Majority Vote for Electroencephalography (EEG)-Based Migraine Classification

Ayat Yousif and Akeel Alsakaa

November 6, 2024

Majority vote for electroencephalography (EEG)-based migraine classification

Ayat Yaqoob Yousif
Computer Science Department
College of Computer Science and Information Technology
Iraq – Kerbala
ayat.y@s.uokerbala.edu.iq

Dr. Akeel Alsakaa
Computer Science Department
College of Computer Science and Information Technology
Iraq – Kerbala
akeel.a@uokerbala.edu.iq

Abstract— **Migraine (MD) is a neurological disorder that can present with auditory and visual symptoms known as aura, affecting approximately one billion people globally. This condition causes temporary disability and can progress to serious diseases such as epilepsy or stroke, resulting in significant losses in society's productivity. The overlap of migraine symptoms with other illnesses complicates the diagnosis process for medical professionals. To improve healthcare and patient care beyond traditional methods, we have developed a machine learning model to help doctors diagnose and differentiate between migraine types, with and without neurological aura. The model uses EEG signals from visual stimuli and analyzes them using discrete wavelet transform (DWT) to extract frequency bands: alpha, beta, delta, theta and gamma. The data is then augmented without exceeding the original frequency bands. Each participant's data is organized into a matrix, with rows representing channels and columns for the frequency bands. A majority voting mechanism determines the final classification; if most channels indicate a specific type of neural activity, the participant is classified accordingly. Our model achieved a classification accuracy of 90.58%, effectively diagnosing migraines and distinguishing their main types. By integrating advanced signal processing with machine learning, our model represents a significant advancement in migraine diagnosis and enhances patient care.**

Keywords—migraine, aura, EEG, DWT, frequency bands

I. INTRODUCTION

Migraine is a complex neurological disorder with a genetic origin, involving intricate interactions between various nervous systems and manifesting through a range of symptoms. These symptoms include increased sensitivity to light, sound, touch, and smell [1]. Additionally, there are trigger factors such as certain hormones and psycho-physiological stress [2]. It affects approximately one billion people, leading to social and economic burdens as well as absenteeism from work and study [3]. Migraine is the third most common disease and the leading neurological disorder globally [4]. There are various forms of migraine, each with overlapping yet distinct clinical symptoms. Migraine headaches are divided into two primary types: Migraine without Aura (MwoA), which occurs without any preceding neurological symptoms, and Migraine with Aura (MwA), characterized by neurological signs such as visual disturbances or sensory changes prior to the onset of the headache. MwA appears to be more closely related to anxiety and epilepsy compared to MwoA. Additionally, MwA increases the risk of vascular conditions like stroke and may be linked to silent brain damage. Clinical observations indicate that the slow spread of migraine aura symptoms occurs at a rate of approximately 3 mm per minute, leading to the proposition that cortical spreading depression (CSD) serves as the pathophysiological basis for migraine aura [5]. The diagnosis of migraine relies on a specific set of symptoms, making it challenging to rule out other potential causes, and traditional methods (such as symptom assessment and medical tests) are often inadequate [6]. Personalizing clinical care is essential due to the limitations of conventional symptom-based evaluations, which tend to be slow, burdensome, and frequently inaccurate [7]. In cases of atypical presentation, untreated migraine attacks can last anywhere from 4 to 72 hours, significantly impacting the patient's quality of life and the overall health of the community. In recent years, numerous machine learning techniques have been explored proving effective in addressing diagnostic challenges [8]. Two notable approaches that have gained considerable attention for studying the neural mechanisms of migraine and distinguishing between its types are EEG (electroencephalogram) and fMRI (Functional Magnetic Resonance Imaging), particularly when combined with machine learning. Recent studies suggest that EEG is the more commonly used method [9].

Electroencephalography (EEG) is an economical and non-invasive neuro-electrophysiological technique that is extensively utilized in both medical and non-medical applications [10]. It records electrical signals from the brain over time, which are inherently complex and often disorganized[11]. EEG microstate analysis enables the assessment of the brain's functional state on a sub-second timescale, offering very high temporal resolution [12]. To capture a patient's brain signals, electrodes are placed on the scalp following the 10-20 international electrode positioning system.

EEG signals are analyzed by breaking them down into multiple components, which helps identify the active frequency components at any given moment [13]. These brain signals consist of various fundamental flows, organized into EEG rhythms or frequency bands, each corresponding to different mental or cognitive states. Rhythms such as theta, delta, alpha, beta, and gamma can be observed, reflecting varying brain functions. Minor variations in these patterns can assist in diagnosing neurological disorders [14]. For example, low alpha band power has been observed, along with a lack of similarity in relation to the painful side before and during episodes without aura, compared to the partial phase. This inconsistency in the alpha range has been noted prior to migraine episodes with aura [2].

Additionally, individuals experiencing migraines with episodes of altered consciousness and neurological deficits exhibit frontal intermittent rhythmic delta activity (FIRDA) during and immediately after migraine attacks. This suggests dysfunction not only in the upper brainstem but also in the occipital and medial temporal lobes [15].

Signal processing algorithms are employed to extract symptoms and diagnose neurological disorders from complex EEG data. In addition, machine learning (ML) and deep learning (DL) techniques offer powerful tools for analyzing these signals [16]. Due to the non-linear nature of EEG data, the expertise of a trained neurologist is crucial for identifying abnormal patterns linked to such disorders. However, the effectiveness of visual assessments can vary significantly. Manually reviewing long EEG recordings is time-consuming and may lead to inconsistent results. With some human oversight, an automated system can accurately detect neurological conditions and monitor brain activity [17].

EEG signals are affordable, non-radioactive, and non-invasive, which makes them widely utilized for identifying brain abnormalities [19],[18]. A key advantage of EEG is its remarkably high temporal resolution, enabling the capture of electrical impulses thousands of times each second [19]. For this reason, this method of recording brain signals was utilized in our research.

II. MATERIAL AND METHODS

This section outlines the dataset utilized, the preprocessing techniques employed, and the method for extracting key features to be used as inputs for machine learning classifiers. and Figure 1 provides an overview of the method proposed for diagnosing migraines using EEG signals.

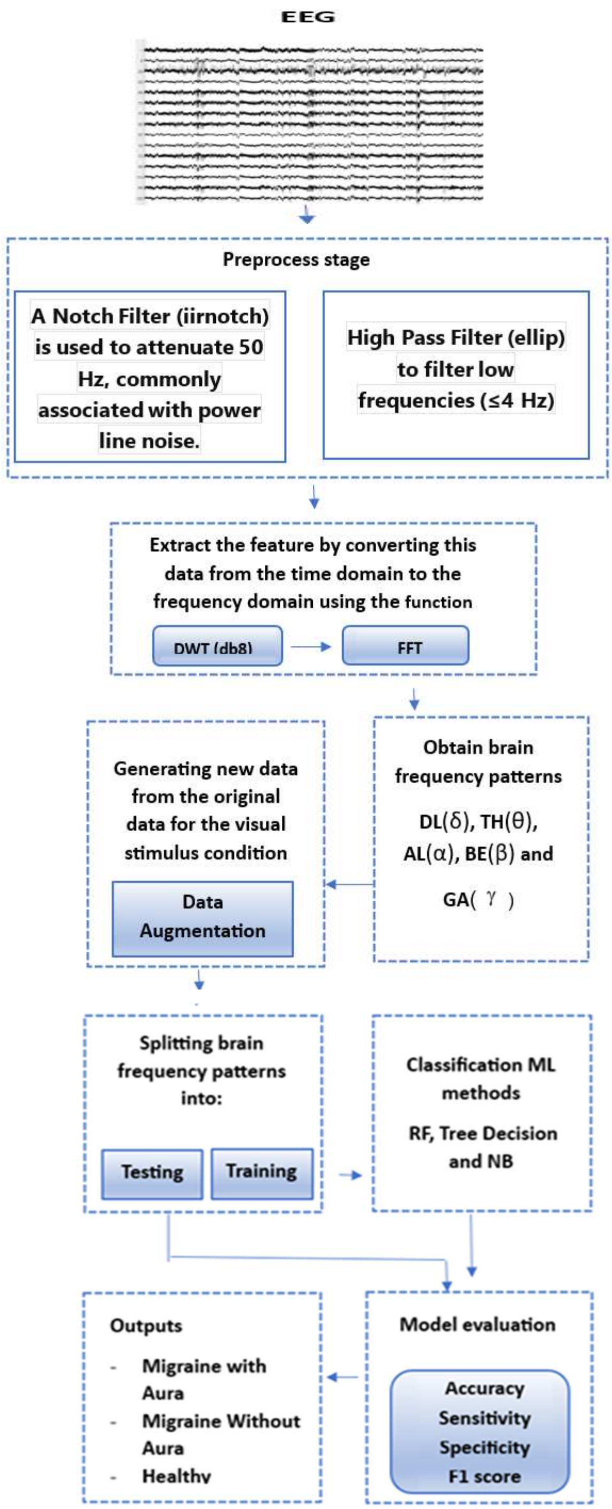

Fig.1. the structural diagram for the Migraine Classification System.

A. *Participants and the recording of data*

The recently released EEG dataset, available on KiltHub, Carnegie Mellon University's online data repository [20], was recorded using the BioSemi Active Two device. It features a sampling frequency of 512 Hz, utilizing a 24-bit analog-to-digital converter (A/D) with 128 channels. The dataset comprises EEG recordings from 18 migraine sufferers (aged 19-54 years; 13 females and 5 males) and 21 control subjects

(12 females and 9 males) during periods of visual and auditory stimulation, as well as during the rest period (without stimuli). Participants were recruited from the Pittsburgh area and Carnegie Mellon University, and they had no neurological or psychological diagnoses (other than migraine) or a history of severe head injury or concussion, and all participants had normal hearing. According to their self-reports, their vision was either normal or corrected to normal.

For visual stimulation, vertical sinusoidal-wave gratings were presented at a spatial frequency of 0.05 cycles per degree (cpd), meaning the grating pattern repeated every 20 degrees of visual angle. This low spatial frequency produced widely spaced stripes that appeared less detailed. The gratings were shown alongside a fixation cross. Reference [21] details the stimuli, recording methods, and findings on cortical coherence abnormalities in migraine detected with ultra-high-density EEG. In our study, we focused on the visual stimulation condition and selected fifteen out of the 128 channels due to their association with migraine pain sites [22] and their common use in migraine classification research [23], [24]. This selection also aimed to reduce data dimensionality and model complexity. The channels used were: (Fp1, F7, C3, Pz, Fp2, Fz, F8, Cz, C4, F3, F4, P3, P4, O1, O2), and their locations on the head are depicted in Fig.2.

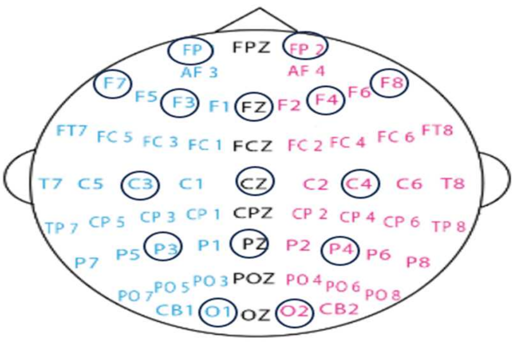

Fig.2. Positioning of EEG electrodes

B. *Preprocessing stage*

The experiment was conducted for visual stimulation, during which 15 channels associated with migraine pain areas were recorded to simplify the analysis. The data for these channels were converted from BDF format to EDF format using EDF Browser software, as EDF is more compatible with our research requirements and is commonly used for EEG data. During the preprocessing stage, EEG signals are filtered to minimize noise. Various filtering techniques are employed to eliminate unwanted low-frequency and high-frequency signals. EEG data frequently contains artifacts and noise from multiple sources, such as electrical appliances and lighting, which can introduce interference into the EEG recordings.

Signal interference may occur if the patient's eyes or muscles move as a result of breathing during recording, which affects the recorded electrical signals.First, a notch filter is applied to remove the specific 50 Hz frequency, Which helps eliminate alternating current interference from power lines from electroencephalogram (EEG) signals. [25]. Next, a high-pass filter is used to remove low frequencies, specifically filtering out frequencies below 4 Hz. This process preserves signals in the intermediate frequency range between 4 and 50 Hz, enhancing the signal-to-noise ratio and improving classification accuracy [26].

In the final stage, the detrend function with the 'constant' option is applied to eliminate the signal's mean value, effectively removing any constant bias or offset. After applying the notch filter and high-pass filter, the detrend function calculates the mean of the filtered signal and subtracts it from each data point. This enhances signal quality by removing any constant offset, facilitating the analysis of the true physiological components of the signal. For instance, if an EEG signal exhibits baseline drift due to sensor movement, the detrend function will correct this by centering the signal around zero while retaining all original changes and patterns. This ensures that the signal contains important information without consistent bias, allowing for more accurate interpretation of brain activity.

C. *Feature Extraction*

Once the waves are read and filtered, a high-dimensional array of overlapping signals is obtained. To simplify the analysis and focus on essential data, the features must be meaningful for model learning tools; they should be discriminatory and non-redundant to fully leverage the data. This is accomplished through optimal feature selection and dimensionality reduction [27].

The feature extraction process transforms raw data into meaningful features, capturing relevant information and patterns for easier analysis and modeling. This reduces data dimensionality and filters out noise, enhancing machine learning algorithm performance.

The Discrete Wavelet Transform (DWT) uses discrete wavelet coefficients (db8) to characterize EEG signals, increasing their relevance through statistical representation [28]. It converts discrete temporal signals into wavelet representations [25]. In the DWT process, the initial signal is divided into two components: approximation, which captures low-frequency information, and detail, which highlights high-frequency details. Only the approximation component undergoes further decomposition, continuing until a predetermined level is reached [29]. The approximation component typically extracts low-frequency activities like theta and delta waves, while the detail component captures high-frequency activities such as alpha, beta, and gamma waves.

The db8 function uses wavelet analysis to decompose the signal into 8 different scales, providing a detailed view of the frequency components. Specific frequency bands are reconstructed from the wavelet coefficients, isolating the detailed components of each band. We then analyze the frequency content using the Fast Fourier Transform (FFT), identifying the dominant frequency within each band and plotting the frequency spectrum.

Thus, we obtain a matrix of dimensions (15 x 5), where the first dimension (15) indicates the number of channels used to record brain electrical activity, and the second dimension (5) represents the five known brain frequency bands: delta, theta, alpha, beta, and gamma.

D. Data Augmentation

Because the dataset we obtained was small and we were unable to gather further real data from migraine patients to integrate with the Carnegie Mellon University data, we generated supplemental data in the frequency domain based on the original data [30]. A machine learning (ML) prediction algorithm leverages hand-crafted features of EEG signals from the time domain, frequency domain, or time-frequency domain to make predictions [31]. The original data for visual stimulation was used to expand the data set, as it yielded good results and is more commonly used than auditory stimuli. Each category was organized into three separate Excel files: one for migraine without aura, one for migraine with aura, and one for healthy individuals. We augment the original data by generating new synthetic samples. The minimum and maximum values of the columns representing brain frequencies (delta, theta, alpha, beta, and gamma) are calculated from the original data for each category separately. A new set of samples is then created by generating random values between the minimum and maximum of each column (frequency range). The data in the last column remains unchanged as it represents classifications. This method increased data diversity and balance across three categories, yielding a total dataset size of 7,545 data points (503 persons). There were almost 2,400 data points for the HC class (160 individuals), 2,550 for the MWoA class (170 individuals), and 2,505 for the MWA class (167 individuals). This method succeeded in reducing the significant difference between categories in the original version, the augmented samples are saved in a new Excel file.

E. Migraine Classification

At this stage, we will split the data into training and test sets to develop a model that can detect migraines and support clinical assessments. We focus on machine learning classifiers due to the small dataset size and the variety of parameters they offer, enabling optimal settings for improved accuracy. Their effectiveness with digital data and popularity in neurology also make them suitable. Most importantly, these classifiers operate in a supervised manner, which is essential for classifying migraine-related features and distinguishing them from those of healthy individuals. These classifiers provide fast and efficient performance, making them preferable. Among these classifiers are: Naive Bayes (NB) is a classification technique grounded in Bayes' theorem. It generates frequency tables that display the frequency of attribute values for each potential class. These tables are then converted into probability tables using class and overall frequency ratios, with prior probabilities for both the class and predictor calculated [32].

Decision Trees (DTs) are tree-like models utilized in supervised data mining. They feature internal nodes that represent attribute tests, branches that reflect test outcomes, and leaf nodes that indicate class names. The root node contains all tuples, and classification is performed by branching and splitting based on data properties [33].

Random Forest (RF) classifiers consist of an ensemble of randomly generated trees. Leaf nodes are labeled based on posterior distributions for different classes, while internal nodes perform tests for data partitioning [27]. Randomness is introduced by subsampling the data and selecting node tests during training [34]. Classification is achieved by aggregating predictions from the individual trees to arrive at a final decision. Since each participant has multiple rows (channels), the data from multiple channels for each participant is organized into a matrix or a multidimensional data structure. Typically, the rows of the matrix represent the channels, while the columns correspond to the delta, theta, alpha, beta, and gamma frequency bands. A majority voting mechanism is then applied to determine the final classification for that participant. Although this method does not directly reduce dimensions, it simplifies the decision-making process. For example, if most channels indicate a particular type of neural activity, the participant is classified accordingly [35].

We start with reading data from an Excel file. Features are extracted from this data (specifically, medical frequencies in this case) along with labels indicating the categories into which participants are classified. The participants' data is then divided into two sets: training and testing. Using the start and end indexes for each participant, a random index for selection is generated, allocating 75% of the data for training and 25% for testing. The following models are then trained:

The models used are Naive Bayes (NB) and Random Forest (RF). The fitcnb function creates the NB model, with several key parameters specified. The 'DistributionNames' and 'kernel' parameters set the data distribution using kernel density estimation, while the 'Width' parameter, set to 0.05, controls the smoothness of the estimated distribution by defining the kernel width. Additionally, the 'Prior' parameter is set to 'uniform', ensuring that prior probabilities for each class are evenly distributed, meaning no class is favored before training. The Random Forest model is trained using the bagging technique with 75 learning cycles, employing decision trees as individual learners. For prediction, the model applies majority voting across these decision trees to classify each row of the test data. In this method, each of the 15 rows for each participant is independently predicted using the trained model. The final classification for each participant is then determined through majority voting among the predictions from the 15 rows. If the majority of the rows indicate a specific type of neural activity, such as migraine with aura, migraine without aura, or healthy, that type is considered the final classification for the participant. This approach helps reduce the 15 classifications to a single final classification for each participant, facilitating the classification process and improving accuracy in the results.

To evaluate the models' performance, a confusion matrix is employed, comparing the actual ratings to the predicted ratings.

Various performance metrics, including accuracy, sensitivity, and specificity, are calculated for each class, along with overall performance metrics such as overall accuracy and the F1 score.

This organization and design of the code aim to achieve accurate and efficient classification of the available medical data using Naive Bayes and Random Forest classifiers in MATLAB. For further verification, the classification process was conducted using a Random Forest model implemented with the fitcensemble function to analyze EEG signals and identify patient cases, whether healthy, suffering from

migraine without aura, or experiencing migraine with aura, using k-fold cross-validation.
Initially, data is read from the Excel file, where the extracted features are the brain frequencies: delta, theta, alpha, beta, and gamma, while the labels represent the classifications in the dataset. The number of folds for cross-validation is set to 5 (k = 5), and a matrix is initialized to store the model accuracy for each fold. The start and end indexes for each participant are specified to ensure their data is grouped together.

To achieve data balance among the different classes, the number of samples in the smaller classes is increased to match the largest class. Variables necessary for calculating true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are initialized. A table is created to store the results (model accuracy, sensitivity, specificity, and F1 score) for each fold, along with another table for the test results of each participant across the folds. Random participant indices are generated and stratified for cross-validation, ensuring that the model is trained and tested on different samples in each fold. After training the model, evaluation is performed on the test data Performance indicators—accuracy, sensitivity, specificity, and F1 score—are calculated for each fold, and overall performance scores are aggregated across all folds.

The overall performance metrics are defined as follows:
Accuracy: The percentage of samples that are classified correctly.
Sensitivity: The ability to correctly identify positive cases.
Specificity: The ability to correctly identify negative cases.
F1 Score: A harmonic measure that combines accuracy and sensitivity.
The final results are presented, along with the distribution of patients according to their classifications: (0 = healthy, 1 = migraine without aura, 2 = migraine with aura).

III. Result

Here, the data was divided consistently into 25% test set and 75% training set

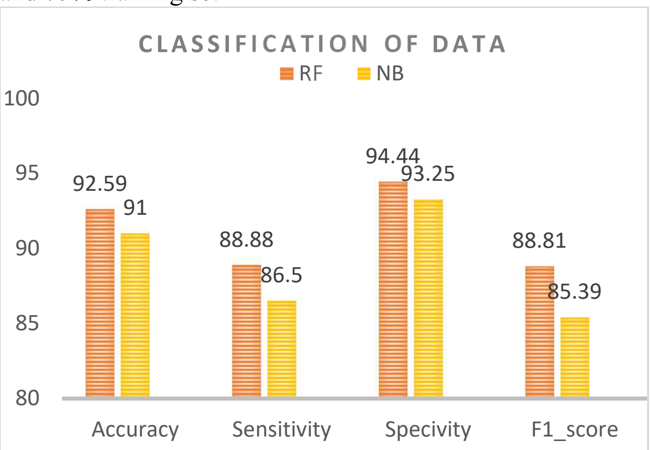

Fig.3. shows the result obtained for RF and NB classifiers

To accurately validate the performance of this method, we employed the Random Forest classifier using five-fold cross-validation. The results are shown in Fig.4 below, with the highest accuracy achieved across the folds being 92.73%.

Results Table

'Fold'	'Accuracy'	'Sensitivity'	'Specificity'	'F1 Score'
[1]	[89.4389]	[84.2424]	[92.0529]	[84.3322]
[2]	[91.4191]	[86.6156]	[93.8809]	[85.8935]
[3]	[92.7393]	[89.5924]	[94.4500]	[89.3976]
[4]	[89.4389]	[83.8095]	[92.1139]	[83.1496]
[5]	[89.8990]	[85.2874]	[92.3107]	[84.8958]
'Average'	[90.5871]	[85.8847]	[92.9423]	[85.5337]

Overall mean accuracy (Random Forest) visual model: 90.5871%
Overall sensitivity: 85.8847%
Overall specificity: 92.9423%
Overall F1 score: 85.5337%

Fig.4. shows the average accuracy obtained

IV. Discussion

In this study, we utilized EEG signals from visual stimulation, focusing on the following channels: Fp1, F7, C3, Pz, Fp2, Fz, F8, Cz, C4, F3, F4, P3, P4, O1, and O2. After processing and filtering the signals, distinctive features were extracted using the db8 function, a Daubechies wavelet of order 8, to effectively analyze the signals in the frequency domain, where the signal is decomposed into various frequency levels. Additionally, the (FFT) was employed to identify the dominant frequencies. As a result, for each participant, a matrix with 15 rows (representing channels) and 5 columns was created, representing the dominant frequencies for the delta, theta, alpha, beta, and gamma bands.

The visual stimuli data were then augmented, and the participants' data were represented as matrices. The final classification was based on majority voting using this matrix representation. The Random Forest classifier achieved higher accuracy compared to the Naive Bayes classifier. This study is the first to use this data set, after augmenting it, to distinguish between migraine types and healthy controls, while previous studies focused only on diagnosing migraine versus healthy individuals. It achieved a randomization success rate of up to 90%. Despite these advantages, there are certain limitations. The focus was placed on channels believed to be more sensitive to migraines, with only 15 channels out of 128 being used, leaving the rest of the channels ignored. To our knowledge, no previous study has investigated the effect of visual stimulation in this context, and therefore, there is no research to directly compare our results with.

V. Conclusion

We introduced a robust model that integrates db8 feature extraction with machine learning algorithms, specifically Random Forest (RF) and Naive Bayes (NB), to detect migraines and their various types. This study highlights two key aspects:

(a) The utilization of channels that are particularly sensitive to migraines,

(b) Implement the db8 wavelet function and FFT to extract important features represented by brain frequencies known as delta, theta, alpha, beta, and gamma.

The objective of the proposed method is to leverage machine learning for the automatic diagnosis of migraines through the analysis of EEG signals across 15 channels. Experimental findings indicate that the RF algorithm delivers superior performance. This model is expected to aid clinicians in accurately diagnosing migraines and distinguish their types.

REFERENCES

[1] F. J. Hsiao et al., “Resting-state magnetoencephalographic oscillatory connectivity to identify patients with chronic migraine using machine learning,” J. Headache Pain, vol. 23, no. 1, Dec. 2022, doi: 10.1186/s10194-022-01500-1.

[2] E. A. Tolner, S. P. Chen, and K. Eikermann-Haerter, “Current understanding of cortical structure and function in migraine,” Cephalalgia, vol. 39, no. 13. SAGE Publications Ltd, pp. 1683–1699, Nov. 01, 2019. doi: 10.1177/0333102419840643.

[3] A. Stankewitz et al., “Migraine attacks as a result of hypothalamic loss of control,” NeuroImage Clin., vol. 32, p. 102784, 2021, doi: 10.1016/j.nicl.2021.102784.

[4] M. Pazzaglia, I. Petrusic, N. Meylakh, S. Zhan, and B. Liu, “Predicting response to tVNS in patients with migraine using functional MRI: A voxels-based machine learning analysis.” [Online]. Available: http://www.chictr.org.cn/hvshowproject.aspx?id=11101

[5] F. Riederer, J. Beiersdorf, A. Scutelnic, and C. J. Schankin, “Migraine Aura—Catch Me If You Can with EEG and MRI—A Narrative Review,” Diagnostics, vol. 13, no. 17. Multidisciplinary Digital Publishing Institute (MDPI), Sep. 01, 2023. doi: 10.3390/diagnostics13172844.

[6] H. Yang, J. Zhang, Q. Liu, and Y. Wang, “Multimodal MRI-based classification of migraine: Using deep learning convolutional neural network 08 Information and Computing Sciences 0801 Artificial Intelligence and Image Processing,” Biomed. Eng. Online, vol. 17, no. 1, Oct. 2018, doi: 10.1186/s12938-018-0587-0.

[7] T. Mari, J. Henderson, M. Maden, S. Nevitt, R. Duarte, and N. Fallon, “Systematic Review of the Effectiveness of Machine Learning Algorithms for Classifying Pain Intensity, Phenotype or Treatment Outcomes Using Electroencephalogram Data,” Journal of Pain, vol. 23, no. 3. Elsevier B.V., pp. 349–369, Mar. 01, 2022. doi: 10.1016/j.jpain.2021.07.011.

[8] R. Gautam and M. Sharma, “Prevalence and Diagnosis of Neurological Disorders Using Different Deep Learning Techniques: A Meta-Analysis,” J. Med. Syst., vol. 44, no. 2, Feb. 2020, doi: 10.1007/s10916-019-1519-7.

[9] P. A. Sanchez-Sanchez, J. R. García-González, and J. M. Rúa Ascar, “Automatic migraine classification using artificial neural networks,” F1000Research, vol. 9, p. 618, Jun. 2020, doi: 10.12688/f1000research.23181.1.

[10] N. Zhang et al., “Application of EEG in migraine,” Frontiers in Human Neuroscience, vol. 17. Frontiers Media S.A., 2023. doi: 10.3389/fnhum.2023.1082317.

[11] G. Sharma, A. Parashar, and A. M. Joshi, “DepHNN: A novel hybrid neural network for electroencephalogram (EEG)-based screening of depression,” Biomed. Signal Process. Control, vol. 66, Apr. 2021, doi: 10.1016/j.bspc.2020.102393.

[12] Y. Zhou et al., “Spatio-temporal dynamics of resting-state brain networks are associated with migraine disability,” J. Headache Pain, vol. 24, no. 1, Dec. 2023, doi: 10.1186/s10194-023-01551-y.

[13] S. K. Khare and V. Bajaj, “Constrained based tunable Q wavelet transform for efficient decomposition of EEG signals,” Appl. Acoust., vol. 163, Jun. 2020, doi: 10.1016/j.apacoust.2020.107234.

[14] 2020 17th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP). IEEE, 2020.

[15] H. J. Pelayo-González et al., “Quantitative Electroencephalographic Analysis in Women with Migraine during the Luteal Phase,” Appl. Sci., vol. 13, no. 13, Jul. 2023, doi: 10.3390/app13137443.

[16] F. Orhanbulucu, F. Latifoğlu, and R. Baydemir, “A New Hybrid Approach Based on Time Frequency Images and Deep Learning Methods for Diagnosis of Migraine Disease and Investigation of Stimulus Effect,” Diagnostics, vol. 13, no. 11, Jun. 2023, doi: 10.3390/diagnostics13111887.

[17] V. Joshi and N. Nanavati, “A review of EEG signal analysis for diagnosis of neurological disorders using machine learning,” Journal of Biomedical Photonics and Engineering, vol. 7, no. 4. Samara National Research University, 2021. doi: 10.18287/JBPE21.07.040201.

[18] S. Taran and V. Bajaj, “Motor imagery tasks-based EEG signals classification using tunable-Q wavelet transform,” Neural Comput. Appl., vol. 31, no. 11, pp. 6925–6932, Nov. 2019, doi: 10.1007/s00521-018-3531-0.

[19] L. Tong, “Evaluation of Different Brain Imaging Technologies,” 2022.

[20] A. Chamanzar, S. M. Haigh, P. Grover, and M. Behrmann, “Ultra high-density EEG for interictal migraine and controls : stimuli description and matlab codes,” pp. 8–10.

[21] A. Chamanzar, S. M. Haigh, P. Grover, and M. Behrmann, “Abnormalities in cortical pattern of coherence in migraine detected using ultra high-density EEG,” Brain Commun., no. i, 2021, doi: 10.1093/braincomms/fcab061.

[22] N. Padmavathy and G. Srilakshmi, “Approaches to Detect Migraine using EEG Signals: A Review,” Papers.Ssrn.Com, no. January, 2022, doi: 10.13140/RG.2.2.25958.80964.

[23] H. Göker, “Automatic detection of migraine disease from EEG signals using bidirectional long-short term memory deep learning model,” Signal, Image Video Process., vol. 17, no. 4, pp. 1255–1263, 2023, doi: 10.1007/s11760-022-02333-w.

[24] D. Tuncel, A. Alkan, and S. Batuhan Akben, “Classification of multi-channel EEG signals for migraine detection.” [Online]. Available: www.biomedres.info

[25] Arumugam M, Sangaiah AK. Arrhythmia identification and classification using wavelet centered methodology in ECG signals. Concurrency and computation: practice and experience. 2020 Sep 10;32(17):e5553.

[26] Alturki FA, AlSharabi K, Abdurraqeeb AM, Aljalal M. EEG signal analysis for diagnosing neurological disorders using discrete wavelet transform and intelligent techniques. Sensors. 2020 Apr 28;20(9):2505.

[27] Nafea MS, Ismail ZH. Supervised machine learning and deep learning techniques for epileptic seizure recognition using EEG signals—A systematic literature review. Bioengineering. 2022 Dec 8;9(12):781.

[28] Subasi A, Ahmed A, Aličković E, Hassan AR. Effect of photic stimulation for migraine detection using random forest and discrete wavelet transform. Biomedical signal processing and control. 2019 Mar 1;49:231-9.

[29] M. S. M. Naqiuddin, M. S. Leong, L. M. Hee, and M. A. M. Azrieasrie, “Ultrasonic signal processing techniques for Pipeline: A review,” MATEC Web Conf., vol. 255, p. 06006, 2019, doi: 10.1051/matecconf/201925506006.

[30] F. P. Carrle, Y. Hollenbenders, and A. Reichenbach, “Generation of synthetic EEG data for training algorithms supporting the diagnosis of major depressive disorder,” Front. Neurosci., vol. 17, no. October, pp. 1–17, 2023, doi: 10.3389/fnins.2023.1219133.

[31] K. Rasheed, J. Qadir, T. J. O’Brien, L. Kuhlmann, and A. Razi, “A Generative Model to Synthesize EEG Data for Epileptic Seizure Prediction,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29. pp. 2322–2332, 2021. doi: 10.1109/TNSRE.2021.3125023.

[32] Mitrović K, Petrušić I, Radojičić A, Daković M, Savić A. Migraine with aura detection and subtype classification using machine learning algorithms and morphometric magnetic resonance imaging data. Frontiers in neurology. 2023 Jun 23;14:1106612.

[33] Priyanka, Kumar D. Decision tree classifier: a detailed survey. International Journal of Information and Decision Sciences. 2020;12(3):246-69.

[34] Boateng EY, Otoo J, Abaye DA. Basic tenets of classification algorithms K-nearest-neighbor, support vector machine, random forest and neural network: a review. Journal of Data Analysis and Information Processing. 2020 Sep 29;8(4):341-57.

[35] A. M. Ismael, Ö. F. Alçin, K. H. Abdalla, and A. Şengür, “Two-stepped majority voting for efficient EEG-based emotion classification,” Brain Informatics, vol. 7, no. 1, 2020, doi: 10.1186/s40708-020-00111-3.