Migraine types identification based on EEG signals using machine learnings techniques

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Abstract

Migraine (MD) is a neurological disorder that can be accompanied by auditory and visual symptoms called aura, affecting the lives of approximately one billion people worldwide. This condition causes temporary disability and may progress to serious diseases such as epilepsy or stroke, affecting both individual health and societal productivity by leading to a significant loss of working hours. The overlap of migraine symptoms with those of various other diseases makes identifying and diagnosing migraines challenging and time-consuming for medical professionals.

To advance healthcare and improve the medical care provided to patients beyond traditional methods, which are often cumbersome and time-consuming, we developed a machine learning model to assist doctors in diagnosing migraines and distinguishing between its types, whether accompanied by neurological auras or not. The model utilizes EEG signals obtained from auditory stimuli (A) and visual stimuli (V) of 17 migraine patients and 20 healthy control (HC) subjects. These EEG signals were analyzed using discrete wavelet transform (DWT) to extract frequencies known as alpha, beta, delta, theta, and gamma. These frequency features were then used to train machine learning algorithms. Our model achieved a classification accuracy exceeding 90%, effectively diagnosing migraines and distinguishing between its main types.

This innovative approach not only enhances the accuracy and efficiency of migraine diagnosis but also provides valuable insights into the neurological underpinnings of the disorder. By integrating advanced signal processing techniques with machine learning, our model represents a significant advancement in the medical field, offering a more efficient and accurate method for diagnosing migraines and improving patient care.

1. Introduction

Migraine is a debilitating neurovascular condition Characterized with spells of headache with accompanying autonomic and perhaps neurological symptoms, vomiting, and nervous system malfunction [1]. Approximately one-third of migraine patients experience transient neurological disturbances before, during, or after their headaches, known as migraine aura. [2]. an aura—typically a visual illusion or sensory manifestation—occurs before the migraine headache. This manifestation is frequently described as tingling or numbness in the face, arms, or other parts of the body. According to numerous studies, migraine with aura (MWa) is linked, in comparison to migraine without aura (MWoA) or healthy individuals, to cortical hyper-responsiveness and an alteration in how sensory information is processed as a result, even during the interictal phase [3].

Migraines are the second most common neurological condition in the world, causing more disability than all other neurological diseases combined [4,5]. Migraine is frequently misdiagnosed since its symptoms coincide with those of other conditions such as tension headache, epilepsy, and stroke [6]. Therefore, studies have shown that relying on and analyzing EEG data is an effective way to detect migraines and other neurological diseases, Electroencephalography (EEG) is a neuroimaging technique that measures electrical impulses produced by electrodes applied to the scalp to record brain activity [7]. The EEG signals are inexpensive, non-radioactive, and non-invasive. As a result, they are now frequently employed to identify brain abnormalities [8,9]. The most significant benefit of EEG is its exceptionally high temporal resolution, which makes it possible to capture electrical impulses thousands of times per second [7]. Since the nature of EEG signals is non-linear, a trained neurologist is needed to investigate abnormal EEG patterns associated with these disorders. And efficiency varies greatly in visual evaluation of these signals. Evaluating long EEG recordings can be tedious manually, and results may not always be consistent. With a little help from humans, the automated system can identify neurological conditions and track brain activity [10]. To develop an effective model that will support the doctor's diagnosis choice. The electrical activity of the brain is recorded using electrodes that adhere to international standards, such as the 10-20 system. This record is referred to as electroencephalogram (EEG) activity. EEG data represent the electrical activity of the human brain, which fluctuates in response to neurological conditions. EEG signals are key indicators of neurological diseases and can help with disease diagnosis [11]. Where EEG, magnetic resonance imaging, and computed tomography are employed to supplement expert judgment in the disease diagnosis. However, because EEG is less expensive and requires less equipment, it is favored for disease identification in computer-assisted diagnosis systems [12].

Many research employs EEG signals, particularly for the diagnosis of neurological illnesses. Machine learning algorithms are used to classify features extracted from EEG data using various ways. In this perspective, the relevant literature includes research that use EEG signals and machine learning algorithms to diagnose migraine [13].

The EEG signals of migraine patients were analyzed under auditory and visual stimulation, and power spectra were obtained from 15 channels mentioned in the scientific literature as directly related to migraine detection, namely (Fp1, F7, C3, Pz, Fp2, Fz, F8, Cz, C4, F3, F4, P3, P4, O1, O2)

With an indication of the location of each, as in **Figure 1.** Thus, a matrix was obtained representing the overlapping brain signals for each participant (15 x 307201), where the first dimension (15) represents the number of channels mentioned previously and the second dimension (307201)**.** represents the number of time samples that were extracted within the specified time range from 100 seconds to 700 seconds**.** It is possible to benefit later from several techniques to extract important features from these overlapping EEG signals for later use in analysis and processing [13]. One of these techniques is the use of the "dbwavf" or "dbwavfilt" function, which stands for "Daubechies Wavelet Filter". This function is used to implement the Daubechies wavelet transform based on decomposition level 8 (db8). This conversion is used to effectively analyze signals in the frequency domain, where the signal is divided into a set of different frequency levels. Then use them as features and divide them into training and testing sets. Many classification algorithms have been applied, such as SVM, LDA, Random Forest, NB, KNN, Tree Decision and FFNN neural network.

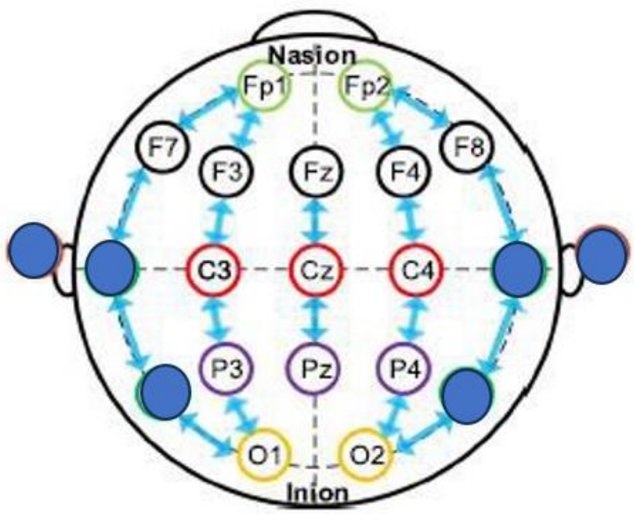


Figure 1 - EEG electrode placement

This research is set up as follows. In Section 2, we provide a summary of the dataset used. This section also provides a brief theoretical review of the methodologies used in the proposed strategy. In Section 3, we put the suggested methods to the test in order to assess a number of machine learning algorithms and suggest the most effective model for classifying migraines. Lastly, some closing thoughts and conclusions are included in Section 4.

2. Materials and methods

This section describes the dataset used, preprocessing techniques, and the method for extracting important features for later use as inputs for machine learning classifiers. The proposed approach scheme is presented in Section 1 and **Figure 2** shows an overview of the proposed method for diagnosing migraine using EEG signals.

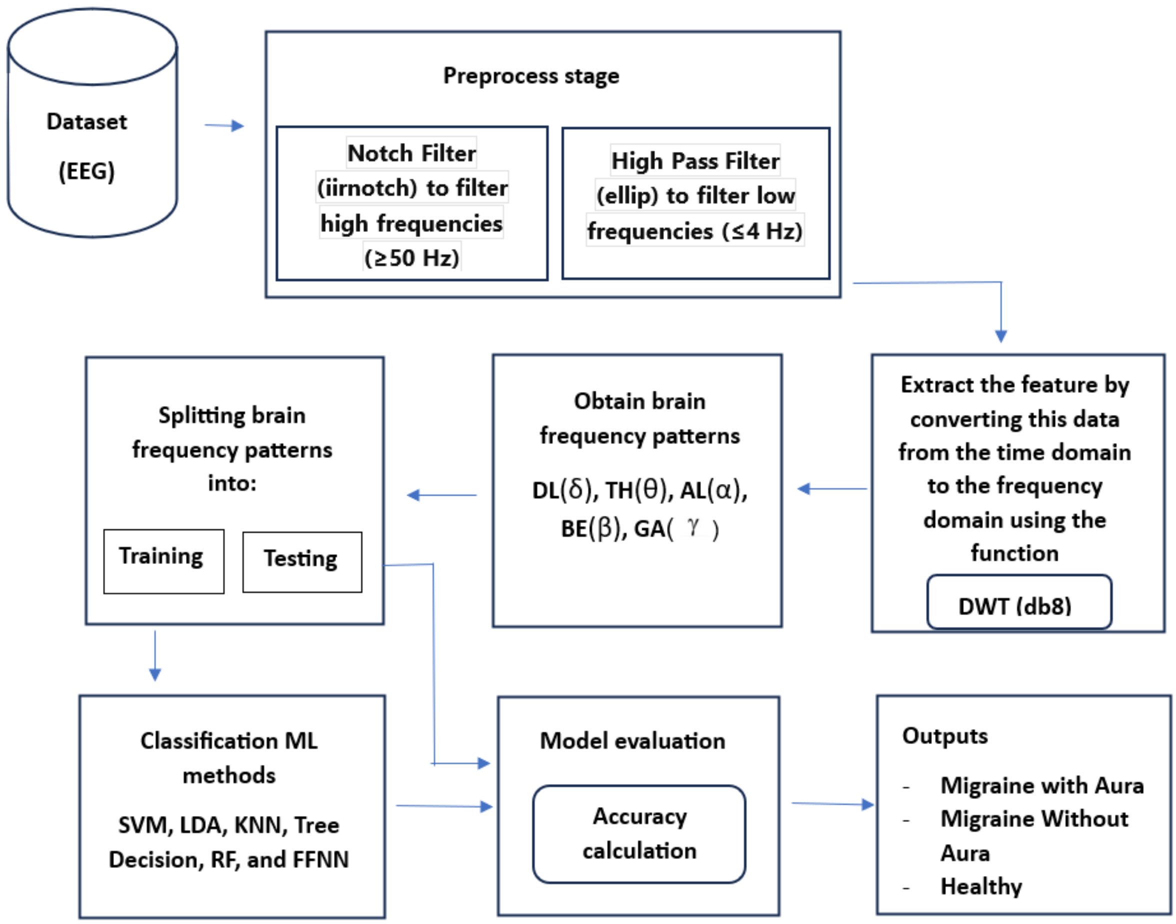


Figure 2 - The Migraine Classification System's structural diagram.

2.1. dataset collecting stage

In this study, migraine sufferers and healthy people were categorized using the recently released EEG dataset that available on KiltHub, Carnegie Mellon University's online data repository. The Bio Semi Active Two device was used to record the EEG dataset [15]. With a sampling frequency of 512 Hz, a 24-bit analog-to-digital (A/D) converter with 128 channels, and a recording time of approximately 10 minutes. It includes an electroencephalography (EEG) data set from 18 migraine sufferers (19-54 years old; 13 females, 5 men) and 21 control groups (12 females, 9 males) in the case of visual and auditory stimulation [12], they were chosen for the study from Pittsburgh's surrounding areas and Carnegie Mellon University. Participants did not have any neurological or psychological diagnoses (excluding migraine), no history of severe head injury or trauma, normal hearing, and, according to their own reports, normal or corrected-to-normal eyesight. The Carnegie Mellon University Institutional Review Board reviewed and approved all procedures.

The stimuli in this study included both visual and auditory components. The visual stimulation involved the presentation of vertical sinusoidal-wave achromatic gratings at a spatial frequency of 0.05 cycles per degree (cpd) cycles per degree, accompanied by a fixation cross. The auditory stimulation consisted of 1 kHz tones modulated by sinusoidal carrier frequencies of either 4 Hz or 6 Hz, delivered through insert earphones, reference [14] provide detailed information on the dataset and experimental setting. In our study participants M13 and C14 were excluded because they do not have EEG recordings for auditory stimulation.

2.2. Preprocessing stage

Two experiments were conducted, the first for visual stimulation and the second for auditory stimulation. A recording of 15 channels was made for migraine pain areas to reduce the complexity of the work. These channels were previously mentioned, but before reading those waves, it was converted from Bdf format to Edf format because it is more compatible with our research requirements and is the most common and used format for EEG data using the EDF Browser program. In the preprocessing step, EEG signals are filtered to reduce noise before being separated into specific signal fragments using a sliding window [16]. Filtering techniques were used to remove unwanted low-frequency and high-frequency signals. Where the EEG data were recorded with artifacts, noises, and interferences from many sources, such as electrical appliances, lighting, and other electronic devices in introducing unwanted signals to the electrodes of the EEG device.

Signal interference can occur when the patient moves during the EEG recording. This can cause interference and changes in the recorded electrical signal.

First, a notch filter is used to remove the specific high frequency of 50 Hz. This means that the filter reduces the strength of any signal containing this frequency. The elimination of AC interference caused by Power-line (PLI) from biological signals, such as the ECG and the EEG, to discrete wavelet form is one of the classic uses of digital notch filters [17]. Then, a high pass filter is used to remove low frequencies. In this case, frequencies below 4 Hz are filtered out. This means that the filter removes low-frequency signals and leaves only high-frequency signals. Thus, low-frequency signals (below 4 Hz) and high-frequency signals (above 50 Hz) are eliminated, thus preserving signals in the intermediate frequency range between 4 and 50 Hz. The filtering approach seeks to eliminate all noise and interference, improving the signal-to-noise ratio and thereby improve classification accuracy outcomes [18].

In the final stage, the detrend function is used with the 'constant' option to eliminate the signal's mean value, essentially eliminating any constant bias or offset. After applying the notch filter to remove power-line interference (50 Hz) and the high-pass filter to reduce low frequencies (below 4 Hz), the detrend function calculates the mean of the filtered signal and subtracts it from each data point. This method enhances signal quality by removing any constant offset, allowing for easier analysis of the signal's true physiological components. For example, if an EEG signal has a baseline drift due to sensor movement, the detrend function will rectify this by centering the signal around zero. But it will retain all the original changes and patterns in the data. This means that the signal will still contain the important information but without any consistent bias or skew, allowing for more accurate interpretation of brain activity.

2.3. Feature Extraction

When the waves are read and filtered, a high-dimensional array of overlapping signals will be obtained. In order to reduce them to reduce the complexity of the work and in order to focus on the most important data in our work These attributes must be significant to model learning tools; thus, they must be discriminatory and non-redundant in order for the data to be fully utilized. This is done through optimal characteristics are chosen while minimizing the number of features (dimensionality reduction) [19] so the feature extraction process involves converting raw data into meaningful features. It aims to capture relevant information and patterns in the data to facilitate analysis and modeling. By extracting informative features, the dimensionality of the data can be reduced and noise can be filtered out. This leads to improved performance of machine learning algorithms in learning and making predictions.

Discrete wavelet transform (DWT) allows us to use discrete wavelet coefficients(db8) to characterize EEG signals. When these signals are characterized by statistical data, their relevance increases. The signal's dimensionality is decreased by those statistical qualities [6]. It converts discrete temporal signals to discrete wavelet representations [17].

In the process of Discrete Wavelet Transform (DWT), the initial signal is broken down into two key components: approximation, which captures the low-frequency information, and detail, which highlights the high-frequency details. Following the first stage of decomposition, only the approximation component proceeds to undergo further decomposition, while the detail component remains unchanged. This iterative process continues until a predetermined level of decomposition is achieved [32]. Where the approximation component in wavelet analysis contains low-frequency information and is typically used to extract low-frequency activities such as theta and delta waves. On the other hand, the detail component often contains high-frequency information, which can be utilized to extract high-frequency activities such as alpha, beta, and gamma waves.

Therefore, the (db8) function analyzes the EEG brain signal and converts it from the time domain to the frequency domain, whereby five main frequency bands are obtained: GM (Gamma), BT

(Beta), AP (Alpha), TH (Theta), and DT (Delta), Through an iterative loop, it is used to calculate the coefficients for each frequency band, where the highest frequencies of alpha, beta, delta, theta, and gamma are taken for each of the mentioned channels and stored in a matrix for later use.

The following table summarizes the main characteristics of different brain wave rhythms, including frequency bands and functional correlates. It provides a useful reference for understanding the neurophysiological basis of various cognitive and behavioral processes.

Table 1. displays the frequency and rhythms of the EEG.

Rhythms	Band of Rhythmic Frequency (Hz) Visual	Band of Rhythmic Frequency (Hz) Audio	Related Functions
Delta (δ)	0.001 –0.599 HZ	0.001-0.591 HZ	show up in babies and during profound sleep [20,21].
Theta (θ)	7.999–14.713 HZ	8.0133-14.468 HZ	Children's brains process tasks in the temporal and parietal areas. Temporal manages hearing, memory, and recognizing faces/emotions, while parietal handles sensory and motor info. [22,23]
Alpha (α)	16.003–28.523 HZ	16.194-28.118 HZ	An adult who is awake has it. It can also be found in the parietal, frontal, and scalp regions. It also appears in the occipital area. [24].
Beta (β)	32.188–60.536 HZ	32.026-60.038 HZ	Reducing the Beta rhythm conveys the idea of movement, whether it is through actual activity, planning, visualization, or preparation. The contralateral motor cortex is where this decline is most noticeable. These waves are detectable from the frontal and central scalp lope during movements. [25,26].
Gamma (γ)	64.863- 105.003HZ	65.861-105.003 HZ	The rhythms with frequencies higher than 30 Hz are the higher ones. It has to do with how ideas are formed, how language is processed, and different kinds of learning. [27]

Thus, we obtain a matrix (15 x5), where the first dimension (15) represents the number of channels that are relied upon to record brain electrical activity, and the second dimension (5) represents the sum of the brain frequencies known as delta, theta, alpha, beta, and gamma.

2.4. Migraine Classification

At this stage we will begin by dividing the data into a training and test set to create a model capable of detecting the disease and supporting the opinion of doctors. We focused on machine learning classifiers because the size of the data is small and because most of these classifiers are characterized by a variety of parameters, which allows us to choose the optimal parameters to achieve better accuracy, in addition to their strength in light of our use of digital data, and also because of their popularity in the field of neurology, and most importantly, they are subject to supervision, because Our practice requires data classifications in order to train migraine-related features and distinguish them from those of healthy people, and these classifiers have fast and good classification performance, which makes them better than others and among these classifiers are :

Linear discriminant analysis (LDA) is frequently used to reduce dimensionality and identify a feature subspace in which the data samples are separable. [2], **Support vectors machine (SVM)** used for regression analysis and classification. It aims to find the optimal hyperplane with the largest margin between classes in an n-dimensional classification space [28] ,**K-nearest neighbors (KNN)** determine similarity between training and testing instances using Euclidean distance. Nearest neighbors are determined based on these similarities, and the testing sample's class label is determined by majority voting. The choice of distance metric, K value, and majority voting method affect categorization performance [29], **Naive Bayes (NB)** is a classification technique based on the Bayes theorem. For characteristics, it generates frequency tables. which display the frequency of attribute values in each potential class. These tables are transformed into probability tables using class and overall frequency ratios. Prior probabilities for the class and predictor are calculated [2], **Random Forest (RF) classifiers** are ensembles of randomly grown trees. Leaf nodes are labeled based on posterior distributions for different classes. Internal nodes have tests for data partitioning [19]. Randomness is introduced through subsampling the data and selecting node tests during training [28]. Classification involves aggregating predictions from individual trees to make the final prediction, **Tree Decision (DTs)** are tree-like models used in supervised data mining. They consist of internal nodes representing attribute tests, branches reflecting test results, and leaf nodes indicating class names. The root node stores all tuples, and classification is achieved by branching and splitting based on data properties [30]

And Finally, **FFNN (Feed-forward neural network)** which consists of input, hidden, and output layers with multiple neurons. Neurons are connected through weighted connections, representing the strength of the connections. They receive inputs; after applying an activation function and computing a weighted total, the result is passed to the following layer. The final network output is generated by the output layer. [31].

As a first step, the sum of the frequencies (alpha, beta, theta, delta, and gamma) is calculated for the 15 channels that were read and analyzed separately, so that we obtain 5 values representing the sum of these frequencies for each person, and then we use them as features, where they are divided statically into a training set by 75 percent. % and a 25% one-time test set using the Holdout method. Then the SVC, LDA and KNN algorithms were applied.

This step was then followed by dividing the data in a balanced way with regard to the training data, using the cross-validation technique (K-fold). As for the classifier, the random forest algorithm was used, where the best results were searched using two loops, the first for the number of trees [100, 300, 500, 1000] and the second for the depth of those trees [5, 10, 15, 20]. This is to avoid bias towards a fixed division and to obtain a more comprehensive result than the previous one.

In order to try another way to represent data as features, we took into account all the data for each participant by converting them into vectors. After obtaining 3 7vectors for the visual stimulation condition and 37 vectors for the auditory stimulation condition, they were divided statically into 75% training sets and 25% test sets, and apply SVM, LDA and KNN classifiers.

When dividing the vectors in a balanced manner and using the K-fold intersection technique and network search using three different types of kernels in the SVM classification, which are:

1. linear

2. rbf (Radial Basis Function)

3. polynomial

Performance will be tested using the kernel that achieves the highest accuracy.

The same vector data representation method was then applied but for multiple classifications, i.e. creating a model capable of distinguishing between migraine sufferers with auditory and visual symptoms and those with silent type migraines, as well as healthy subjects using the Feedforward Neural Network (FFNN), which is a derived type from artificial neural networks, where the signal flows from the input layers to the output layers, only in one direction

without any feedback links after dividing the vectors into a set for training (70%) and the remaining set (30%) for testing.

In order to obtain higher accuracy and greater reliability, a model of five sub-models was created (SVM, Tree Decision, LDA, KNN and RF), and the classifications were predicted based on majority voting after applying the Up-sampling technique, in which the data is repeated in the few categories (1, 2), where duplicate copies of the samples were added in these categories, which helped the model to recognize the few categories better.

3. Result

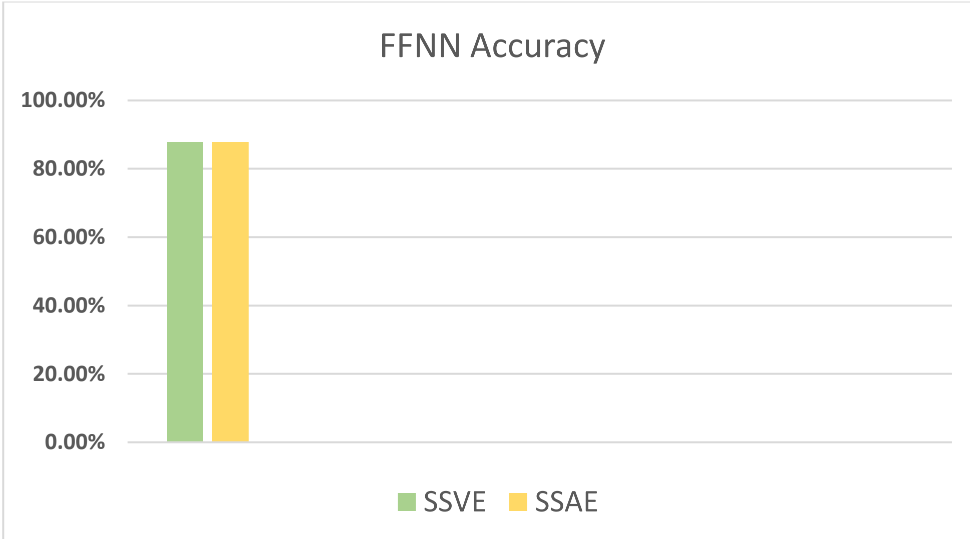
Section 2.4's procedures were applied to classify the MD and HC groups. The two scenarios of visual and auditory stimulation, as well as the techniques for gathering frequencies and displaying the data as vectors, the following are the results obtained using the models (SVC, LDA and KNN) When data is partitioned consistently, once and statically:

Accuracy	For representing data as a vector			For using summation of frequencies		
	SVC	LDA	KNN	SVM	LDA	KNN
SSVE	100 %	88.8 %	100 %	100%	88.8 %	77.7 %
SSAE	100%	88.8 %	88.8 %	88.8 %	77.7 %	88.8%

Here are the results for splitting the data using the five-fold cross-validation method:

Accuracy	For representing data as a vector		For using summation of frequencies		The highest fold accuracy was obtained for both models
	SVM		RF		
	Lowest accuracy rate	Highest accuracy rate	Lowest accuracy rate	Highest accuracy rate	
SSVE	64.64%	86.42%	81.78%	92.14%	100 %
SSAE	70.35 %	81.42 %	89.28 %	97.14%	100 %

Below are the results for classifying healthy subjects versus MWA and MWoA using the FFNN neural network:



These are the results for the majority voting model for the sub-models:

Accuracy	No.Chanel	No.Particip ant	SVM	Tree	LDA	KNN	RF	Final accuracy
SSVE	15	37	73 %	80 %	80 %	93 %	73 %	100%
SSAE	15	37	80 %	86.6 %	86.6 %	86.6 %	80 %	100%

4. Discussion

In this study, we relied on EEG signals in the case of visual and auditory stimulation after reading and filtering them, as we relied on these channels (Fp1, F7, C3, Pz, Fp2, Fz, F8, Cz, C4, F3, F4, P3, P4, O1, O2) and then the distinctive features were extracted using the (db8) function, a Dibelt wave of degree 8, to effectively analyze the signals in the frequency domain, where the signal is divided into a group of different frequency levels. As a first step, the sum of the alpha, beta, delta, theta, and gamma frequency values was taken separately for each 15 channels and relied on as training and testing data. This experiment achieved great random success using an RF classifier especially with the auditory stimulation condition to detect migraine versus healthy controls. As for the second step, the data for each 15 channels, which belongs to one person, was converted to a vector and so on. Thus, we had vectors with the number of participating people. They were relied upon as training and testing data, where they were used first to distinguish between migraine headaches versus healthy subjects. The highest result was obtained with the SVM classifier, Then, these vectors were used to distinguish between the types of migraine headaches (MWA(Migraine With Aura) and MWot (Migraine Without Aura)), in addition to healthy people, the highest result was obtained with the KNN classifier especially with the visually stimulation condition.

5. Conclusion

we proposed an effective model that combines db8 feature extraction with a set of machine learning algorithms, most notably SVM, LDA, KNN, Random Forest (RF) and FFNN for migraine disease detection.

Three salient features of the study deserve to be underscored:

(a) Utilize channels that are considered to be more sensitive to migraines.

(b) Comparing machine learning algorithms for various EEG data representation techniques in tasks related to migraine disease classification, and

(c) use of the db8 function to extract important features and comparison with the latest studies.

The proposed method aims to use machine learning to create a model for automatically diagnosing migraines by analyzing 15-channel EEG signals. The experimental results showed that the highest performance algorithm was obtained using SVM and RF machine learning algorithms. A model of five sub-models was also designed, based on the majority opinion, in classifying migraines and distinguishing their types. It is believed that this proposed model will support doctors' opinions in diagnosing this disease and its main types.

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