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A Comparative Analysis of Stimuli Response among People with Migraine Classification: A Machine Learning Approach

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***Abstract*—Recurrent, throbbing headaches are the hallmark of the neurological condition known as migraines. Other symptoms that are frequently present with migraines include nausea, vomiting, and light and sound sensitivity. This work developed a machine learning model that can almost perfectly identify migraine by analysing electroencephalography (EEG) signals. The data set used in this study consists of EEG signals recorded from 21 healthy and 18 migraine patients and obtained in three different stimuli: resting state, visual stimulus and auditory stimulus. From a total of 144 channels, 14 channels were considered as the data source. The filtered raw EEG signals were converted into raw amplitude representation within a data frame. We used a total of 3 cases for this comparative analysis by taking a single stimuli at a time, a two-stimuli hybrid approach and all three stimuli combined approach. After the basic preprocessing steps were applied, the data were fed into some Machine learning algorithms. Among the algorithms, Logistic Regression with a two-stimuli hybrid approach showed 99.74% accuracy. This approach, marked by its high accuracy, may pave the way for a reliable point-of-care solution in the diagnosis and management of migraine, offering a potential breakthrough in enhancing patient care and treatment strategies within the realm of neurological disorders. This proposed lightweight machine learning model can be effective for less calculation time and less cost.**

***Index Terms*—Electroencephalogram (EEG), Hybrid Stimuli, Migraine, Machine Learning.**

I. Introduction

Migraine is a chronic neurovascular condition that produces significant pain and autonomic nervous system disturbances. In addition to severe headaches, migraine disorder can cause symptoms such as light sensitivity, vomiting, sleepiness, and nausea. Recurrent bouts of headache, nausea, and vomiting are its hallmarks; these symptoms can be incapacitating and severely affect one's quality of life. Migraine headaches can last anywhere from four to seventy-two hours if left untreated or managed ineffectively, requiring bed rest [1]. It also indicates a longer recovery period, more impairment, and a higher chance of a headache recurrence. In addition to aggravating impairment, anxiety, depression, asthma, and other chronic pain conditions are also thought to coexist with migraines. Migraine is associated with an increased risk of vascular disease. It is one of the most frequent neurological diseases that has a substantial impact on sufferers' quality of life. It is a prevalent condition that affects approximately one billion individuals globally. Its widespread prevalence and related handicaps have a lot of negative and severe consequences for those immediately affected, as well as their families, employers, coworkers and society [2]. There are two kinds of Migraines. (a) Migraine without aura (Common migraine), (b) Migraine with aura (MwA) (Classical Migraine) is a warning or signal that occurs before the onset of a headache; symptoms include flashing lights, zigzag lines, and difficulty focusing. This subtype of migraine affects the majority of migraineurs, with more frequent and severe attacks than migraine with aura [3].

Electroencephalography is a brain signal that is used for different brain condition analysis like sleep stage, stress, state of mind analysis etc [4]. The clinical study of EEG signals aids in the management and prognosis of migraine sickness. Biomedical signal processing has made significant strides recently, leading to the creation of multiple algorithms for multi-resolution analysis of EEG data and disease diagnosis.

There are few studies for detecting migraine using EEG signals. Akben et al. [5] used the Support Vector Machine

(SVM) classifier to identify migraine disease with an accuracy of 85% based on analysis of the EEG data from migraine sufferers during flash stimulation. Tunable Q-Factor Wavelet was used by Aslan [6] to divide the signals into sub-bands. In his research on the diagnosis of migraine disease, he applied the transform (TQWT) approach to the EEG signals. Through the process of feature extraction from these sub-bands, the Rotation Forest method was used to classify migraine disease. Because of the classification, 89.6% accuracy was achieved in the process. In a related study, Subası et al. [7] discriminated migraine disease with an accuracy of 85.95% by applying the Discrete Wavelet Transform (DWT) and the RF method. Considering the point-of-care solution, the proposed model is lightweight and cost-effective for further medical use.

In this study, a hybrid approach for classifying migraine is proposed. Comparative analysis of Random Forest, Support Vector Classifier, Naïve Bayes and Logistic Regression machine learning classification algorithms were performed. The accuracy of the proposed model using logistic regression classifier was more successful than other models in the literature. So, the Logistic Regression classifier has been implemented to build a cost-effective model with higher accuracy.

II. Methodology

In the study, a hybridized two-stimuli-based machine learning approach was found to be the most effective in migraine detection. The overall methodology of the proposed study is given in Fig. 1.

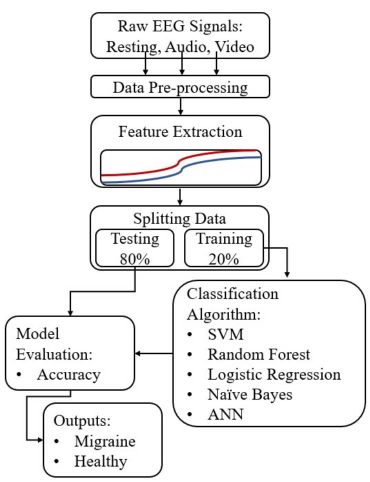

Fig. 1. Overall methodology of the proposed study

A. Participants and Dataset

The selected dataset for our study contains EEG signals of both migraine patients and common people and was created by Carnegie Mellon University. There were 21 common peoples group (12 females and 9 males, all between 19 to 54 years old) without any migraine symptoms and 18 migraine patients in the interictal period (13 females and 5 males, all between 19-54 years) making a total of 39 people. The EEG signals were collected having a sampling frequency of 512 Hz [8]. EEG signals were collected using the BioSemi Active Two system. The migraine patients didn't have any other neurological or psychological disease other than migraine. Three different stimuli (Audio, Video and Resting-state) were used during the data fetching period.

B. Signal Processing

Distinct tasks influence different portions of the brain more than others, such as smelling, touching, hearing, fantasizing, and doing mathematical procedures [5]. Therefore, instead of taking all the 128 channels data, using the data of the specific channels with intense cerebral activity allows to capture the best feature for classification. A total of 14 channels that were used to extract data from the participant are P3, P4, C3, C4, O1, O2, T7, T8, F7, F8, C5, C6, Fpz, and Oz channels from the parietal, occipital, temporal and frontal regions of the brain [9], [10].

Biosignals are contaminated with unwanted noises such as baseline wander, power line noise, muscle noise etc. [11]. Preprocessing is necessary for further analysis of the signals. Data preprocessing was performed by filtering the data using 'firwin' design, setting the low frequency to 1 Hz and the high frequency to 30 Hz. Clearing the unwanted signals from the data ensures better extraction of data by the models. Fig. 2 portrays both the 'Raw' and 'Filtered' EEG signals of Channel 1. This shows that after filtration, the signal came down to baseline.

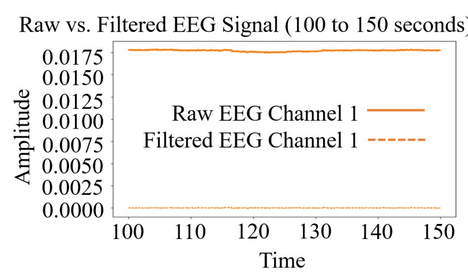

Fig. 2. Raw vs Filtered EEG Signal

C. Feature Extraction

Manual feature extraction techniques were used bypassing traditional techniques like wavelet transform or power spectral density. At first, the raw signal data were transformed into data frame of the raw numerical value of the signal. Then the resourceful columns were picked.

D. Splitting dataset

The recordings of the dataset were divided into two groups between which 80% were for training purposes and the rest 20% for testing. The dataset was partitioned using the Holdout method, where the data was split into two distinct and non-overlapping segments. These segments were employed separately for training and testing purposes. The segment allocated for testing is referred to as the holdout section. This specific portion is set aside for testing purposes, while the model is trained using the remaining data. The Holdout method proves effective when dealing with sufficiently large datasets, especially when there is a balanced representation of each class, ensuring even distribution across the dataset [12]. Different machine learning models were trained with the training dataset. Random forest, SVM, Logistic Regression, Naïve bayes, ANN were used to find out the best model.

E. Classification Model

Feature vector was formed by the manual selection of columns from the data frame and normalizing that. Then the classification algorithms were applied to the features vector of the training portion. The goal of classification involves predicting the category to which data with similar traits belongs, based on the pre-existing labels assigned to data groups. After all processing steps, data were fed into Machine Learning algorithms. Among all models, Logistic Regression model performed the best in the study. Therefore, the mathematical foundations of this algorithm are explained in detail.

Logistic regression is a method for modelling the probability of a discrete outcome given an input variable. Logistic regression models generally reflect a binary result, which can have two values, such as true or false, yes or no, and so on. Multinomial logistic regression is a useful tool for modelling scenarios that contain more than two unique discrete outcomes [13].

The chances in logistic regression are transformed using a logit function, which is the probability of success divided by the probability of failure. The log odds or natural logarithm of odds are other names for this logistic function. It is expressed by the following equations:

$$Logit(pi) = 1/(1 + exp(-pi)) \tag{1}$$

$$ln(pi/(1 - pi)) = Beta_0 + Beta_1 * X_1 + \ldots + B_k * K_k \tag{2}$$

In this logistic regression equation, logit(pi) is the dependent or response variable while x is the independent variable. Maximum likelihood estimation (MLE) is used to estimate the beta parameters or coefficients. This algorithm iterates frequently by testing various values of beta until it finds the best match for the log odds. Each of these repetitions produces a log-likelihood function, which logistic regression seeks to maximize in order to provide the best possible parameter estimate. If the ideal coefficients are found, the conditional probabilities for each observation can then be calculated, logged, and summed together to forecast a probability. Estimated probability greater than 0.5 will predict 1, while a probability lower than 0.5 will predict 0.

Logistic regression stands out in migraine detection using EEG signals due to its provision of interpretable coefficients, facilitating a clear understanding of each feature's impact on the likelihood of a migraine event. This interpretability is particularly valuable in medical contexts, where comprehending contributing factors is essential. The model implicitly assigns weights to each feature, indicating their contribution to predictions, thereby aiding in the identification of crucial EEG features for migraine detection. Additionally, logistic regression's assumption of a linear relationship between features and the log-odds aligns well with the underlying structure of the EEG data in certain cases, potentially leading to superior performance compared to more complex models with different relationship assumptions. Fig. 3 depicts the internal architecture of the Logistic Regression model and Fig. 4 shows how the sigmoid function aligns the output value between 0 and 1.

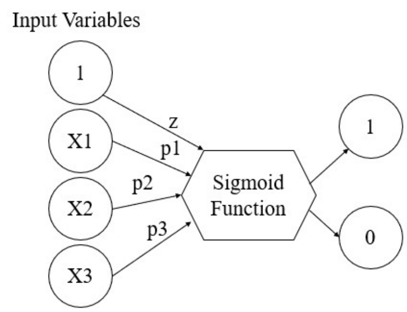

Fig. 3. Logistic Regression Architecture

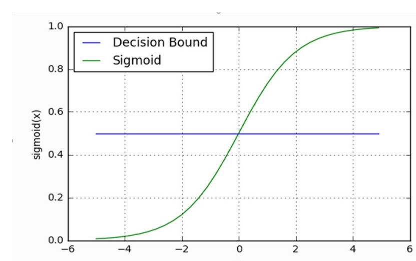

Fig. 4. Sigmoid Function Graph

F. Performance Evaluation Metrics

Accuracy was chosen to be the performance criteria in migraine classification. While calculating the criteria, True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four parameters that are employed. These metrics have to do with how many samples are correctly and incorrectly classified [14]. While FP and FN classes display data that was mistakenly predicted, TP and TN classes display the quantity of correctly anticipated data. The confusion matrix provides these parameters. The following are the fundamental model performance criteria that were computed during the model's evaluation using these parameters that were derived from the confusion matrix

$$Accuracy = \frac{(TN + TP)}{(TP + TN + FP + FN)} \tag{3}$$

III. Performance Analysis

In the dataset, three stimulations were considered to record the dataset, (a) Resting state, (b) Audio stimulation and (c) Video stimulation. Three types of responses were analyzed which are, (a) Single stimuli response, (b) Double stimuli response (first approach, second approach) and (c) Three stimuli response. The classification models used are, Random Forest, Logistic Regression, Support Vector Classifier and Naïve Bayes.

The result for Single stimuli response is presented in Table I. Here, for the "resting" state the classification model providing the best accuracy is Logistic Regression which is about 97.2577%. For "audio" stimulation, the classification model showing the highest accuracy is Logistic Regression which is about 98.45593%. Lastly, for "video" stimulation, the classification model providing maximum accuracy is also Logistic Regression which is about 97.44286%. Comparing the three stimulations results, for single stimuli response, "audio" stimulation has the best accuracy over all the stimulation results.

Again, the result for the Double stimuli response is presented in Table II and Table III. Here, the result for the first approach is shown in Table II. For "audio and resting" stimulation the classification model with the highest accuracy is Logistic Regression which is about 97.9595%. For "video and resting" stimulation, the classification model with the highest accuracy is Logistic Regression which is about 95.9733567%. Lastly, for "audio and video" stimulation, the classification model with the highest accuracy is Logistic Regression which is about 97.960378%. Comparing the three stimulations results, for single stimuli response, "audio and video" stimulation has the best accuracy over all the stimulation results. The result for the second approach is shown in Table III. In the second approach, the combination of two stimulations was combined for a single person. In this case, the classification model with the highest accuracy was found for Logistic Regression which is about 99.74%.

And, in Table IV, Three stimuli response is shown. Here, the classification model with the highest accuracy was found for Logistic Regression which is about 95.27%.

TABLE I
Results for Single Stimuli Response

Cases	Model	Accuracy
Resting	Random Forest	95.05921%
	Support Vector Classifier	57.27%
	Logistic Regression	97.25771%
	Naive Bayes	54.55%
Audio	Random Forest	95.95407%
	Support Vector Classifier	61.54%
	Logistic Regression	98.45593%
	Naive Bayes	53.85%
Video	Random Forest	95.05587%
	Support Vector Classifier	48.18%
	Logistic Regression	97.44286%
	Naive Bayes	56.36%

TABLE II
Results for Double Stimuli Response(First Approach)

Cases	Model	Accuracy
Audio & Resting	Random Forest	92.76442%
	Support Vector Classifier	58.60%
	Logistic Regression	97.95951%
	Naive Bayes	46.98%
Video & Resting	Random Forest	92.769469%
	Support Vector Classifier	53.88%
	Logistic Regression	95.9733567%
	Naive Bayes	47.03%
Audio & Video	Random Forest	92.76442%
	Support Vector Classifier	54.63%
	Logistic Regression	97.960378%
	Naive Bayes	48.61%

TABLE III
Results for Double Stimuli Response(Second Approach)

Cases	Model	Accuracy
Combined	Random Forest	98.52%
	Logistic Regression	99.74%

Traditional machine learning approach is done in this study for comparative analysis of stimuli response among people in migraine classification. The dataset was recorded with the 128-channel BioSemi ActiveTwo system. Among them the channels of interest were, P3, P4, C3, C4, O1, O2, T7, T8, F7, F8, C5, C6, Fpz, Oz. Results showed that the best classification of migraine can be possible by following simple steps instead of using deep learning or other big machine learning approaches.

From the results of double stimuli response approach-2, the highest performance is achieved by logistic Regression machine learning algorithm. It is compared with the related studies of migraine diagnosis from EEG signal which is shown in Table V.

Aslan [6] used the same dataset and they achieved 89.6% success using random forest classifier. In this study, 99.74% accuracy was obtained by using the EEG signal collected from selected 14 specific channels and the logistic Regression classifier. An improvement over 10% was found in the current study than the relevant literature. The hybrid approach shown in the study using logistic regression classifier was the most successful among the different models in the literature. Using the Logistic Regression classifier about 99.74% accuracy was achieved.

TABLE IV
Results for Three Stimuli Response

Cases	Model	Accuracy
Audio, Video & Resting	Random Forest	91.17%
	ANN	92.42%
	Logistic Regression	95.27%

TABLE V

A COMPARATIVE STUDY WITH RELEVANT LITERATURE STUDIES

References	No. of Channels	Subjects	Approach	Classifier	Accuracy
Akben et al. [5]	4	60	Resting	SVM	85%
Aslan [6]	128	39	Resting	Random Forest	89.6%
Subasi et al. [7]	2	30	Resting	Random Forest	85.95%
Jindal et al. [8]	6	26	Resting	Random Forest	88%
Cao et al. [15]	4	80	Resting	AdaBoost	81%
The proposed model	14	39	Hybrid(Resting, Audio, Video)	Logistic Regression	99.74%

IV. CONCLUSION

In this study, we proposed a hybrid approach of classifying migraine. We considered a total of three cases for this comparative analysis by taking a single stimuli at a time, a random two-stimuli hybrid approach and all three stimuli combined approach. Here, among 144 channels, 14 channels were used that are said to be more sensitive to migraine. Finally, after all processing steps, data were fed into different machine Learning algorithms. From the different approaches, the highest performance of 99.74% accuracy is obtained with the Logistic Regression along with a two-stimuli hybrid approach. In the future, more subjects can be employed for better analysis. This study of the hybrid approach can help in different biomedical aspects as well as in migraine classification studies.

REFERENCES

[1] 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

[2] P. Amiri et al., "Migraine: A Review on Its History, Global Epidemiology, Risk Factors, and Comorbidities," *Front. Neurol.*, vol. 12, no. February, pp. 1–15, 2022, doi: 10.3389/fneur.2021.800605.

[3] T. A. Pearl, G. Dumkrieger, C. D. Chong, D. W. Dodick, and T. J. Schwedt, "Sensory Hypersensitivity Symptoms in Migraine With vs Without Aura: Results From the American Registry for Migraine Research," *Headache J. Head Face Pain,* vol. 60, no. 3, pp. 506–514, 2020, doi: https://doi.org/10.1111/head.13745.

[4] F. E. Chowdhury, M. Chowdhury, A. Chowdhury and M. Quamruzzaman, "Stress Detection Through Single Channel Real-Time EEG Signal from Temporal Lobe Using Machine Learning Model," *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT),* Delhi, India, 2023, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10306599.

[5] S. B. Akben, D. Tuncel, and A. Alkan, "Classification of multi-channel EEG signals for migraine detection," *Biomed. Res.*, vol. 27, no. 3, pp. 743–748, 2016.

[6] Z. Aslan, "Migraine detection from EEG signals using tunable Q-factor wavelet transform and ensemble learning techniques.," *Phys. Eng. Sci. Med.*, vol. 44, no. 4, pp. 1201–1212, Dec. 2021, doi: 10.1007/s13246-021-01055-6.

[7] A. Subasi, A. Ahmed, E. Alickovic, and A. Rashik Hassan, "Effect of photic stimulation for migraine detection using random forest and discrete wavelet transform," *Biomed. Signal Process. Control*, vol. 49, pp. 231–239, 2019, doi: https://doi.org/10.1016/j.bspc.2018.12.011.

[8] K. Jindal et al., "Migraine disease diagnosis from EEG signals using Non-linear Feature Extraction Technique," *2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, Madurai, India, 2018, pp. 1-4, doi: 10.1109/ICCIC.2018.8782341.

[9] A. Chaman Zar, S. Haigh, P. Groverand M. Behrmann, "Ultra high-density EEG recording of interictal migraine and controls: sensory and rest", Carnegie Mellon University, 21-Jul-2020, doi: 10.1184/R1/12636731

[10] 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.*, vol. 3, no. 2, p. fcab061, 2021, doi: 10.1093/braincomms/fcab061.

[11] A. Chowdhury, D. Das, A. B. M. Eldaly, R. C. C. Cheung, and M. H. Chowdhury, "Photoplethysmogram-based heart rate and blood pressure estimation with hypertension classification," *IPEM-Translation*, p. 100024, 2024, doi: https://doi.org/10.1016/j.ipemt.2024.100024.

[12] K. Kourou, T. P. Exarchos, K. P. Exarchos, M. V Karamouzis, and D. I. Fotiadis, "Machine learning applications in cancer prognosis and prediction," *Comput. Struct. Biotechnol. J.*, vol. 13, pp. 8–17, 2015, doi: https://doi.org/10.1016/j.csbj.2014.11.005.

[13] G. Zeng, "On the confusion matrix in credit scoring and its analytical properties," *Commun. Stat. - Theory Methods*, vol. 49, no. 9, pp. 2080–2093, 2020, doi: 10.1080/03610926.2019.1568485.

[14] A. Chowdhury, D. Das, K. Hasan, R. C. C. Cheung, and M. H. Chowdhury, "An FPGA Implementation of Multiclass Disease Detection From PPG," *IEEE Sensors Lett.*, vol. 7, no. 11, pp. 1–4, 2023, doi: 10.1109/LSENS.2023.3322288.

[15] Z. -H. Cao, L. -W. Ko, K. -L. Lai, S. -B. Huang, S. -J. Wang and C. -T. Lin, "Classification of migraine stages based on resting-state EEG power," *2015 International Joint Conference on Neural Networks (IJCNN)*, Killarney, Ireland, 2015, pp. 1-5, doi: 10.1109/IJCNN.2015.7280582.