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Cognitive Disability Prediction & Analysis using Machine Learning Application

R. Kishore Kanna
Department of Biomedical Engineering
Jerusalem College of Engineering
Chennai, India
kishorekanna007@gmail.com

V. Subha Ramya
Department of Biomedical Engineering
Vels Institute of Science, Technology & Advanced Studies [VISTAS]
Chennai, India

Asraa Ahmed Khafel
Collage of Engineering
National University of Science and Technology,
Dhi Qar, Iraq

Kadim A.Jabbar
Collage of Engineering
National University of Science and Technology,
Dhi Qar, Iraq

Mustafa Al-Tahee
Medical Laboratory Techniques Department
Al-Farahidi University
Iraq, Baghdad

Raed Khalid
Medical Laboratory Techniques Department
Al-Farahidi University
Iraq, Baghdad

Abstract*— A person with mild cognitive disability (MCD), a kind of memory loss that affects both memory and thinking skills, may be at an increased risk of acquiring dementia brought on by Alzheimer's disease or other neurological diseases. MCD affects between 13 and 19% of those who are 60 years of age or older. People who suffer from cognitive abnormalities should seek therapy and diagnosis as soon as they can. The major effect of MCD on the target is its effect on memory. Accurate MCD diagnosis is quite challenging with the current approaches. A hybrid approach is put forward in this study to identify MCD at an early stage. EEG data from MCD individuals and healthy controls was collected for this purpose. With the use of machine learning models including Support Vector Machines (SVM), Decision Trees (DT), k-Nearest Neighbour (KNN), and the hybrid approach ACO KNN, Renyi entropy (RE) and Discrete Wavelet Transform (DWT) characteristics were retrieved (combined Ant Colony Optimisation with k-Nearest Neighbour). The performance of the system is assessed based on an accuracy comparison with machine learning models. When compared to other models, RE and ACO KNN had an accuracy of 85.0%.

Keywords—EEG, MCD, DWT, KNN, SVM, ML

I. INTRODUCTION (*HEADING 1*)

Patients with Alzheimer's disease (AD) mostly experience memory loss, which may become life-threatening in severe instances [1]. However, memory issues are often brought on by the destruction of brain neurons, which slows down the storing, remembering, and retrieval of memories [2]. Forgetfulness may be a natural aspect of ageing. MCD is the period of transition between cognitive deterioration and normal ageing, and it may sometimes cause significant dementia that progresses to Alzheimer's disease [3]. The signs of MCD will be present in the patient.

Patients with MCD may sometimes, but not always, be at risk of developing AD [4]. The chance of acquiring AD is decreased by taking the required measures and studying the symptoms as soon as they appear. It is crucial for the patient to take medicine in order to delay the development process [5].

The chemical study that is used to identify MCD is performed on cerebral spinal fluid (CSF). This kind of examination is more costly, intricate, and time-consuming [6]. MRI is another examination for evaluating the MCD using scanning, which is more difficult. This kind of examination is more costly, intricate, and time-consuming [6]. MRI is another examination for evaluating the MCD using scanning, which is more difficult. An electroencephalogram (EEG) is a substitute method for identifying MCD [7].

The EEG is a tool that aids in capturing the electrical activity of the brain. By positioning the electrodes on the scalp and taking into account the four major sections of the head—the nasal edge of the nose, the inion at the rear of the head, and two pre-auricular locations slightly anterior to the ear—we are able to capture EEG data [8]. The electrodes are positioned on the head using the international 10-20 method, and the EEG data are then gathered [8].

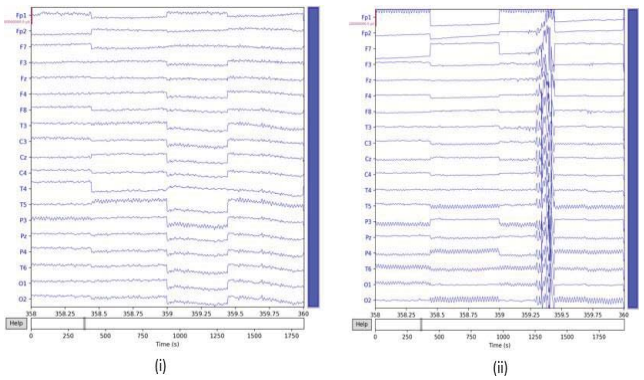

Figure 1 shows the channel information for the I HC and (ii) MCD sample EEG data.

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EEG has been extensively used during the last 20 years to identify brain illnesses such as dementia and Alzheimer's disease (AD) [9]. EEG is widely used nowadays and is less costly when compared to other methods [10]. The development of diagnostic instruments for gathering EEG data is aided by advances in computer technology [11]. These are often used by neurologists and healthcare professionals while analysing EEG signals (QEEG). To identify and diagnose AD and MCD, a variety of machine learning and deep learning (DL) models are applied [12].

This section discusses numerous strategies that researchers have developed for identifying MCDO. Globally, researchers use the Hjorth Descriptor to extract characteristics from the EEG data in comparison to the pre-existing neuroimaging signals [13]. From the EEG data, the Hjorth Descriptor aids in the extraction of complexity, mobility, and activity aspects. For ten participants, an accuracy of 80% was achieved when classifying normal and MCD EEG signals using the k-Nearest Neighbour classifier [14].

Additionally, some researchers suggested a method for using QEEG to identify MCD. The EEG signal's power spectrum analysis components are retrieved, and the k-nearest neighbour model is used to estimate the use of the model to diagnose MCD in 27 patients, 16 of whom were normal and 11 of whom had the condition, with an accuracy of 81.5% [15].

As an alternative to signal features, a few researchers developed the hybrid feature extraction algorithm by fusing the wavelet transform and empirical mode decomposition [16]. This method demonstrated a significant difference using the multivariate analysis of variance (MANOVA) test and correctly classified 27 subjects using weighted k-nearest neighbours (w kNN) with an accuracy of 85.7%.

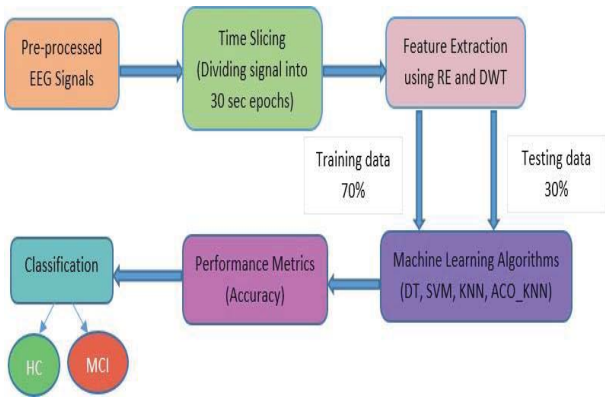
Below are several issues and research gaps that were found in the literature review.

Traditional machine learning approaches have been applied in earlier studies.
There's a potential for categorization errors, and current models could not provide the desired accuracy.
This study suggests using a hybrid algorithm (ACO KNN) to train the EEG data for the most accurate separation of MCD patients from HC patients. This will help us solve the misclassification issue.

II. Methodology

The suggested methodology's framework is shown in Figure 2. Epochs of 30 seconds are separated into each processed EEG wave (time slicing). MCD individuals from the HC were discovered in two stages. In this study, feature extraction and machine learning are both used [17]. To identify MCD from EEG data, Renyi entropy (RE) and discrete wavelet transformation (DWT) features are extracted and trained using conventional machine learning models SVM, KNN, DT, and hybrid models ACO KNN [18]. One of the excellent algorithms that can handle a variety of challenging datasets is K-nearest neighbour (KNN). 30% of the data is used to assess the model's performance, while 70% is used for training [19]. Its performance was evaluated using an accuracy measure. The hybrid model ACO-KNN performs better at identifying MCD in HC patients [20].

Figure 2 Classification Overview



III. Description of the Dataset

A dataset of 61 patients with an average age of 55, comprising 32 normal cases and 29 MCD cases, is gathered from the Isfahan MISP (online database for medical images and signals) [21]. In the morning sessions, these EEG signals are recorded while keeping the eyes closed. Galileo NT is used to record EEG data in accordance with international standards, which call for recording EEG signals using 10–20 systems and 19 electrodes (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, C3, Cz, P3, P3, P4, T6, O1, and O2) [22]. These signals have a 256 Hz frequency and a duration of 30 minutes. EDF files are used to hold the recording results [23].

EEG data were separated into 30 second epochs with no overlap after being acquired from each subject for 30 minutes at 256 sampling frequencies [24]. Thus, the maximum number of samples per epoch is N = 7680 (30256). A total of 3766 EEG samples, comprising 1808 from MCD patients and 1958 from healthy controls, will be used as input.

A. MCD detection via feature extraction

In order to increase the effectiveness of the classifier model, feature extraction techniques are often used to identify the most crucial set of features from the training data and to extract the output from the testing data [25]. The characteristics of the EEG signal are retrieved based on the classification's accuracy. If the features are incorrectly extracted, the classification's performance suffers.

B. Renyi Entropy (RE)

Entropy is a metric used to estimate a random variable's level of uncertainty. The Renyi entropy may convey data in numerical form regarding the variety or randomness of a system. Renyi entropy R is denoted technically as:

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$$R_{ent}(X) = \frac{1}{(1-\propto)} log \sum_{i=1}^{n} p(X_i)^{\propto} \qquad (1)$$

An example of a discrete random variable is XN = X1, X2,..., Xn, where Xi = xi and I = 1, 2,..., n, with pi denoting the chance that event P(Xi) will occur and denoting the order of the entropy computation. The metric distance in the simplex is changed. A value is computed for each property, the sensitive values are extracted, and the attribute is defined as being chosen or not. For the estimate of Renyi entropy for MCD detection in this work, = 2 is used. Here, the Renyi entropy value is calculated every two seconds.

Renyi entropy $= \frac{7680}{2 \times 256}$ = 15 features/ sample

So, each data sample 15 features are shown in Fig 3 for both HC and MCD.

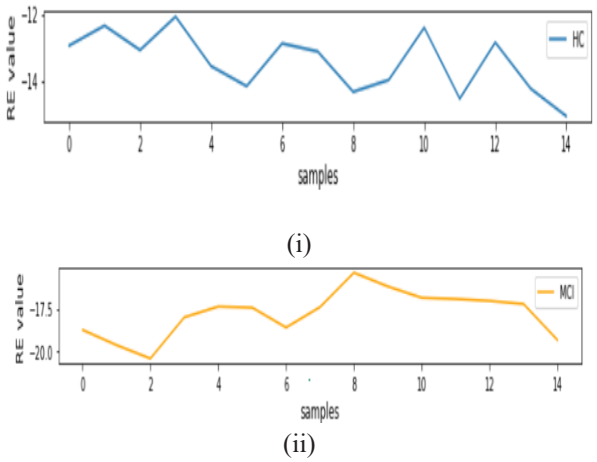

Fig 3: Extracted Renyi Entropy features for (i) HC, (ii) MCD from sample EEG signals

IV. Discrete Wavelet Transform (DWT)

The representation of a non-stationary signal is where the wavelet transform (WT) is most often used. The EEG signals, which include many data points and tiny metrics, are compressed using WT to save time. DWT is one of the methods that divides the input signal into a number of groups, each of which has a time series of coefficients that explain how each signal in the related frequency band evolved over time.

The DWT separates the x [n] signal into components in order to control the time frequency resolution. Here, high-pass and low-pass filters are used to separate the input signal x [n] into its two components [29]. The approximation (A) and detail (D) coefficients, respectively, are the outputs of these filters. These "A" coefficients are once again divided into "A" and "D" coefficients, and this procedure is repeated until the required number of stages of decomposition has been obtained.

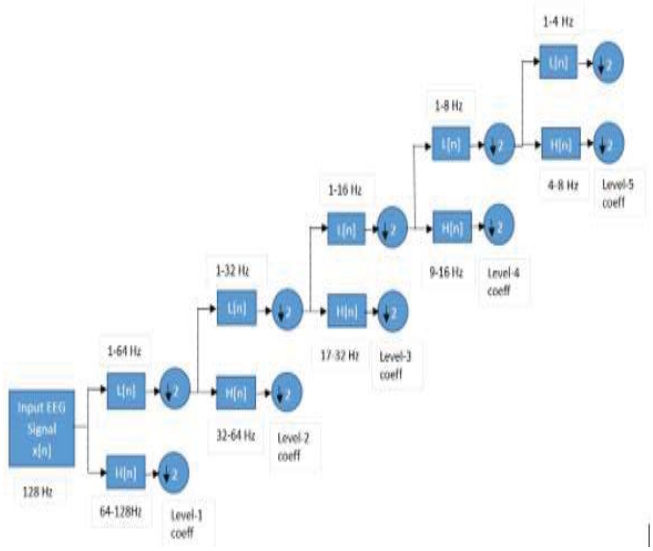

Fig 4: Discrete Wavelet Transform (DWT)

Two factors, such as approximation coefficients and detail coefficients, are used to partition the EEG data in Fig. 4. The aforementioned graphic displays stages 1 through 5. Daubechies wavelets are the most widely utilised collection of discrete wavelet transformations. The Daubechies wavelets (db2) are used to decompose the EEG signals.

The approximation coefficients are split into a coarser low-pass (approximation) and high-pass (detail) component at each succeeding level. In this method, the signal is divided into many time frames, and the frequency and amount of decomposition of the EEG signals determine how many characteristics may be retrieved from each time frame. Fig. 5 displays the DWT characteristics for HC and MCD that were derived from sample EEG recordings.

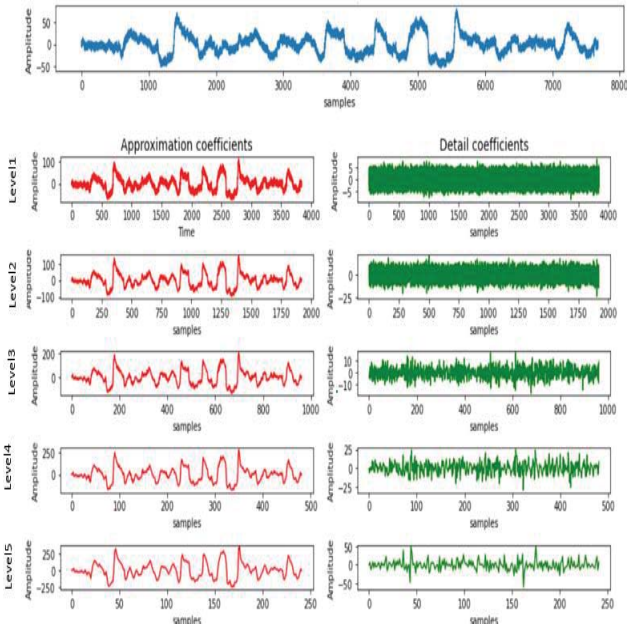

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Fig 5: Extracted DWT features for (i) HC

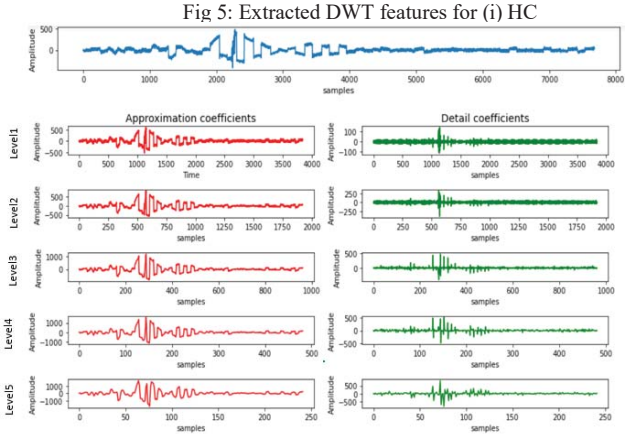

Fig 5: Extracted DWT features for (ii) MCD from sample EEG signals

V. Machine Learning Models for MCD Detection

A. Decision Tree (DT)

The most common machine learning (ML) model that can be used to address both regression and classification issues is the decision tree (DT). In DT, the tree nodes stand in for the feature (attributes), the link (child) represents the decision (rule), and the leaves represent the output.

The whole training dataset X = x1, x2,... xn is used to form the tree, which is then applied to 'n' EEG samples as illustrated in Fig 6. Each sample has the characteristic A = "q," and the EEG signal with frequency data is included in each sample.

The internal nodes are kept in test attributes. MCD and HC labels are regarded as leaf nodes. The internal nodes in SET A are chosen according to how the characteristics in their samples are split into classes. In the training dataset, set A divided the characteristics into the subsets X1, X2,..., and Xw..

The supplied dataset, X, is used to compute entropy using:

$$E(X) = \sum_{i=1}^{c} - p_i log_2 p_i \qquad (2)$$

Where p_i represents the samples with probabilities in dataset X which is belongs to class i and c is overall classes.

$$\text{Info Gain}(X, A) = E(X) - E(X|A) \qquad (3)$$

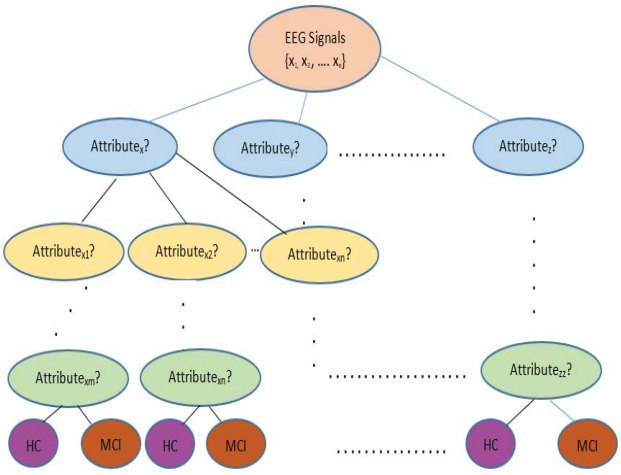

Fig 6: Classification of MCD and HC using DT

B. K-Nearest Neighbor (KNN)

This machine learning technique is used in classification and regression to address various predicted problems. By comparing an input EEG sample with the training data, this classifier makes a determination. Each fresh EEG input signal is compared one at a time with each training sample set of data. The 'k' alternative designs with the shortest distance are often chosen. At first, the value of "k" is given. Euclidean distance is used to determine how similar things are. Based on the relevant characteristics in the dataset, the similarities between the fresh sample and trained samples are found, and the closest patients afflicted by MCD and HC are located, as shown in Fig. 7.

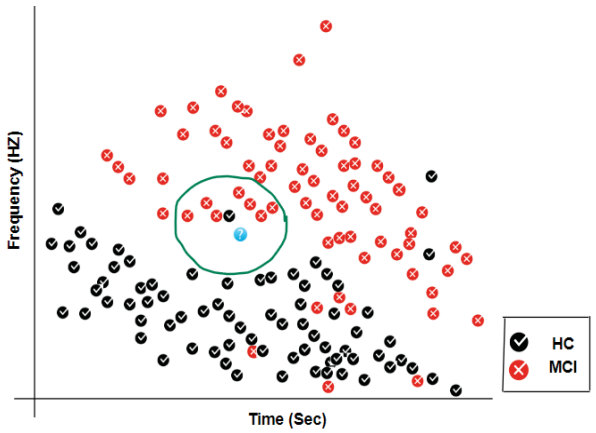

Fig 7: Classification of MCD and HC using KNN

C. Support Vector Machines (SVM)

The well-known machine learning method, SVM, is often used for classification problems. For the purpose of identifying MCD, this is employed to resolve classification issues for the EEG signal processing MCD, this is employed to resolve classification issues for the EEG signal dataset. SVM's primary goal is to determine the best decision (whether the input sample is affected by MCD or not) by displaying boundaries in an N-dimensional space that can divide data points based on the EEG input signal into MCD and HC classes, as shown in Fig. 8. The best decision boundary is also referred to as a hyper plane. Support vectors are the extreme vectors that SVM chooses in order to locate the hyperplane.

The two-dimensional data is linearly split using a separated line. Y=ax+b is the line's function. Here, x is changed to x 1, and y is changed to x 2, and the result is:

$$If\ we\ define\ x = (x_1, x_2) and\ w = a, we\ get:$$

$$w * x + b = 0 \qquad (4)$$

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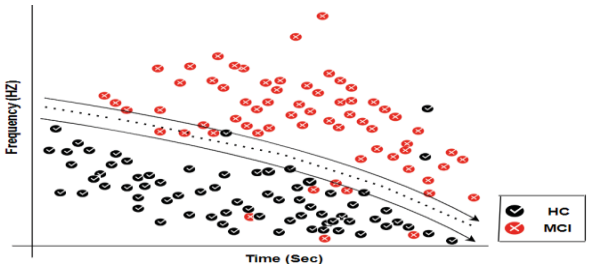

Fig 8: Classification of MCD and HC using SVM

VI. PROPOSED HYBRID ALGORITHM

The ACO KNN technique is used to train the model to identify MCD from HC. The characteristics that were taken from the RE and DWT separately will be processed by this method.

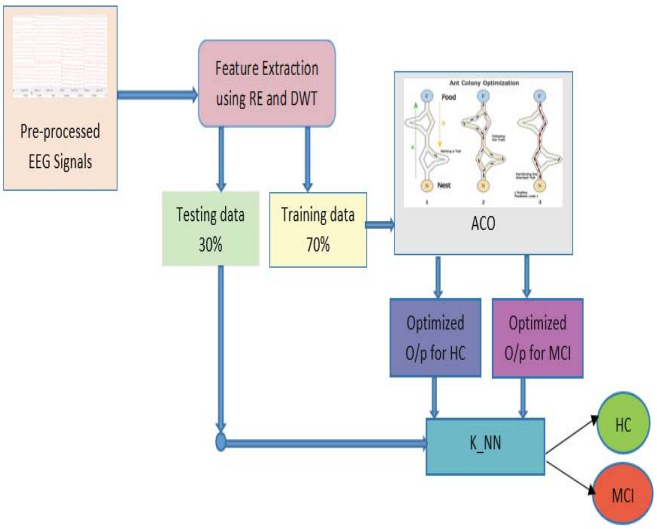

Fig 9: Classification of MCD and HC using ACO_KNN

the ACO KNN using EEG data in the following stages

1.Enter the EEG signal with the characteristic retrieved.

2.Sort the data into training (75%) and testing (25%) data.

3.Now provide training data to ACO as input.

4.Initialize the population size (k), pheromone, and ACO settings.

5.do for each ant continue until

Determine the likelihood of choosing a certain move from I to pick the route from I to j as

$$P_{ij}^{k} = \frac{(\tau_{ij}^{\alpha})\,(\eta_{ij}^{\beta})}{\Sigma(\tau_{ij}^{\alpha})\,(\eta_{ij}^{\beta})}$$

α and β are the influence parameters of τ_{ij}^{α} and η_{ij}^{β} respectively, must be greater than zero.

end

update trial level by using

$$\tau_{ij} = (1 - \rho)\tau_{ij} + \Delta\tau_{ij} \qquad (6)$$

Where ρ is the rate of trail move evaporation

End

6. The outcome will be the best route for HC and MCD detection. The KNN uses this EEG signal as input.

7.Send the test results to KNN.

8.Let's say we have data points (ai, bi) with i=1, 2...d.

9.Wherein for each I "a" initialises the feature values and "b" initialises the overall labels.

10.Calculating the Euclidean distance between two places.

11.The order of 'n' Euclidean distances is not decreasing.

12.Choose the first k distances from the sorted list by initialising k to be a positive integer. These k- distances apply to all k places.

13.Determine the signal's classification using distances (either MCD or HC).

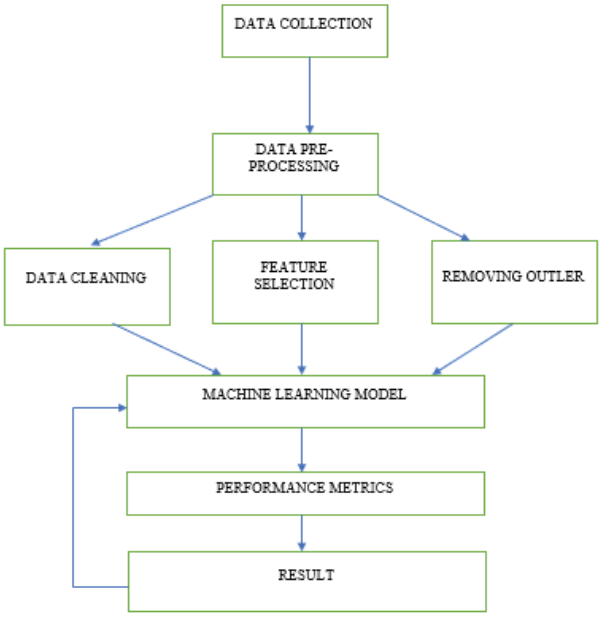

Fig 9: Proposed Work Flowchart

VII EVALUATION OF RESULTS

A. Dataset

EEG signals were recorded for 30 minutes at 256 sample frequencies on 61 subjects. EEG signals are split into 30 second epochs with no overlap every 30 minutes. Therefore,

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each epoch may include a maximum of N=7680 (30256) samples of samples, and there will be a total of 3766 input signals. The features are then retrieved from these epochs, and the data is split into training data (70%) and testing data (30%), which together include 2636 signals and 1130 signals, respectively.

No=1130 inputs	**SVM**		**KNN**		**DT**		**ACO_KNN**	
	HC	***MCD***	***HC***	***MCD***	***HC***	***MCD***	***HC***	***MCD***
HC	419	113	425	147	418	136	464	106
MCD	192	406	135	423	152	424	98	462
Accuracy	**73**		**75**		**74.5**		**82**	

Table 1: Confusion matrix table for DT, SVM, KNN, ACO_KNN using Renyi entropy

61 subjects in total, of whom 32 were normal and 29 had MCD.

1.61 participants were observed for 30 minutes.

2. Epochs of 30 seconds each make up each 30 minutes. (30 min.) is (30 x 60 sec.) 1800 sec. Thus, 1800/30 sec equals 60 samples, each lasting 30 sec. *B. Performance measure*

The accuracy of each model is used to assess its performance. Accuracy: MCD and HC's total accurate illness predictions.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \qquad (7)$$

B. MCD detection using RE

Utilizing RE, features are retrieved. The input data used to train conventional machine learning models like SVM, DT, KNN, and the new hybrid ACO KNN model is compared to test data consisting of 1130 inputs that comprise MCD and HC. The accuracy rates for DT, SVM, KNN, and ACO KNN were determined to be 74.5%, 73.0%, 75.0%, and 82.0% respectively.

3.256 samples per second is referred to as a 256-sampling frequency. So, 256 samples are taken per second. Sample values: 30 Sec = 256 x 30 Sec = 7680

4.Every 30 minutes, there are 460800 values (7680 Sample x 60).

C. MCD detection using DWT

The characteristics that are retrieved from the DWT are provided as input for DT, SVM, KNN, and ACO KNN training and testing as well as other machine learning algorithms. The detected accuracy rates for DT, SVM, KNN, and ACO KNN are 73.0%, 72.0%, 70.0%, and 79.5%, respectively.

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