Artificial Intelligence-Aided Headache Classification Based on a Set of Questionnaires: A Short Review

Bob Daripa 1, 2, Scott Lucchese 3, 4

1. Internal Medicine/Neurology, Singapore General Hospital, Singapore, SGP 2. General Physician, Grant Government Medical College and Sir J.J. Group of Hospitals, Mumbai, IND 3. Neurology, Headache, University of Arkansas for Medical Sciences, Little Rock, USA 4. Neurology, Headache, University of Missouri School of Medicine, Columbia, USA

Corresponding author: Bob Daripa, bobdaripa@gmail.com

Abstract

Wielding modern technology in the form of artificial intelligence (AI) or deep learning (DL) can utilize the best possible latest computer application in intricate decision-making and enigmatic problem-solving. It has been recommended in many fields. However, it is a long way from achieving an ambitious genuine intention when it comes to understanding and identifying any headache condition or classification, and using it error-free. No studies hitherto formalized any headache AI models to accurately classify headaches.

A machine’s job can be arduous when incorporating an emotional dimension in decision making, re-challenging its own diagnosis by keeping a differential at all times, where even experienced neurologists or headache experts sometimes find it demanding to make a precise analysis and formulate a methodical plan. This could be because of spanning clinical presentation at a given moment of time or a change in clinical pattern over time which apparently could be due to intercrossing multiple pathophysiology.

We did a short literature review on the role of artificial intelligence and machine learning in headache classification. This brings forth a minuscule insight into the vastness of headaches and the perpetual effort and exploration headache may demand from AI when trying to scrutinize its classification. Undoubtedly, AI or DL could better be utilized in identifying the red flags of headache, as it might help our patients at home or the primary care physicians/practicing doctors/non-neurologists in their clinic to triage the headache patients if they need an imperative higher center referral to a neurologist for advanced evaluation. This outlook can limit the burden on a handful of headache specialists by minimizing the referrals to a tertiary care setting.

Introduction And Background

Headache is mostly an intricate multifarious brain manifestation to manage, despite how simple it looks. Even experienced neurologists or headache experts sometimes find it demanding to make a precise diagnosis and formulate a methodical plan. This could be because of a spanning clinical presentation apparently due to intercrossing multiple pathophysiology. Wielding modern technology in form of artificial intelligence (AI) or deep learning (DL) can utilize the best possible latest computer application in intricate decision-making and enigmatic problem-solving. It has been recommended in many fields, but then it is a long way from achieving an ambitious genuine intention when comes to understanding and identifying any headache condition or classification, and using it error-free [1, 2].

Successful utilization of AI is appreciated in law and regulation, plant disease, and medical problems [3]. For instance, its utility in hypertension diagnosis, drug discovery, and nephropathy detection among newborns is well known [3]. Furthermore, its application in cancer-associated thrombosis risk assessment and breast cancer progression risk calculation is noteworthy [4]. There are many more applications in the process of development like Alzheimer’s and Parkinson’s disease diagnosis and brain tumor classification [5].

A primary headache is a subjective phenomenon. It is challenging to integrate technology asking to make it a diagnosis considering that we do not have any objective parameters to feed into or utilize in a computerized expert system as done in the above medical situations for effortless interpretation. Constant endeavors from engineering and technology may bring high-yielding outcomes; thus, AI should be coaxed for the betterment of mankind and the healthcare system. Headache has many undeciphered dimensions. Hence, the current era demands an AI technology that can auto-upgrade and sculpt as per the new updates in this discipline.

How to cite this article

Daripa B, Lucchese S (September 23, 2022) Artificial Intelligence-Aided Headache Classification Based on a Set of Questionnaires: A Short Review. Cureus 14(9): e29514. DOI 10.7759/cureus.29514
Method
We did a literature search in PubMed and Google scholar. Title searches were "artificial intelligence (AI) in headache classification", "machine learning (ML) in headache classification" or "deep learning use in headache classification". After excluding the duplicates, only 12 studies were included that were written in the English language and met the above search criteria. Studies were from technology and technical science, neuroscience, engineering, medicine, and emergency medicine department, from 2010 to December 2021. Studies included projects, where a set of questionnaires were used, at least classified one headache type by using assorted algorithms, or where set-up models were employed in the emergency departments to codify headaches. Opinions about AI on headaches or unpublished projects were also included. As our understanding of computer programming, software, and detailed working pattern of these sophisticated models/technology was limited, we did not elaborate on the algorithmic logic, processing, and application part.

Result
The inference drawn from various studies from the department of technology, engineering and neurosciences conducted worldwide expressing the application of AI in headache classification are charted, summarized and illustrated well in a tabular format below (Table 1) for a better understanding. It enumerates the year and place of study, number of subjects participated, particulars of AI or ML software used, advantages and the limitations in each study.

| Sl.No. | Author Name, Year, Place of Study | Nature of Study | Number of participants (N), Software/Application Used | Key elements/Outcome/ Learning Points | Limitations in the Study | Reference |
|-------|-----------------------------------|----------------|-----------------------------------------------------|---------------------------------------|--------------------------|-----------|
| 1     | Almadhoun et al [1], March 2021, Gaza, Palestine. Engineering Department | Subjects not used; Designed an expert system | Delphi programming language and clips | Diagnoses 11 headache problems | 11 questions to answer, and each question has multiple sub-questions describing many symptoms. Overlapping of symptoms can cause errors in diagnosis | [1] |
|       |                                   |                |                                                     | Does not require any training before using this expert system | Inability to diagnose other headache types not listed in the system |           |
|       |                                   |                |                                                     | N=2162. Divided into 2 cohorts: Training=1286, Test=876. | Not checked the accuracy, specificity, or sensitivity of the expert system |           |
|       |                                   |                |                                                     | 75 screening questions were used in details | Other less prevalent although significant primary headaches and secondary headache (other than the causes of thunderclap headaches) were excluded because of a long list of heterogenous diseases causing them. |           |
|       |                                   |                |                                                     | Stacked classifier model used with 4 layers of binary XGBoost classifiers for differentiating: Migraine, (tension-type headache) TTH, (trigeminal autonomic cephalalgia) TAC, Epicranial headache, and thunderclap headache. | Used only 3 clinical features in each stack to draw insight about headache types and the clinical symptoms used here are different from (the International Classification of Headache Disorders) ICHD-3 criteria. |           |
| 2     | Kwon et al [2], 2020 Seoul, South Korea | Retrospective study | LASSO (least absolute shrinkage and selection operator) used for each stacked classifier layer. LASSO compared to SVM-RFE (support vector machine recursive feature elimination) and mRMR (minimum-Sensitivity for: Migraine=88%, TTH=69%, TAC=53%, Epicranial=51%, Thunderclap=51%. | Stacked XGBoost classifier result: Accuracy: 81% | The clinical course cannot be understood from these 75 questionnaires, so accurate diagnosis is difficult. | [2] |
The selected features used XGBoost classifier which was compared to k-NN (k-nearest neighbor), SVM (support vector machine), and random forest.

| Study | Year | Country | Department | Study Type | Participants | Methods | Results |
|-------|------|---------|------------|------------|-------------|---------|---------|
| Krawczyk et al [3], 2012 | Wroclaw, Poland | Mixed department: Technology, Technical Sciences & Medicine | Questionnaire filled by subjects where headache patients also included; ML algorithms developed and tested; a Prospective study | 579 | Age: 20–65 years | Used algorithms: Naive Bayes (a probabilistic classifier), C4.5 (based on ‘Top-Down Induction of Decision Tree’ (TDIDT), Support vector Machine (SVM), Bagging (or bootstrap aggregating), Boosting, Random Forest. | Best results noticed in with accuracy %: Random Forest=79.97±3.13, Bagging=78.24±2.98, Boosting 76.68±2.43 |
| Julian et al [8], 2019 | Study conducted in a hospital, Emergency Department. | Aim: Detection of probable secondary headache | Retrospective study | 7972 | N=7972. Primary headache=7098. Secondary headache=874. | Records were processed using: Latent Semantic Analysis (LSA). Support Vector Machine (SVM) model used for training. Used Python program. | Probable secondary headache: Sensitivity=89%, Specificity=73%, Negative predictive value (NPV)=96.2%. |
| Messina et al. [7], April 2020 | Mila, Italy. Neurosciences Department | Opinion | An opinion about Machine Learning in Headache | - | - | - |
| Celik et al [8], 2009 | | Retrospective collecting records | Artificial immune system (computational artificial intelligence) | - | - | - |

Specificity for: Migraine=95%, TTH=55%, TAC=46%, Epicranial=48%, Thunderclap=51%.

Data derived from a single center.

Performance report in migraine classification was excellent, rest was inferior. This study can be used as pre-screening.

Conventional machine learning utilized here. No use of deep learning.
| 7 | Tezel et al. [9], 2019. Neurology, Neurosurgery Department. Aim: Designed and developed an AI system | Subjects not used. **Designed and developed an AI system** | Clonal selection algorithm (an artificial immunity approach) diagnosis. Included 250 different symptoms for the training set. 150 symptoms related to headaches. |
|---|---|---|---|
| | | Based on the clonal selection principle | For Test set: Correctly classified symptom set: 96.74% |
| | | Inspired by biological immunology. | Incorrectly classified symptom set: 3.26% |
| 8 | Katsuki et al [10], 2020. Neurology, Neurosurgery Department. Aim: Retrospective investigated headache database and developed a DL system | Retrospective investigated headache database and developed a DL system | **N=848** Accuracy: 0.7759 The sample size is small. |
| | | Age: 40-74 years | They did the study in a single hospital. |
| | | Used Deep learning framework-Prediction One. | External validation not done |
| | | Utilized artificial neural network (ANN) with internal cross-validation. | No separation between chronic and episodic frequent headaches of >=15 days per month to >15 days per month for migraine or TTH headache. |
| | | Also used Confusion matrix of model | |
| | | Used Japanese language with onomatopoeia, therefore utilized Japanese natural language processing (NLP) | |
| 9 | Keight et al., [11]. Engineering, Medicine and Neurosurgery Department | Retrospective headache dataset collection from two medical facilities | **N=836** Classified headache into Tension-Type Headache, Chronic Tension-Type Headache, Migraine with Aura, Migraine without Aura, Trigeminal Autonomic Cephalalgia. |
| | | Study was done in two medical centers in Turkey. | Area under the curve (AUC): 0.985 |
| | | 9 machine learning classifiers used in a supervised learning setting | Sensitivity: 1 Specificity: 0.966 |
| | | **Clinical decision support systems (CDSSs) are based on case-based reasoning (CBR).** | **Can be a diagnostic tool for the general practitioner.** |
| | | K-Nearest Neighbor (KNN) method implemented. | **Accuracy is very high in recognizing these two headaches.** |
| | | This comprehensive study worked on 3 steps viz. data acquisition through clinical interviews, construction of a case library, and lastly development of a case-based | **Inadequate case library due to complex headaches.** |
| 10 | Yin et al [12], 2015. China. Aim: To diagnose two headache types namely probable migraine and | This comprehensive study worked on 3 steps viz. data acquisition through clinical interviews, construction of a case library, and lastly development of a case-based | **Probable migraine (PM) 56.95% Probable TTH (PTTH): 43.05%** |
| | | | **Earlier CBR used: (1) CASEY: to diagnose heart complication** |
| | | | **(2) Decision-based support system to diagnose (chronic obstructive pulmonary disease)** |
| | | | **Needs multi-centric study and validation** |
| Probable TTH reasoning system | COPD |
|------------------------------|------|
| Test set: N=222, PM: 76.1%, PTTH: 23.9% | (3) Hybrid case-based reasoning approach to diagnose breast cancer and thyroid disease. |

| Qawasmeh et al [13], 2020, Jordan | Developed an ML-based system where its prediction accuracy checked by a web-based questionnaire’s answer |
|-----------------------------------|---------------------------------------------------------------|
| N=614 patients records. Public hospital. Males=199; Female=415. Different age group. | Hybrid model (clustering and classification): Integrated K-means clustering with Random Forest classifier |
| High-performance headache prediction support system (HPSS) was employed based on a hybrid machine learning model. | Migraine prediction accuracy=99.1% |
| Used 19 questions related to headache symptoms, according to ICHD-3 criteria. | Excluded migraine with aura from this study as its differential could be a stroke. |
| 26 classification algorithms were applied to 614 patients. | |

| Woldeamanuel et al [14], 2021, Division of Headache & Facial Pain, Stanford, CA, USA | A meta-analysis of 41 studies |
|---------------------------------|-----------------------------|
| Total=41 studies. Median age 43 years, 77% women. The median sample size was 288. | Used case-based reasoning, DL, classifier ensemble, anti-colony, artificial immune, random forest, white and black box combination, hybrid fuzzy expert system |
| 4 studies were based on a questionnaire | 60% of the digital tools were based on ICHD criteria. |
| Phone interviews in 2 studies | 12% of tools were evaluated in non-clinical centers |
| Face-to-face interview: 82% (a strong feature) | Interstudy heterogeneity of software |
| | No proper patient selection method in 39% of included studies |
| | No description of age or sex ratio in 25 studies |

| Sah et al [15], 2017, Bhopal, India | Database created from headache diary and employed selection technique for analysis |
|---------------------------------|-------------------------------|
| Work on migraine headache classification. Used: data mining classifiers K-NN, support vector machine (SVM), Random Forest, Naïve Bays. 18 questionnaire | The best result was derived from the Naïve Bays classification. AUC 0.475, Precision 0.905 |
| Used ML for identifying | Data collected from headache diary |

2022 Daripa et al. Cureus 14(9): e29514. DOI 10.7759/cureus.29514
Liu et al [16], 2022. Shanghai, China. School of medicine

A cross-sectional study

Primary headaches. This is a cross-sectional study design.

N=173 patients (84: migraine, 89: TTH), collected information in neurology clinics using a questionnaire (19 questions)

Logistic regression has an accuracy of 0.84 and an area under the receiver operating characteristic curve (ROC) of 0.90

Only 2 types of headaches were worked on. Mild headache cases could not be included in this study as they did not come for medical advice.

Used: Decision tree, Random forest, gradient boosting algorithm, logistic regression, support vector machine (SVM) algorithms

Helped distinguish migraine and TTH and their important symptomatic distinguishing features

Sanchez et al [17], 2020. Colombia

The study was designed to test the classifier system to distinguish types of migraine

Aimed at classifying migraine based on symptoms

N=400 retrospective medical records

ANN provided excellent results with an accuracy of 97.5% and a precision of 97%

Small sample size

Used set of 23 variables/questionnaire of symptoms or signs

Implemented artificial neural network (ANN) models, logistic regression models, SVM, nearest neighbor, decision tree

Celik et al [18], 2017.

A cross-sectional study to evaluate the accuracy of a classifier algorithm to diagnose primary headache type using web-based questionnaire

Aimed to diagnose primary headache based on ant colony optimization algorithm.

Classification Accuracy=96.9412%

26 patients were misdiagnosed by the ant colony classification

The web-based questionnaire system used www.migbase.com. Used MySQL database and PHP hypertext preprocessor (PHP) programming language, 40 attributes/questions were included

Accuracies of migraine, TTH, and cluster headache were 98.2%, 92.4%, and 98.2% respectively

A similar study was done in Turkey using the same set of patients and the same website for questionnaire but implemented the artificial immune algorithms for primary headache (2015) which reached an accuracy of 99.6471% (used AIRS2-Parallel algorithm) [19]

N=850 headache patients from 3 cities who visited a neurologist

Age range=15 to 65 years. 70% female and 30% male.

TABLE 1: A simplified summary review of use of artificial intelligence in headache classification

| Study | Design Type | Participant Details | Methodology | Accuracy/Results |
|-------|-------------|---------------------|-------------|-----------------|
| Liu et al [16] | Cross-sectional | N=173 (84: migraine, 89: TTH) | Logistic regression | 0.84 (ROC 0.90) |
| Sanchez et al [17] | Cross-sectional | N=400 | ANN | 97.5% (Precision 97%) |
| Celik et al [18] | Cross-sectional | N=850 (3 cities, neurologist) | Classification | 96.9412% |

Discussion

Identification of focal cortical dysplasia, the evolution of neuroimaging biomarkers in Alzheimer’s and prognosticate clinical consequences in depression therapeutics undoubtedly prove AI’s success and...
expanding boundaries [7]. With regards to migraine and cluster headaches, there can be a functional variation in terms of activation of separate structures in the brain, namely the trigeminovascular system, brainstem, hypothalamus and cortical areas. There could be an adjoining structural alteration of cortical thickness and its surface area. Perhaps, these changes could be related to ictal or interictal phases, and may be dynamic in nature [7]. The use of ML algorithms in functional and morphometric MRI analysis helps to distinguish these headache features [7]. It is appropriate to mention here that AI has invested a decade’s drudgery in recognizing just one headache disorder: migraine [4].

In short, numerous AI models, namely artificial neural networks (ANNs), artificial immune system (AIS) or support vector machines (SVM) are grappling to diagnose/categorize the phenotypes of only one headache type as they need further studies and validation; the exemplary model hunt is on-going. A handful of studies from the past provide little insight into AI’s influence on headache as illustrated above in table 1. and the perpetual effort that headache demands from AI when attempting to explore its own classification can be well anticipated from their limitations. Machine learning or deep learning has already been used in scouting neuroimages related to headaches [2]. In the time ahead, we anticipate AI/ML may provide neuroimage brain ‘signatures’ for specific headache categories, aided by clinical data [4].

Challenges AI May Face Over The Classification of Headaches And Our Viewpoint

The application of patient-oriented digital health gadgets can shrink the healthcare-pertinent levy as evidenced by telehealth utilization in the current COVID-19 pandemic. E-diary based headache monitoring, ML-driven products predicting headache onset or digital wearables identifying sleep time or even smartphone aided biofeed-back are a few cardinal achievements for our patients [14].

Adroit clinical interviews and reminiscence is the archetype when diagnosing primary headache which undoubtedly necessitates a holistic approach and involves neurophysiological, neuroimaging or blood biomarkers to which AI’s headache database, library and engineering part relies upon [2]. Overlapping clinical presentation at a given moment of time, change in clinical pattern over time and keeping a differential diagnosis at all times are challenges that may be confronted by AI. Imparting an emotionally delicate touch from the patient’s side of conversation and being empathetic from the physician’s end is difficult to simulate by AI technology.

It is interesting to note that one study attempted to classify emergency headache types using AI (particularly primary as well as secondary headache types). Undoubtedly, it excellently explored the secondary headache category with high sensitivity, specificity and negative predictive value while using an AI model, but meagerly addressed the primary emergent headache [6]. Optimum utilization and guidance of AI technology is not only limited to diagnosing probable migraine or probable TTH to help our general practitioner [12], but could also be extended to identify any alarming headache condition.

In our view, AI or DL could be utilized in identifying the red flags of headache, as it might help our patients at home or the primary care physicians/practicing doctors/non-neurologists in their clinic to triage the headache patients if they need an urgent higher center referral to a neurologist for advance evaluation, or whether they can continue with the current treatment in their clinic or home. This would minimize patient’s as well as doctor’s judgment errors, lessen panic situations, and finally both would feel confident when participating in a mutual discussion about symptom management. This approach can limit the burden on a handful of headache specialists by minimizing the referrals to a tertiary care setting.

Conclusions

Supervised ML algorithms use training data which are processed and model trained to predict or classify a test data/input into predefined groups with the help of a ‘classifier’ whereas unsupervised machine learning models process input/test data via algorithm and vectors of a training set to declare result in a cluster format. Subtle changes in the brain can be picked up with AI neuroimaging for a better understanding of the disease state as mentioned earlier. However, AI/DL needs to combine anamnesis, clinical signs, and dynamic functional variation with adjoining structural imaging alteration to accurately recognize headache types. Ironically, no studies hitherto formalized any headache AI models to accurately classify headaches.

AI needs a multidisciplinary approach from neurology, neurosurgery, neuroradiology, technology, engineering, and opinions from various other related disciplines for accelerated work that should undoubtedly be patient-centric. In the words of Gandhi, ‘The patient is the most important person in our hospital. He is not dependent on us. We are dependent on him. We are not doing him a favor by serving him. He is doing us a favor by giving us an opportunity to do so.’

Additional Information

Disclosures

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: Payment/services info: All authors have declared that no financial support was received from
any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

**References**

1. Almadhoun HR: Diagnosis of headache problems using an expert system. Int J Acad Info Sys. 2021, 5:77-81.
2. Kwon J, Lee H, Cho S, Chung CS, Lee MJ, Park H: Machine learning-based automated classification of headache disorders using patient-reported questionnaires. Sci Rep. 2020, 10:14062. 10.1038/s41598-020-70992-1
3. Krawczyk B, Simić D, Simić S, Wozniak M: Automatic diagnosis of primary headaches by machine learning methods. Open Med. 2015, 8:157-165. 10.2478/s11536-015-0098-5
4. Ferroni P, Zanzotto FM, Scarpato N, et al.: Machine learning approach to predict medication overuse in migraine patients. Comput Struct Biotechnol J. 2020, 18:1487-96. 10.1016/j.csbj.2020.06.006
5. Segato A, Marzullo A, Calimeri F, De Momi E: Artificial intelligence for brain diseases: A systematic review. APL Bioeng. 2020, 4:041505. 10.1063/5.0011697
6. Acosta JN, Dorr F, Goicochea MT, Sleizak DF, Farez M: Acute headache diagnosis in the emergency department: accuracy and safety of an artificial intelligence system. Neurology. 2019, 92:515.
7. Messina R, Filippi M: What we gain from machine learning studies in headache patients. Front Neurol. 2020, 11:221. 10.3389/fneur.2020.00221
8. Artificial immune systems for headache diagnosis. (2009). Accessed: June 19, 2022: https://www.researchgate.net/publication/339102673.
9. Headache disease diagnosis by using the clonal selection algorithm. (2011). Accessed: June 19, 2022: https://www.researchgate.net/publication/365562459.
10. Katsuki M, Narita N, Matsumori Y, Ishida N, Watanabe O, Cai S, Tominaga T: Preliminary development of a deep learning-based automated primary headache diagnosis model using Japanese natural language processing of medical questionnaire. Surg Neurol Int. 2020, 11:475. 10.25259/SNI_827_2020
11. Keight R, Alijaaf AJ, Al-Jumeily D, Hussain AJ, Özge A, Mallucci C: An intelligent systems approach to primary headache diagnosis. Intelligent Computing Theories Appl. 2017, 10362:61-72. 10.1007/978-3-319-63312-1_6
12. Yin Z, Dong Z, Lu X, Yu S, Chen X, Duan H: A clinical decision support system for the diagnosis of probable migraine and probable tension-type headache based on case-based reasoning. J Headache Pain. 2015, 16:29. 10.1186/s10194-015-0512-x
13. Qawasme A, Alhusan N, Hanandeh F, Al-Atiyat M: A high-performance system for the diagnosis of headache via hybrid machine learning model. Int J Adv Comp Sci Appl. 2020, 11(5):10.14569/IJACSA.2020.0110580
14. Woldeamanuel YW, Cowan RP: Computerized migraine diagnostic tools: a systematic review. Ther Adv Chronic Dis. 2022, 15:20466232211065255. 10.1177/20466232211065255
15. Sah RD, Sheetlani J, Kumar DR, Sahu IN: Migraine (Headaches) Disease Data Classification Using Data Mining Classifiers. J Res Env Earth Sci. 2017, 5:10-16.
16. Liu F, Bao G, Yan M, Lin G: A decision support system for primary headache developed through machine learning. PeerJ. 2022, 10:e12743. 10.7717/peerj.12743
17. Sanchez-Sanchez PA, Garcia-González JR, Rúa Ascar JM: Automatic migraine classification using artificial neural networks. F1000Res. 2020, 9:618. 10.12688/F1000research.23181.2
18. Ufuk C, Niğüfer Y: An ant colony optimization algorithm-based classification for the diagnosis of primary headaches using a website questionnaire expert system. Turk J Elec Eng Comp Sci. 2017, 25:4200-10. 10.3906/elk-1612-178
19. Çelik U, Yurtay N, Koç ER, Tepe N, Gullüoğlu H, Ertuş M: Diagnostic accuracy comparison of artificial immune algorithms for primary headaches. Comput Math Methods Med. 2015, 465192. 10.1155/2015/465192