Anticipating menstrual migraine using deep learning

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Abstract: Menstrual Migraines are headaches that occur without any typical aura or sensory disturbances. They can be labelled as 'Migraine without Aura'. A woman could undergo menstrual migraine just before or during her period starts. This is majorly due to the drop in oestrogen levels in the body. Menstrual migraines can be intense, and they must be identified accurately and treated separately from regular ones. Anticipating Menstrual Migraines using Deep Learning methodology can help women in taking precautions beforehand and aid in improving their health. This paper provides an efficient approach by checking various feature correlations and implementing ANN model with tuned hyperparameters providing stronger accuracy.

1. Introduction

There is a link between migraine and hormonal changes in a woman's life, this type of migraine is known as menstrual migraine, it is a primary classification type of migraine caused mostly in 20-30 age group women which starts two days prior to periods and ends three post the menstrual cycle, this migraine recurs along every month periodic cycle. Although doctors typically diagnose migraine in women who report with persistent, incapacitating headaches, they first need to rule out other headache conditions. Assessment of the impact of hormones (such as menses) on these recurrent incapacitating headaches is necessary for women who fit the criteria for migraine (International classification criteria, 2004). For menstrual related migraine (MRM), often known as pure menstrual migraine, many women fit the requirements (PMM).

Dysmenorrhea is strongly associated to menstruation in itself. Women who are taught to distinguish between the symptoms of PMDD and migraines will be better able to control their migraine attacks. These are listed as follows in the International Classification Criteria Appendix:

1.1. Pure menstrual migraine:

Pure menstrual migraine that doesn't have an aura meets the diagnostic standards for migraine without an aura and episodes only happen on day 12 of menstruation and never at any other period during the cycle, according to at least two out of every three menstrual cycles.

1.2. Menstrual related migraine without aura:

Episodes occur on day12 (i.e., days-2 to +3) of menstruation in at least two out of three menstrual cycles and also at other periods of the month, and they fulfil the diagnostic criteria.

Menstrual migraine symptoms are analogous to those of other types of migraines. subtle or extremely painful headache is the most common symptom followed by other various symptoms like feeling very hot or chilly, sensitivity to sounds and odors and light, sensitive scalp, decrease in appetite, vision blur and dizziness light skin tone (pallor), being worn out. abdominal pain, stomach distress, and nausea, a fever or diarrhea Footnotes

2. Literature Review

Ahmet, Alkan, and Batuhan Akben Selahaddin [1] covers many strategies for detecting migraines that have been put forth in earlier studies. However, the majority of these earlier studies were founded on frequency domain analysis of EEG data. The frequency domain transformation of the EEG data required the use of sophisticated mathematical algorithms. The FIR filter is used to filter the beta band of each flash stimulated and non-stimulated EEG data for both migraine patients and healthy people. Comparing the figures, it is clear that the beta band of EEG signals has smaller amplitudes. The time domain-based preprocessing approach known as the histogram is then used for all of the filtered EEG data. The outcome demonstrates how flash stimulation affected patients with and without migraines' beta band EEG data. In this analysis, characteristics were extracted from flash stimulated and non-stimulated EEG data using a time domain-based histogram approach, which was then clustered to represent healthy people and migraine patients. It was shown that, for migraine sufferers, the amplitude frequency histograms (Cluster 2) grouped very strongly with silhouette values greater than or equal to 0.63. Similar results are also attained with healthy people. The accurate clustering accuracy for all the data may be computed to be 86.6%.

Akben, Selahaddin Batuhan, Abdulhamit Subasi, and Deniz Tuncel [2], here, the frequency of flash stimulation that is most beneficial is identified, as well as how quickly a migraine can be diagnosed. The primary goal of this study was to identify the most effective flash stimulation frequency for migraine detection. As a result, it was discovered that 4 Hz was the most efficient flash stimulation frequency for identifying migraines. Finding the shortest window of time to detect a migraine is the second goal. It was discovered that 8 seconds was the absolute minimum needed to detect a migraine. The amplitude increase at the beta band of the EEG signal in the T5-T3 channel is applied to select the optimal flash stimulation frequency and shortest time duration in EEG recordings for migraine identification.

Akben, Selahaddin Batuhan, Abdülhamit Subaşı, and Mahmut Kemal Kıymık [3] reported that 23% of people suffer from the severe and excruciating brain ailment known as migraine. There is no documented or widely accepted automatic approach for diagnosing migraines using biomedical equipment. EEG signal changes caused by flash stimulation are typically utilized as a tool to gather information on migraines. The purpose of this study is to automatically diagnose migraines by performing a performance analysis of classification algorithms using EEG signals from migraine patients who have been provoked with a flash light. First, the (AR) Burg method is used to convert EEG signals from both migraine patients and healthy people into the frequency domain. Additionally, the artificial neural network and support vector machine classification algorithms are used to categorize these frequency spectrums. These classification findings allow for the determination of which classification method performs best for migraine diagnosis.

Charles, Andrew [4], the migraine aura is a spectacular neurologic occurrence with intricate neuronal and vascular mechanisms that may have significant effects on diagnosis and treatment. The biology of migraine and its ideal treatment can be better understood with a more in-depth study of its clinical characteristics, comorbidities, patterns of propagation in the human brain, and unique responses to therapy.

Chong, Catherine D., Nathan Gaw, Yinlin Fu, Jing Li, Teresa Wu, and Todd J. Schwedt [5], The classification of migraine using rs-fMRI sheds light on the altered pain circuits in migraine and may help in the creation of a novel, noninvasive migraine biomarker. Longer disease duration may cause remodeling of brain circuitry, as shown by the fact that migraineurs with longer disease duration were categorized more accurately than migraineurs with shorter disease duration.

Ang, Kai Keng, Cuntai Guan, Kerry Lee, Jie Qi Lee, Shoko Nioka, and Britton Chance [6], Using light in the near-infrared spectrum, near-infrared spectroscopy (NIRS) permits non-invasive recording of cerebral hemoglobin oxygenation in human subjects through the whole skull. Using data from single-trial NIRS brain signals, this research suggests a novel BCI for detecting changes caused by increases in the magnitude of operands employed in a mental arithmetic problem. Twenty healthy volunteers completed three-leveled mental arithmetic problems while having their hemoglobin responses monitored. Then, using 55-fold cross-validations on the gathered data, accuracy in differentiating one difficulty level from another is provided. The results showed a potential for the suggested NIRS-based BCI in identifying the difficulty of issues faced by mental arithmetic problem solvers, with an overall average accuracy of 71.2%.

Garcia-Chimeno, Yolanda, Begonya Garcia-Zapirain, Marian Gomez-Beldarrain, Begonya Fernandez-Ruanova, and Juan Carlos Garcia-Monco [7], In comparison to individual feature selection approaches, the suggested feature selection committee method enhanced the performance of migraine diagnosis classifiers, resulting in a robust system that obtained above 90% accuracy in all classifiers. The outcomes point to the potential utility of the suggested strategies in assisting experts in the classification of migraines in patients undergoing magnetic resonance imaging. The suggested committee-based feature selection method showed the highest increases in classification accuracy when the migraine group was considered. When using the Naive Bayes classifier, the accuracy of classification into three categories increased from 67 to 93%; when using the support vector machine classifier, it increased from 90 to 95%; and when boosting, it decreased from 93 to 94%. The attributes associated to pain, analgesics, and the left uncinate brain were shown to be the most helpful for classification (connected with the pain and emotions).

Jackowski, Konrad, Dariusz Jankowski, Dragan Simić, and Svetlana Simić [8], A reliable migraine diagnosis is a challenging decision. An ensemble classifier system for headache diagnosis is presented in the paper. Here, it is anticipated that the system will quickly diagnose a problem using simply the information gathered during the questionnaire. The majority of traditional classification algorithms could not be applied under such an assumption since they could not achieve a respectable degree of accuracy. It is chosen to use an ensemble solution as a result. As a result, we used a two-stage technique. First, a sizable pool of basic classifiers was created. By choosing algorithms with various kinds, structures, and learning methods, its diversity was guaranteed. Second, we chose the ensemble's ideal size and its members by employing exhaustive search techniques. Experiments conducted on data gathered at the University of Novi Sad revealed that the proposed system greatly surpassed all traditional methods. We also discuss diversity and accuracy correlation analyses for systems that have been put to the test.

Sanchez-Sanchez, Paola A., José Rafael García-González, and Juan Manuel Rúa Ascar [9] This article describes the creation of an approach for classifying migraines using models of artificial neural networks. The findings support those observed when multiple models provided in the literature are evaluated, showing that artificial neural networks can achieve higher precision and accuracy than other classification models frequently employed in machine learning. In the initial studies, 24 migraine diagnosis-related variables were used, and the artificial neural network model's precision level was 97%. The number of variables was whittled down to 18 in a second testing phase, yielding a precision of 98%. This demonstrates not only that the artificial neural network model is efficient for correctly classifying the various forms of migraine, but also that it can be enhanced by taking into account a smaller collection of variables that have a substantial impact on the classification.

Silberstein, Stephen D., and Susan L. Hutchinson [10] this paper states that women who are sensitive, a reduction in oestrogen is linked to an intensification of migraines. These women frequently get MRM or PMM diagnoses, and they could also experience additional non-headache symptoms brought on by changes in circulating hormone levels (e.g., anxiety, depression, dysphoria, among others). Differential diagnosis is crucial to correctly determining the type of headache so that the appropriate treatments can be suggested. Frequency, severity, non-pain symptoms, and impairment all need to be thoroughly assessed in connection to hormonal impacts because they will all have an impact on treatment decisions. Many MRM patients can benefit from monotherapy, which effectively treats all of their attacks regardless of whether they are related to menstruation or not. However, not all women may benefit from such a strategy; others may require short- or long-term prophylaxis in addition to emergency care and life-saving drugs. The use of polytherapy to treat concurrent disorders or symptoms is possible (e.g., PMDD, depression, anxiety, among others). Although it is now a widely recognized clinical phenomena that fluctuations in circulating oestrogen levels can cause migraines, moderating plasma oestrogen levels as a form of treatment is currently being investigated. Long-term, double-blind, randomized controlled trials are required to better determine the best approach and most efficient medications for treating migraines brought on by changes in oestrogen levels.

3. Proposed system

The designed system will be implemented on 24 attribute datasets containing 400 instances diagnosed with various migraine associated pathologies. The data has been collected through multiple real time surveys and also took support from code ocean capsule data for training and validation purpose. The Bengaluru region has been surveyed through multiple questionnaires regarding their age, duration of migraine, frequency, location of the migraine, its intensity and other factors that play major role in the migraine classification decision. Based on these factors the target variable is classified into three different categories I.e., "Menstrual Migraine", "Non-Menstrual Migraine" and other. Primarily the correlation between the target variable and other features have been displayed through count and percentage plots, showing their variability in a precise manner. Then the data is pre-processed thoroughly by performing data cleaning, data encoding, missing data evaluation along with data visualization for analyzing the symptom severity along the type of migraine and their correlation. ANN classifier has been deployed with optimized hyperparameter tuning to gain required classification predictions. Below is the flowchart describing the process steps.

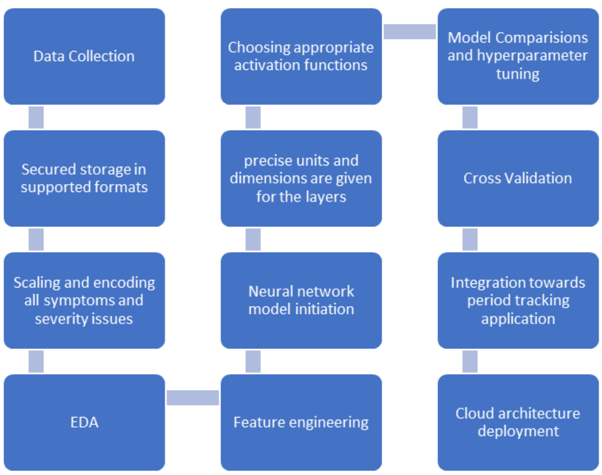

Fig 1 - Flowchart for Menstrual Migraine Classification procedure.

4. Methodology

4.1. Data Collection:

The team conducted a real-time survey in which the symptoms and the severity of each patient's symptoms were securely gathered and converted to a csv file for processing and quick access to the data.

4.2. Importing required libraries:

NumPy and pandas are used for the computing and preparation of complicated data. Matplotlib and Seaborn are used to visualize the correlations, and several methods from the Sci-kit Learn package are then imported, including resample, label encoder, and evaluation metrics. Neural networks containing sigmoid and Relu activation functions are built using the Keras and TensorFlow packages.

4.3. Feature Engineering:

Primarily, the data has been cleaned by handling missing values using data imputation methods, and then the categorical data has been encoded based on the number of classes, wherein we used label encoding and replace methods.

4.4. Exploratory Data Analysis:

The correlation between features and the target variable has been analyzed using various Exploratory Data Analysis methodologies. Count and percentage charts along with various other charts like violin charts, histograms, bar charts, boxplots were used to visualize and gain insights from the feature relations.

4.5. Model Building:

The base model is an ANN with thirty hidden layers, with Relu activation function for the hidden layers and SoftMax function for the output layer, and finally compiled using the Adam optimizer and loss function as categorical cross-entropy. A Keras classifier with 1000 epochs and a batch size of 75 has been created over the baseline model.

4.6. Cross validation:

K-fold cross-validation has been used with a k value of 15 in order to optimize the classification model.

4.7. Correlation Plots:

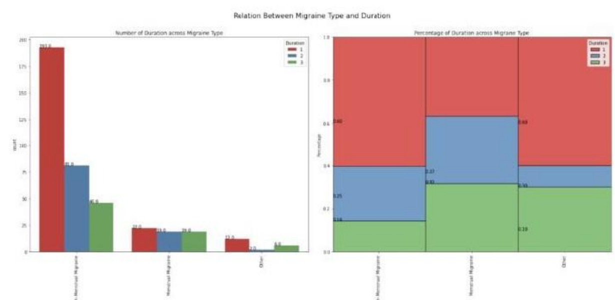

Fig 2 - Relation between Duration and Migraine type.

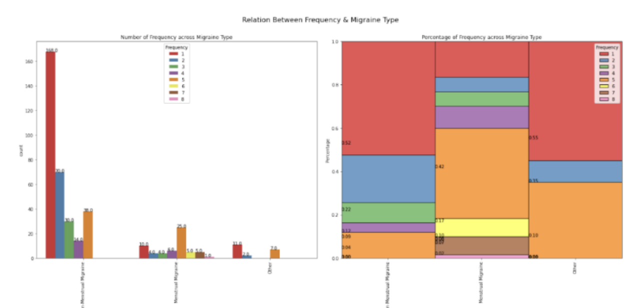

Fig 3 - Relation between Frequency and Migraine type.

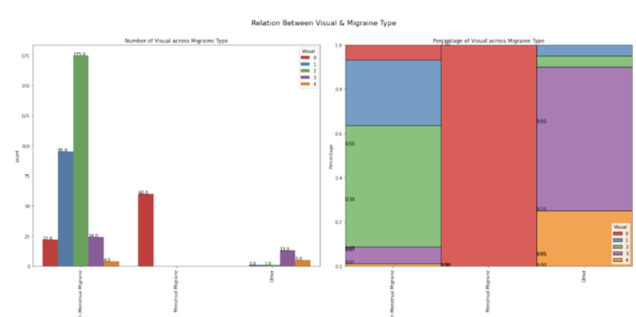

Fig 4 - Relation between Visual and Migraine type.

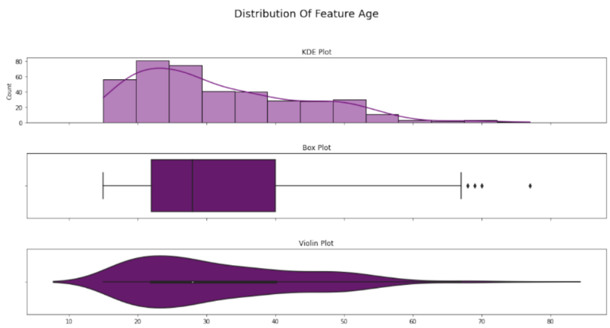

Fig 5 - Distribution of feature age.

5. Results and Conclusion

Based on the data collected and the feature correlation, it is anticipated that age plays a major role in menstrual migraine prediction and evaluating the symptom severity. The deep learning model was optimized using k-fold cross validation, giving an optimized model with a recall value of 0.94, a precision of 0.89, and an accuracy of 90.002%. This is the first model to be implemented for menstrual migraine prediction. It provides an easier diagnostic approach to recognizing the migraine type during the menstruation period, which helps women get early access to appropriate treatment. The developed model can be integrated with period trackers, providing complete information to the user regarding their migraine health condition during menstruation and suggesting appropriate remedies based on the feature evaluation.

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