more accurate and efficient results than human evaluation and can be employed to support medical systems [8]. Giulia Fiscon et. al. [1] found that the integration of wavelet analysis with supervised machine learning techniques can work for automatic detection or classification of brain diseases based on EEG signals. Md Rishad Ahmed et. al. [3] presented a broad survey of automated diagnostic approaches published in recent years to perform dementia diagnosis using combination of medical image analysis and machine learning algorithms. Mohammad-Parsa Hosseini et. al. [9] provided a broad overview of application of Machine Learning techniques for EEG data analysis. Raffaele Nardone et. al. [10] summarized a descriptive review on the pertinent research that aimed to classify FTD from AD disease as well as other forms of dementia through EEG signal analysis.

EEG is a method to record the neural activity generating within the brain by tracking the connectivity of neurons [1]. EEG electrodes when placed according to standard format (international 10-20 standard), records electrical activities of the brain in a readable format so that its detailed analysis can be performed. EEG is sensitive and non-invasive technique used for the diagnosis of brain diseases such as dementia classification and tracking of its severity. Over the past few decades, EEG has become an affordable diagnostic tool having significant scientific applications. Various researches have analyzed EEG techniques to gather beneficial information about different forms of dementia [11]. Dementia diagnosis and classification using EEG signals has become desirable because of its affordable cost, huge availability, greater accessibility, growing robustness and faster performance than the currently used neuroimaging techniques [5,9,12,13]. EEG may work better than the conventional method such as MMSE and can overcome its limitations for early dementia diagnosis [14]. Some studies have also demonstrated that rsEEG or ERP components obtained from EEG signals can distinguish various dementia diseases or other neurological disorders from healthy subjects [14]. More recent applications of EEG include usage of machine learning algorithm for the analysis of any abnormality in the brain [9]. While performing EEG classification using machine learning techniques, variety of features have been used to perform disease diagnosis. These features include mean, variance, skewness, kurtosis, individual band power, various entropies, fractal dimensions, Hjorth parameters etc. The most common feature that has been extracted to perform classification is the relative band power (RBP) of various EEG frequency bands of interest [15]. It is already known that EEG signal shows change in their waveforms according to the severity of dementia [10]. While performing the analysis of EEG frequency bands, AD patients show decreased synchronization in higher frequencies when compared to both FTD and CN, whereas FTD and healthy subjects do not show major differences [10]. The spectrum of the EEG signal is divided into following frequency bands [9,15,16]-

Table 1 – Frequency bands of interest along with their characteristics

S. No.	EEG band	Frequency Range	Remarks
1	Delta	0 – 4 Hz	Occurs during profound sleep
2	Theta	4 – 8 Hz	Signify somnolence or arousal in adults, can be recorded during sleep.
3	Alpha	8 – 13 Hz	Can manifest in adults with no health issues while their wakefulness, during state of relaxation, or when their eyes are closed.
4	Beta	13 – 25 Hz	Correlated with general motor behavior

5	Gamma	25 - 45 Hz	Can be recorded during short-term memory to recognize objects
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Most of the studies published till now focused only on identification of AD and its different stage classification but there is a recognizable absence of investigation in classification of FTD or other forms of dementia [17]. In this paper, we present a machine learning approach for disease detection and diagnostic differentiation (i.e., AD vs. FTD and AD vs. CN vs. FTD) using EEG signals.

Remaining paper is arranged into three sections. Sections 3 consist of proposed methodology which include dataset description, time-frequency analysis, feature extraction and application of machine learning algorithms to perform classification. Section 4 describes the results and discussions on the proposed methodology. Finally, Section 5 concludes the paper.

### 3. Proposed Methodology

The work done in this paper has demonstrated a framework of machine learning techniques using EEG signals to identify AD and FTD patients when compared with control normal (CN) subjects. This research uses individual time-frequency domain analysis of EEG data and frequency band features to perform the classification and shows reasonably good performance than the existing methods. In this study, a balanced EEG dataset has been analyzed for experimental benchmark that includes 23 AD, 23 FTD and 23 CN subjects. Analyzing any channel of EEG data involves a detailed examination of the electrical activity recorded from that specific electrode placement on the scalp. EEG signals extracted from 19 different channels from everyone are analyzed in time-frequency (TF) domain by performing Continuous Wavelet Transform (CWT) and calculating a set of parameters (Hjorth parameters and Kurtosis) from each EEG frequency band. By examining the power of various frequency band components, it becomes easier to understand the brain's engagement while achieving different cognitive states or tasks. These parameters are provided to number of machine learning (ML) classifiers to implement both 2-way (AD vs. CN, AD vs. FTD and FTD vs. CN) and 3-way (AD vs. FTD vs. CN) classifications. Accuracy of each model has been calculated using k-fold and leave one subject out cross validation methods. Figure 1 shows a detailed step-by-step diagram of the proposed methodology.

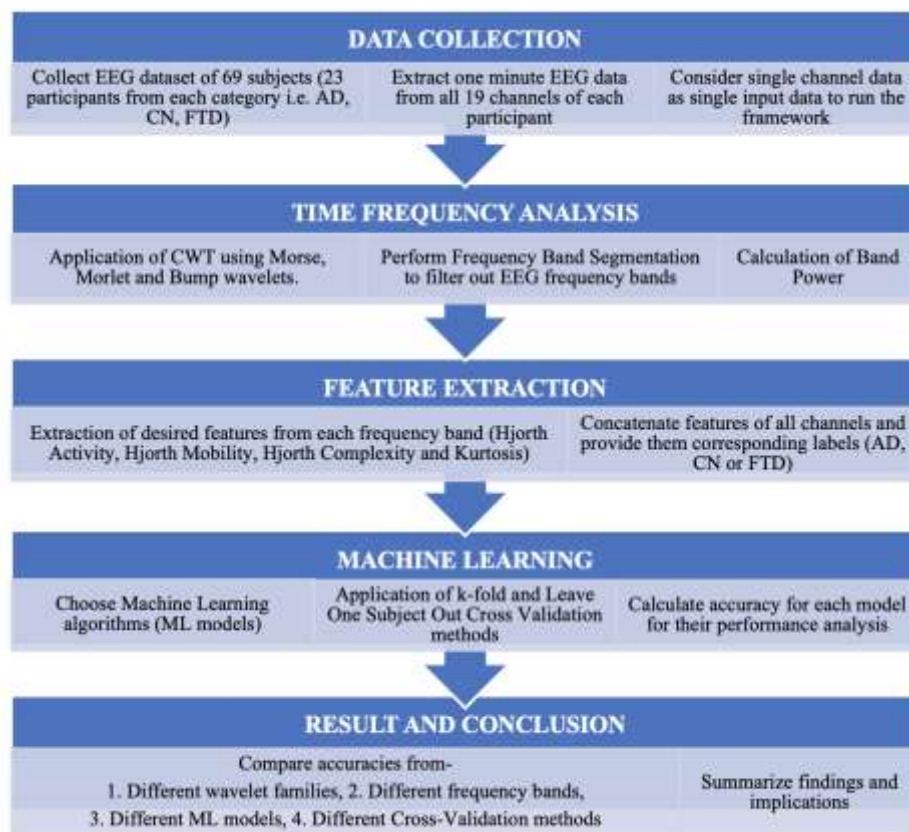


Figure 1: Step-by-step diagram of proposed methodology

### 3.1 Data Collection

The dataset consists of resting state EEG (rsEEG) data of 36 AD, 23 FTD and 29 subjects of same age having no health issues also referred as control normal (CN) in this research [15]. The rsEEG data were recorded when participants kept their eyes closed in a relaxed state and did not move or talk while capturing the 19-channel EEG data. Electrodes were placed in the manner of international 10-20 standard with the sampling rate of 500 Hz and 10uV/mm resolution.

This research has used 69 subjects (23 for each category i.e., AD, CN and FTD) to perform classification using machine learning algorithms as the uniform distribution of each category can provide accurate and impartial results. The recording time of EEG signal is different for each participant therefore single minute data of each subject has been selected to be analyzed in this research. Data from each channel is considered as a separate input data thus  $19 \times 69 = 1331$  channels are considered as input signal (one at a time) for further analysis.

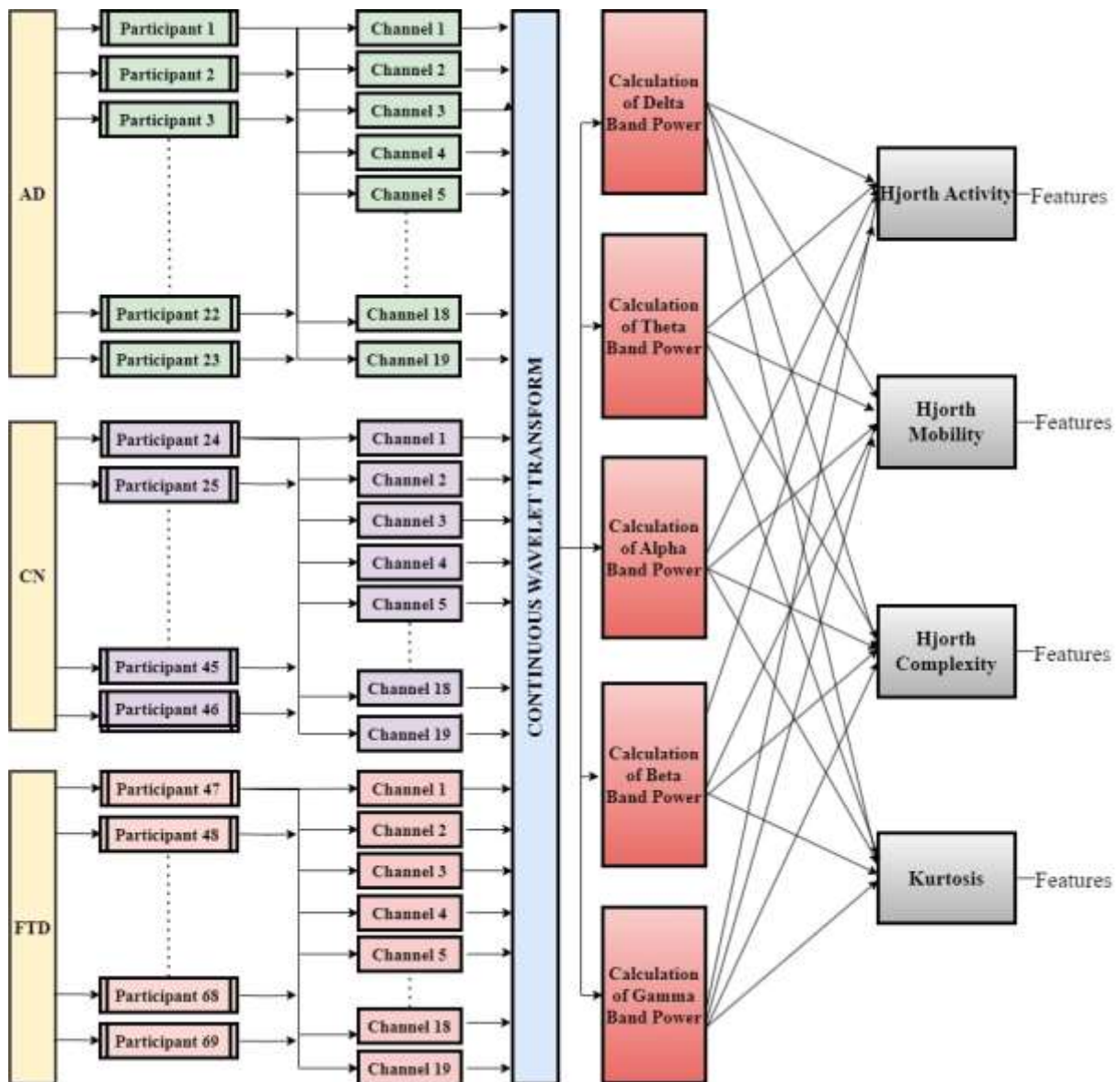


Figure 2: Steps used to extract features from input signal to perform classification using machine learning algorithms.

### 3.2 Time-Frequency Analysis

The time-series data achieved from EEG recordings is non-stationary in nature. Wavelet analysis has proved to be a powerful technique for examining non-stationary signals in time and frequency domain [18, 19, 20, 21].

Continuous wavelet transform (CWT) can provide the time-frequency representation of the signal and decompose them into various frequency bands using variable size windows of wavelets [1]. The EEG signal consists of five basic frequency bands that are Delta, Theta, Alpha, Beta and Gamma bands. CWT proves to be a useful method to extract the signal parameters in frequency domain and can calculate useful features associated with any frequency band. However, the challenge is to select a proper wavelet to perform CWT as each wavelet family has their own properties which can vary the result for the same data. The research done in this paper has utilized three types of wavelet families (Morse, Morlet and Bump) to perform the transformation.

The most useful complex-valued wavelet to perform time-frequency analysis of non-stationary signals is the Morlet wavelet. Morlet wavelet is drafted in such a way that it has equal divergence in both time and frequency domain, forming a zero-mean function and is well suited to analyze time and frequency domain information [18]. The Morlet wavelet is analytic in nature only for large radian frequency, thus, another fully analytic wavelet used to perform same task, is the generalized Morse wavelet. It is a two-parameter wavelet, providing additional freedom in comparison to Morlet wavelet. The Morse wavelets maintain their analytic properties for high time-localized parameter settings unlike the Morlet wavelet [22]. Apart from Morse and Morlet wavelet, there is a third wavelet family defined in the frequency domain having parameters mean ( $\mu$ ), standard deviation ( $\sigma$ ) and wavelet window, named as Bump wavelet [18]. After achieving the time-frequency representation of EEG data by applying all three types of wavelets, the transformed signal is further divided into different EEG frequency bands to perform frequency band analysis.

### 3.3 Feature Extraction

Feature extraction is a process to calculate consequential variables from a dataset for the further execution of succeeding steps of machine learning [19]. Classification using ML models requires an adequate set of features especially when the dataset is large [10]. Feature extraction is the most complex part of the machine learning algorithm as different features can provide different performance results for the same model. In high dimensionality problems, when modelling a framework using ML algorithms, selection of most relevant and useful features is a crucial step [23]. A competent set of EEG parameters can lead to highest classification accuracy for any task [24]. Thus multiple features have been analyzed in this work and four features have been shortlisted to perform the classification according to the result analysis.

The feature extraction process of this research work executes the calculation of four different parameters from each frequency band and generates 20 CWT features for each input data to perform the classification.

$$N = 5(\#EEG \text{ band power}) \times 4(\# \text{ CWT features}) = 20 \text{ CWT features}$$

The details of all four parameters are explained in this section.

#### 3.3.1 Hjorth Parameters (Activity, Mobility and Complexity)

The first three parameters that play important role in analyzing EEG data in time-frequency domain are the Hjorth parameters [2, 13, 25]. It consists of three sub-parameters- Activity, Mobility, and Complexity. Band power of various frequency bands are used to compute these sub-parameters as they can together characterize the EEG pattern in terms of amplitude, time and frequency. The formulation of these parameters can be represented in the form of input signal  $y(t)$ .

$$\begin{aligned} \text{Activity} &= \text{Variance}(y(t)) \\ \text{Mobility} &= \sqrt{\frac{\text{Variance}\left(\frac{dy(t)}{dt}\right)}{\text{Variance}(y(t))}} \\ \text{Complexity} &= \frac{\text{Mobility}\left(\frac{dy(t)}{dt}\right)}{\text{Mobility}(y(t))} \end{aligned}$$

Hjorth parameters are one of the effective features that improve the performance of the classifiers for all types of decomposition of EEG signals [2].

### 3.3.2 Kurtosis

Fourth parameter used in this research work is the Kurtosis which is a statistical parameter and can show the presence of significant peaks in a signal [9, 2]. Kurtosis measures the tailedness of a distribution of an EEG signal relative to normal distribution of that EEG signal [24]. It also determines how high or flat a signal's distribution is in comparison to a normal distribution. The values of kurtosis either positive or negative represent sharper and flatter distribution respectively when compared to a normal distribution [11].

$$Kurtosis = \frac{1}{N} \sum_{j=1}^N \left[ \frac{x_j - \bar{x}}{\sigma} \right]^4$$

EEG data can be estimated in terms of "Gaussianity" with the help of kurtosis values. The lower value of kurtosis represents that the signal is closer to the Gaussian distribution while higher kurtosis represents the opposite [26].

### 3.4 Machine Learning

Uses of automated techniques have increased over the past few decades to perform disease classification and have now become a significant part of research in clinical neuroscientific domain. The main purpose of supervised machine learning technique is to create a predictive model from the known labelled training data, which enables the system to make predictions about the unknown or unseen data [7]. Supervised machine learning techniques automatically classify the dataset with already known categories by processing extracted features and calculating the accuracies [3, 27]. In particular, this paper has used supervised machine learning techniques to classify following categories:

- |                      |                |
|----------------------|----------------|
| (i) AD vs CN vs FTD; | (ii) AD vs CN; |
| (iii) AD vs FTD;     | (iv) CN vs FTD |

Machine learning models are the programs that have been already trained to find patterns within new dataset to make accurate predictions about a particular task. When these machine learning models are used to perform classification then such models can be called as classification algorithms that are used to determine the class of new instances. Some of the most commonly used classifiers are support vector machines, decision trees, kNN, and neural networks etc. The performance of the classifiers can be evaluated in many ways by calculating parameters like accuracy, precision, sensitivity, specificity, recall etc. Parameter estimators such as validation, cross validation, bootstrapping are used to calculate these parameters. This research has used cross validation methods to analyze the performance measures which can be done by using most popular k-fold or leave-one-subject-out cross validation. These methods are discussed in the following sub section. Accuracy results obtained from both CV methods are utilized to compare the results of classification algorithms, which can be affected by changing parameters used in the evaluation process [2, 5, 8, 27, 28].

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \times 100$$

#### 3.4.1 k-fold cross validation

k-fold is the most frequently used cross validation method which casually divides data into k distinct and equal size folds. Each fold is used to evaluate the model performance obtained by any machine learning classifier which is generated from other k-1 folds and the final accuracy is calculated by the mean of all the k accuracies achieved from k-fold cross validation. It is important to note that all folds should contain same number of samples unless explicitly specified [28]. Multiple factors can affect the accuracy of a model obtained while performing k-fold cross validation; one of them is the number of folds [28]. Generally, 10-folds are used while evaluating any model through k-fold cross validation, but this research observed results obtained from other k-folds also.

### 3.4.2 Leave One Subject Out Cross Validation (LOSO-CV)

Although k-fold (Monte Carlo) CV is a frequently used method, but a big concern with this method is the potential use of same data for both training and testing purposes. This can create randomness in the mechanism of k-fold and thus the mean accuracy obtained from multiple runs of k-fold on the same data set does not remain consistent for every run [28]. Hence an alternative cross validation method named as leave-one-subject-out (LOSO) is recommended in which single subject data has been excluded out while training the model and afterwards the excluded data is used as test data of the model. This process is again repeated for each subject until achieving final results. LOSO CV is more realistic and better method to calculate accuracy as compared to k-fold CV [5]. Unlike k-fold, the point estimate of accuracy achieved by LOSO-CV for a given dataset is constant, therefore, it is useless to repeatedly perform LOSO-CV for better results [28]. The results obtained from various models are shown in the result and discussion section of this paper.

## 4. Results and Discussions

The primary contribution of this paper is to develop a feature extraction methodology in time-frequency domain using Continuous Wavelet Transform for multiple disease analysis of EEG signals. In continuous wavelet transform based decomposition of EEG signals; three different wavelet families were evaluated and compared using various machine learning algorithms. Analysis of the features extracted from EEG frequency bands has shown some differences among AD, FTD and CN participants. Healthy subjects show lower kurtosis values than both AD and FTD patients, whereas FTD patients show higher kurtosis values than AD patients. Hjorth activity gives the measure of how much signal values vary from mean value by calculating the variance of the signal. Healthy subjects have higher activity values and AD subjects have lowest activity values among all when evaluated. The Hjorth complexity of healthy and FTD subjects shows very minute difference whereas AD subjects have lowest Hjorth complexity values when compared. The research is implemented using MATLAB R2020b software. Table 2,3&4 present the numerical results of the proposed method employing different classifier models.

Table 2: Accuracies(%) achieved from ML algorithms and k-fold Cross-Validation when CWT is performed using Morse Wavelet

Classes	No. of folds	Decision Tree	Logistic Regression	SVM	kNN	Naïve Bayes	Ensemble Bagged	Neural Network	Kernel
<b>AD vs CN vs FTD</b>	5	80.5	-	84.4	85.5	61.4	<b>91</b>	84.1	60.3
<b>AD vs CN</b>		89.7	76.3	90.6	92.6	75.3	<b>93.8</b>	90.7	74.6
<b>AD vs FTD</b>		89	71.7	91.3	91.8	71.9	<b>94.2</b>	90.6	72.4
<b>CN vs FTD</b>		78.3	67.6	86.5	89	72.4	<b>89.7</b>	88.3	72.3
<b>AD vs CN vs FTD</b>	10	80.8	-	84.7	86.3	63.9	<b>90.8</b>	84.1	59.2
<b>AD vs CN</b>		89.7	74.9	92.1	93.5	86.1	<b>94.9</b>	90.5	73.2
<b>AD vs FTD</b>		91.2	71.4	91.4	92.2	72.2	<b>94.7</b>	92	73.2
<b>CN vs FTD</b>		81.4	68.3	89.1	90.2	71.7	<b>91.4</b>	90.2	71.6
<b>AD vs CN vs FTD</b>	15	79.8	-	85.3	86.4	62.5	<b>91.4</b>	84.1	61.6
<b>AD vs CN</b>		91	73.9	91.5	93.7	77.7	<b>94.9</b>	91.2	75.1
<b>AD vs FTD</b>		90.8	71.6	91.6	92.3	72.3	<b>95.3</b>	91.8	72.8
<b>CN vs FTD</b>		80.7	67.5	88.4	90	73.2	<b>90.5</b>	87.8	72.5

Table 3: Accuracies(%) achieved from ML algorithms and k-fold Cross-Validation when CWT is performed using Morlet Wavelet

Classes	No. of folds	Decision Tree	Logistic Regression	SVM	kNN	Naïve Bayes	Ensemble Bagged	Neural Network	Kernel
<b>AD vs CN vs FTD</b>	5	80.1	-	86.7	89.2	63.5	<b>91.5</b>	84.1	55.5
<b>AD vs CN</b>		90.8	76.9	93	95.1	73.6	<b>95.4</b>	93.5	72

<b>AD vs FTD</b>	10	88.8	69.3	91.9	93	72.3	<b>93.6</b>	90.2	69.5
<b>CN vs FTD</b>		83.1	63.3	89.4	91.2	74	<b>93.2</b>	84.4	66.7
<b>AD vs CN vs FTD</b>		81.7	-	86	89.2	64.5	<b>92.9</b>	86	57.7
<b>AD vs CN</b>		92.1	76.7	93.7	95.7	76.7	<b>95.8</b>	93.6	71.4
<b>AD vs FTD</b>		90	69.8	92.3	93.6	73.9	<b>93.5</b>	90.6	71.3
<b>CN vs FTD</b>		85.9	62	89.6	91.6	73	<b>93.1</b>	89.4	68
<b>AD vs CN vs FTD</b>		15	80.9	-	86.8	89.5	64.2	<b>93</b>	87
<b>AD vs CN</b>	91.4		76.7	94.2	95.7	77.8	<b>95.8</b>	94.3	73.2
<b>AD vs FTD</b>	89.5		69.9	92.2	93.9	73.1	<b>94.1</b>	91.9	69.8
<b>CN vs FTD</b>	85.8		62.4	90.6	91.9	74.7	<b>94.2</b>	90.4	67.6

Table 4: Accuracies(%) achieved from ML algorithms and k-fold Cross-Validation when CWT is performed using Bump Wavelet

Classes	No. of folds	Decision Tree	Logistic Regression	SVM	kNN	Naïve Bayes	Ensemble Bagged	Neural Network	Kernel
<b>AD vs CN vs FTD</b>	5	76.9	-	82.3	86.1	62.1	<b>87.3</b>	83.7	70.6
<b>AD vs CN</b>		89.1	75.3	92.9	<b>94.7</b>	78.5	92.8	91.6	81.5
<b>AD vs FTD</b>		87.1	73.5	91.3	<b>92.3</b>	73.6	<b>92.3</b>	90.3	83.2
<b>CN vs FTD</b>		77.2	65.1	84	85.6	71.2	<b>89.8</b>	85.1	78.1
<b>AD vs CN vs FTD</b>	10	79.6	-	83.6	87	63.9	<b>90.2</b>	83.1	72.5
<b>AD vs CN</b>		88.2	72.8	92.1	94.4	76.7	<b>94.5</b>	92	82.4
<b>AD vs FTD</b>		87.4	73.5	91.9	<b>93.6</b>	72.7	92.7	91.5	82.7
<b>CN vs FTD</b>		80.3	65.3	84.1	86.5	69.8	<b>90.6</b>	85.7	78.7
<b>AD vs CN vs FTD</b>	15	80.6	-	83.4	86.3	62.5	<b>90.2</b>	84.7	72.7
<b>AD vs CN</b>		89.4	72.3	94.2	<b>94.7</b>	77.3	<b>94.7</b>	93	82.8
<b>AD vs FTD</b>		88.6	73.1	91.5	<b>94.1</b>	73.7	93.1	91.8	83.9
<b>CN vs FTD</b>		79.7	64.6	85.2	86.3	70.8	<b>90.7</b>	85	79.2

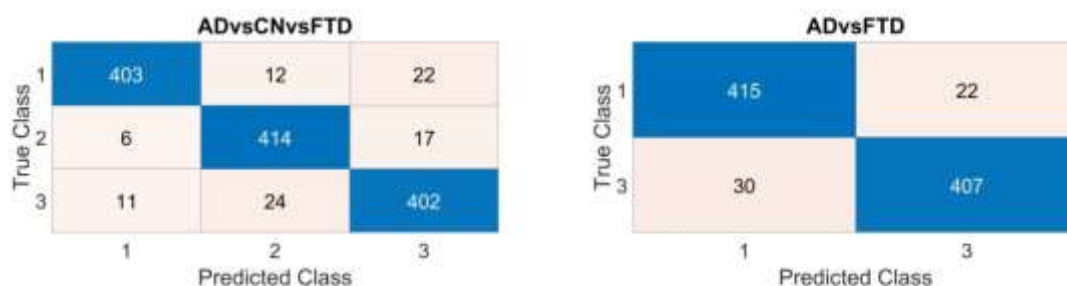
Results as shown in Table 2,3&4 show differences among the performances of multiple classifiers when applied with various wavelet families and k-fold CV methods. It is observed that Morlet wavelet gives the best results among all the wavelets using 15-folds cross validation. Table 5 shows the best results among all the classifications, along with their used wavelet, number of folds and respective machine learning model.

Table 5: Maximum accuracies (%) achieved using k-fold Cross-Validation.

	Morse wavelet	Morlet wavelet	Bump wavelet	No. of folds	ML Model
<b>AD vs CN vs FTD</b>	91.4	<b>93</b>	90.2	15 folds	Ensemble Bagged
<b>AD vs CN</b>	94.9	<b>95.8</b>	94.7	Both 10 and 15 folds	Ensemble Bagged
<b>AD vs FTD</b>	95.3	<b>94.1</b>	<b>94.1</b>	15 folds	Ensemble Bagged and kNN
<b>CN vs FTD</b>	90.5	<b>94.2</b>	90.7	15 folds	Ensemble Bagged

# Best results are in bold.

Fig. 3 shows the confusion matrices of the best performance achieved from k-fold for all the four types of classifications.



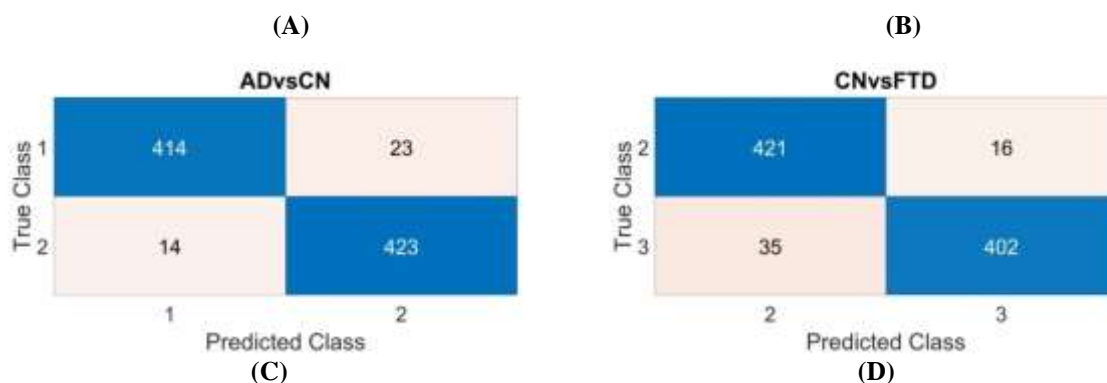


Figure 3: Confusion Matrix of classifier having maximum accuracy. In these subfigures, “1” represents AD, “2” represents CN and “3” represents FTD.

The LOSO-CV method has also been used to evaluate the results of various machine learning models to cross check the results. In this method, all the feature matrices obtained from single channel of any participant are taken as test data and features of all other remaining channels forms the training set. This process is repeated for each channel, and performance of the model is given by the weighted average of the results [17]. Table 6 shows the result of LOSO-CV obtained using random-forest classifier. Random forest classifier and ensemble bagged tree model can be used interchangeably as random forest uses the concept of ensemble learning and is a variant of bagged trees that introduces feature randomness during tree-building to increase diversity and improve generalization. The results obtained from LOSO-CV method for multiple disease classification when executed with different wavelet family is shown in Table 6.

Table 6: Calculation of Average Cross Validation Score using Leave One Subject Out Method using Random Forest Algorithm

Category	Morse wavelet	Morlet wavelet	Bump wavelet
AD vs CN vs FTD	74.90%	<b>75.29%</b>	74.52%
AD vs CN	86.73%	87.87%	<b>88.90%</b>
AD vs FTD	88.22%	87.19%	<b>88.44%</b>
CN vs FTD	78.60%	<b>84.10%</b>	81.01%

# Bold indicates best accuracies

As mentioned in Table 6, the results of the LOSO-CV shows different results than k-fold. The Bump wavelet family also provides good results as compared to other wavelets. From Table 7 it can be seen that the methodology used in this research work provides better accuracies as compared to the exiting work.

Table 7: Comparative analysis of the proposed methodology with existing works in the recent years

S. No.	Author	Year	Modality	ML / DL	Cross Validation	Classes	Accuracies (%)
1	[5]	2021	EEG	ML	k-fold	AD/CN	99.1
						FTD/CN	98
						AD/FTD	97.7
					LOSO	AD/CN	78.5
						FTD/CN	86.3
						AD/FTD	73
2	[29]	2023	MRI	ML	k-fold	AD/FTD/CN	71.3
						AD/CN	90
						FTD/CN	88
						AD/FTD	75
3	[1]	2018	EEG	ML	k-fold	AD/CN	76.4
					LOSO	AD/CN	83.3
4	[30]	2019	MRI	ML	k-fold	CN / Dementia	86.1

						(FTD + AD)	
						AD/FTD	90.8
5	[27]	2019	EEG	ML	LOSO	AD/CN	95.6
6	[15]	2023	EEG	ML	LOSO	AD/CN	77.01
						FTD/CN	73.12
7	[17]	2023	EEG	DL	LOSO	AD/CN	83.28
						FTD/CN	74.96
8	[31]	2023	Clinical Data	ML	k-fold	AD/FTD	91
9	[32]	2021	MRI	DL	CNN	AD / FTD / CN	91.8
						AD/FTD	93.1
10	[33]	2020	MRI	DL	k-fold	AD/FTD/CN	88.28
11	[4]	2022	MRI	DL	k-fold	AD/FTD/CN	87.1
						AD/CN	87.5
						FTD/CN	90.7
						AD/FTD	91
12	[34]	2023	EEG	ML	k-fold	AD/FTD/CN	86.9
						AD/CN	93.6
						AD/FTD	93
						FTD/CN	87
<b>13</b>	<b>Proposed Methodology</b>	<b>2023</b>	<b>EEG</b>	<b>ML</b>	<b>k-fold</b>	<b>AD/FTD/CN</b>	<b>93</b>
						<b>AD/CN</b>	<b>95.8</b>
						<b>AD/FTD</b>	<b>94.1</b>
						<b>FTD/CN</b>	<b>94.2</b>
					<b>LOSO</b>	<b>AD/FTD/CN</b>	<b>75.29</b>
						<b>AD/CN</b>	<b>88.9</b>
						<b>AD/FTD</b>	<b>88.44</b>
						<b>FTD/CN</b>	<b>84.1</b>

\* EEG = Electroencephalography \*MRI = Magnetic resonance Imaging \* AD = Alzheimer's Disease \* FTD = Fronto Temporal Dementia \* CN = Control Normal Subjects \* LOSO = Leave One Subject Out \*ML = Machine Learning \*DL = Deep Learning

Thus it can be concluded that the combination of wavelet family, frequency band features and cross validation method used in this research work has shown the best results than the existing methods to perform the classification of AD and FTD patients when compared with CN subjects. Their differential diagnosis (ADvsFTD and ADvsFTDvsCN) has also become possible with good accuracy and thus proper medication can be provided to the patients in their early days of dementia.

## 5. Conclusion

In this study, a detailed framework for EEG data analysis has explained to detect multiple dementia diseases and to perform their differential diagnosis using machine learning techniques. A balanced EEG dataset has analyzed in this research that includes 23 AD, 23 FTD and 23 CN participants. The process includes analysis of EEG signals (filtered out from 19 different channels of everyone) in time-frequency domain through CWT to perform frequency segmentation. On moving further, calculation of a set of appropriate features (Hjorth parameters and Kurtosis) from various EEG frequency bands has been done and applied to number of machine learning classifiers so that both 2-way (AD vs. CN, AD vs. FTD and FTD vs. CN) and 3-way (AD vs. FTD vs. CN) classifications can be analyzed. These parameters can differentially diagnose the two pathologies i.e. AD and FTD with improved accuracy than the existing methods. Comparative results show that frequency band features of all the EEG channels when applied to Ensemble Bagged classifier outperforms all other models of machine learning while performing k-fold cross validation. Morlet wavelet showed the best results during k-fold cross validation. While performing LOSO-CV method, both Morlet and Bump wavelets provided highest classification accuracy for the disease diagnosis. The results obtained from k-fold CV is not constant at every run hence our analysis is mainly focused on the LOSO CV method. The binary classification of dementia diseases (AD or FTD) with the CN subjects can be accurately performed with LOSO-CV method, achieving 88.9% and

84.1% accuracies respectively. The 2-way (AD vs. FTD) and 3-way (AD vs. FTD vs. CN) differential diagnosis show accuracy results of 88.44% and 75.29% respectively. As per the results obtained from the proposed framework, it can be said that analysis of various parameters of different EEG frequency bands using Machine Learning algorithms can prove to be a useful method for the accurate and precise diagnosis of various dementia diseases.

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