Proceedings of the 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT-2024)
IEEE Xplore Part Number: CFP24CV1-ART; ISBN: 979-8-3503-2753-3

2024 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT) | 979-8-3503-2753-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/IDCIOT59759.2024.10467496

Deciphering Migraine Types: A Machine Learning Odyssey for Precision Prediction

Rohi Velgina Romould
School of Computer Engineering
KIIT Deemed to be University
Bhubaneswar, Odisha, India
rohiromould@gmail.com

Vinayak Singh
School of Computer Engineering
KIIT Deemed to be University
Bhubaneswar, Odisha, India
vinayaksooryavanshi@gmail.com

Mahendra Kumar Gourisaria
School of Computer Engineering
KIIT Deemed to be University
Bhubaneswar, Odisha, India
mkgourisaria2010@gmail.com

Himansu Das
School of Computer Engineering
KIIT Deemed to be University
Bhubaneswar, Odisha, India
das.himansu2007@gmail.com

Bibhuti Bhusan Dash
School of Computer Applications
KIIT Deemed to be University
Bhubaneswar, Odisha, India
bibhuti.dash@gmail.com

***Abstract*— Headache is a common medical complaint affecting people of all age groups. It ranges in severity from mild to severe. Headaches are classified into three types: Tension-type headaches, Cluster headaches, and Migraines. This research study focuses on Migraines which is a severe headaches accompanied by many symptoms and can be caused due to genetic or environmental factors. Migraine is of various types but this research study marks out only 6 types of it. The primary aim of this research is to compare various Machine Learning algorithms to determine the best model with optimal accuracy and precision in predicting the type of migraine based on diverse factors. 6 machine learning algorithms are trained and tested on a machine-generated dataset which contains 23 parameters based on which the algorithm predicts the type of migraine a patient suffers from. The models are finally compared based on 13 metrics or evaluation measures. The model with the best performance is declared to be the one that predicts the type of migraine with the least errors. In this research study, KNN is observed to be the best-performing Machine Learning algorithm with an accuracy and precision of 0.85.**

Keywords—Tension-Type Headache, Migraine, Cluster Headache, K-Nearest Neighbors, Naive Bayes

I. INTRODUCTION

Migraine is one of the most immobilizing neurological disorders that affects about 1 billion people around the globe. The Global Burden of Disease Study states that it ranks second among the most common neurological disorders and is responsible for more disabilities than all other neurological disorders combined. Migraine appears in an individual as chronic attacks of headache with a range of symptoms. It is diagnosed based on some clinical principles provided by the International Classification of Headaches Disorders, (ICHD) 3rd edition. Common symptoms that arise are vomiting, photophobia, nausea, and phonophobia. About one-third of the affected population also report that the headache is sometimes or always preceded by transient neurological disturbances also called an aura which is a symptom comprising visual or hemisensory disturbances [1, 2]. The pathogenesis of migraine is believed to involve the trigeminovascular system, however, the specific pathogenic processes are yet unknown and only a few treatment options exist [3].

According to the International Headache Society, there are different types of migraines [4]. This research study focuses on 6 types of migraines and classifies all the rest that may appear as 'others'. The 6 types are namely: 1. Migraine with typical aura, 2. Migraine without aura, 3. Migraine with Basilar-type aura, 4. Sporadic Hemiplegic migraine, 5. Familial Hemiplegic migraine, 6. Typical aura without migraine. A typical Migraine with aura is a recurrent headache that lasts for a few minutes and is accompanied by an aura, commonly a visual aura. Sensory and aphasic auras can sometimes follow a visual aura. The aura lasts for about an hour but the motor symptoms last longer [4]. An aura-free migraine is a recurrent headache lasting about 4 to 72 hours. It is a pulsating, unilateral ache that ranges in intensity from moderate to severe. It is often associated with nausea, photophobia, and phonophobia and can be aggravated by physical activities [5]. Basilar-type migraine is a type of migraine with an aura that has its source in the brainstem. A typical visual and sensory aura during the attacks is experienced by most people [6]. Hemiplegic migraine is a rare type of migraine with aura associated with transient hemiparesis during attacks. These are of two types: Sporadic and Familial Hemiplegic migraine. The Sporadic Hemiplegic Migraine (SHM) is one in which there is no genetic family history of the disease. It is similar to migraine with aura but occurs with a lower threshold and higher intensity. The Familial Hemiplegic Migraine (FHM) is one in which there is a genetic history of hemiplegic attacks [7]. It is similar to migraine with aura, but its aura has motor weak weakness and sensory, visual, and language symptoms [8]. Typical Aura without migraine is a rare type of migraine with aura in which the person experiences an aura but no migraine. The aura is usually accompanied by visual symptoms and there are no migraine attacks during or after the visual aura [9].

A high quality software for proper recognition of migraine could be quite useful in today's fast world with a huge population suffering from this disabling neurological condition. Machine Learning is a rising tool being used in the diagnosis of various medical problems, both mental and physiological. Some of the mentally disabling illnesses diagnosed by AI models are Alzheimer's disease using SVM, ANN, and Deep Learning, Parkinson’s disease, and Depression [10-12] while some of the physiological illnesses detected by AI models are chronic kidney disease using different ML models, Malaria using deep learning and CNN, and Corona using XGBoost [13- 15]. In this research study, different machine-learning models have been implemented on a small dataset of 24 columns and 400 rows to diagnose the type of Migraine a patient suffers from. There are 6 different ML models implemented in this research study namely Decision Tree, Random Forest, K-Nearest Neighbors, Naïve Bayes, Support Vector Machine, and Gradient Boosting. The dataset contains a comprehensive array of columns, each offering valuable insights into the multifaceted nature of migraines, thus, offering quite a rich resource for uncovering patterns and correlations. The dataset contains various parameters depending on which a model predicts the type of migraine from which the individual suffers. This research study compares the various Machine Learning models and demonstrates which model is most precise in predicting the accurate type of migraine. The models use multivariate analysis to most accurately predict the type of migraine. The rest of the sections are organized as: II. Related work containing some of the remarkable work of this field, III. Material and method describing the dataset, classification models, and soft and hardware used, IV. Experimentation and results describing the formulas used and where the models are compared to find the best-fit model, V. Conclusion and future scope, concluding the research study and describing the aspects of future work.

II. Related Works

Due to Migraine's multifaceted nature, predicting the type of migraine a patient suffers from is quite complex. Research in this field has been going on for quite some time in both medical and technical fields. To predict the right kind of migraine using machine learning a huge dataset is required.

Krawczyk *et al*. (2013) [16] bring forward the automated identification of primary headaches through machine learning. It simplifies the problem into 3-way classification which is solved using Machine Learning algorithms. Random Forest and Bagging and Boosting are found to have the best performance among all Machine Algorithms used. This led to the development of an automatic decision support system which appears to have high accuracy in recognition of migraine based on the experiments carried out on large datasets. Catherine D Chong *et al.* (2016) [17] used machine learning algorithms on Magnetic Resonance neuroimaging data to distinguish migraine patients from healthy patients. There were 58 migraine patients and 50 healthy patients included in this research study. The classification algorithms were trained and tested based on the patient's brain MRI. This study has used the 10-fold cross-validation to achieve an accuracy of 86.1%. The Migraines with a longer disease burden produced an accuracy of 96.7% while those with a shorter disease burden produced an accuracy of 82.1%. Thus, Migraines with an extended disease duration were classified more accurately than those with a shorter disease duration.

Vandewaiele *et al.* (2018) [18] introduced a decision support system aimed at enhancing the accuracy and precision of primary headache diagnosis. The dataset used in this included information on headache attacks of 849 patients. The research uses decision tree induction techniques to attain a superior accuracy as compared to other techniques. This paper has been able to reduce the classification error and achieved high accuracy using the Weifeiler-Lehman kernel which is unsupervised. Decision trees are identified as the perfect candidate for the automated diagnosis of primary headaches. R Messina *et al.* (2020) [19] wrote about the advantages of machine learning studies in headache patients. They mentioned various works in the field including neuroimaging techniques, pharmacological therapeutic approaches, and so on. This paper shows the use of Machine Learning in the diagnosis, treatment, and prognosis of headaches. F J Hsiao *et al*. (2022) [20] used Machine Learning (ML) to identify the neural markers of resting state oscillatory connectivity in individuals with chronic migraines. 240 participants volunteered for the collection of Resting-state Magnetoencephalographic data. A classification model utilizing a support vector machine was established with the collected data, to evaluate the accuracy of chronic migraine identification. Table 1 describes the detailed analysis of the related work.

TABLE I. Tabular Analysis of Related Works

Ref. No.	Authors and Year	Techniques used	Description
[16]	Krawczyk *et al.* (2013)	Automatic Decision support system	Automatic Decision support systems developed based on results produced by Random Forest and Bagging algorithms were used for automatic diagnosis of primary headaches.
[27]	Catherine D Chong *et al.* (2016)	10 fold cross-validation	Machine learning algorithms were used on Magnetic Resonance Neuroimaging data to distinguish migraine patients from healthy patients.
[18]	Vandewaiele *et al.* (2018)	Unsupervised Weifeiler-Lehman kernel for reducing error, Decision support system to improve accuracy and precision, and Decision tree was the best-fit model	Decision trees were used for automated diagnosis of primary headaches using a decision support system and unsupervised Weifeiler-Lehman Kernel.
[19]	R. Messina *et al.* (2020)	Neuroimaging, pharmacological therapeutic approaches	Advantages of Machine Learning algorithms in headache patients.

[20]	F. J. Hsiao et al. (2022)	Support vector machines	Machine Learning algorithms were employed to detect the neural patterns of resting-state oscillatory connectivity in individuals with chronic migraines to obtain accuracy of chronic migraine identification using SVM.

III. MATERIAL AND METHODS

This section describes the methods used to determine the type of migraine. The dataset used is also specified in this section. This section has the following sub-sections: A. Dataset used, B. K-Nearest Neighbor Classifier, C. Decision Tree Classifier, D. Naïve Bayes, and E. Gradient Boosting Machines, F. Random Forest classifier, G. Software and hardware.

A. Dataset Used

The migraine dataset used for this research study was created by Ranzeet Raut and obtained from Kaggle [21]. The dataset includes a wide range of variables that can contribute to migraines, including demographic data, the characteristics of the migraine episode, concomitant symptoms, and sensory and neurological aspects. Overall, the migraine dataset described has the potential to significantly advance our knowledge of this complex condition and result in the development of better diagnostic and treatment strategies. The dataset has been trained and tested using Multivariate Analysis. There are 400 rows and 24 columns in the dataset. The training data of the independent variable contains 320 rows and 24 columns. The dependent variable contains 320 rows and 1 column. The test data of the independent variable contains 80 rows and 24 columns. The dependent variable contains 80 rows and 1 column.

Figure 1 illustrates the correlation matrix of the migraine dataset.

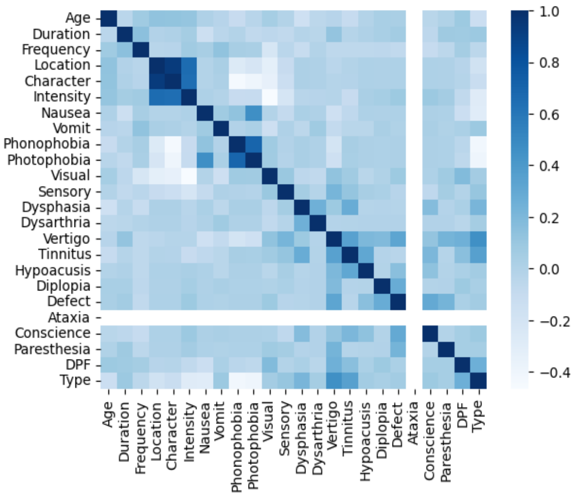

Fig. 1. Correlation Matrix

B. K Nearest Neighbors

KNN is a simple Machine Learning algorithm that finds the k most comparable data points to a new data point and then predicts the value of the new data based on the values of the k closest neighbors. Being a non-parametric algorithm, KNN makes no assumptions about the data's distribution which makes it an extremely flexible technique [22].

C. Decision Tree Classifier

Decision tree, a supervised Machine Learning algorithm, divides the data into subsets based on the most important features. Decision trees are fast-to-train algorithms that can be used to train complex data sets. It traverses the dataset and stores the data obtained in the internal nodes [3]. The algorithm continues this process until it reaches a leaf node where the final predictions are made and presented in the form of a tree data structure to solve classification problems. Figure 2 shows a decision tree.

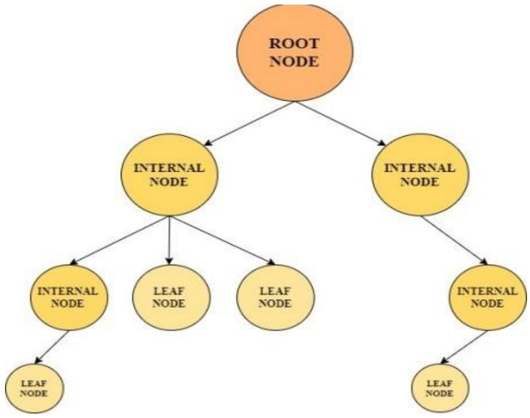

Fig. 2. Decision Tree

D. Naive Bayes

Naive Bayes classifier, another supervised Machine Learning algorithm, follows the principle of Bayes' theorem. It applies the Gaussian Distribution which gives additional characteristics to the algorithm[23]. Predictions can be made more quickly and readily by the algorithm as it assumes that a data point's features are independent of one another. This classifier is known for its simplicity, speed and ease of interpretation [24].

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad (1)$$

E. Gradient Boosting Machines

The Gradient Boosting Machine is an integrated algorithm that builds multiple learners and summarizes the final predictions from these learners [3], thus reducing the overall estimation error. Its primary objective is that the predicted outputs of the model have fewer errors as compared to the model used before. Considering that GBM can handle both continuous and discrete values, it performs better than most classifiers [24]. Figure 3 describes the mechanism of the Gradient Boosting Machine.

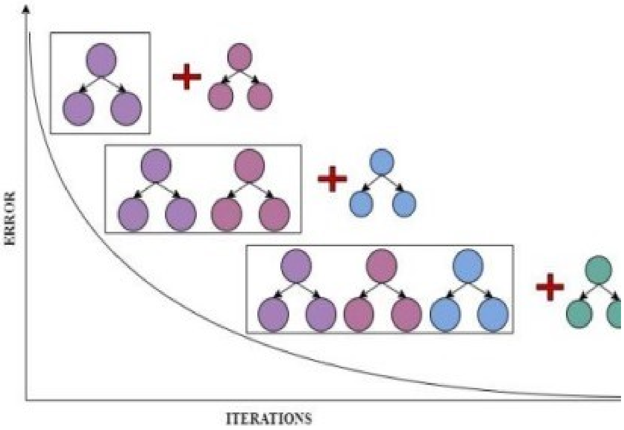

Fig. 3. Gradient Boosting

F. Random Forest Classifier

The Random Forest Classifier is a classifier with many decision trees that uses the ensemble technique of Bagging also called majority voting [3]. It reduces over-fitting while successfully increasing accuracy. Using several data subsets, the random forest classifier trains multiple decision trees. The final prediction is made by arranging the outcomes of individual decision trees [25]. Figure 4 illustrates the mechanism of the Random Forest algorithm.

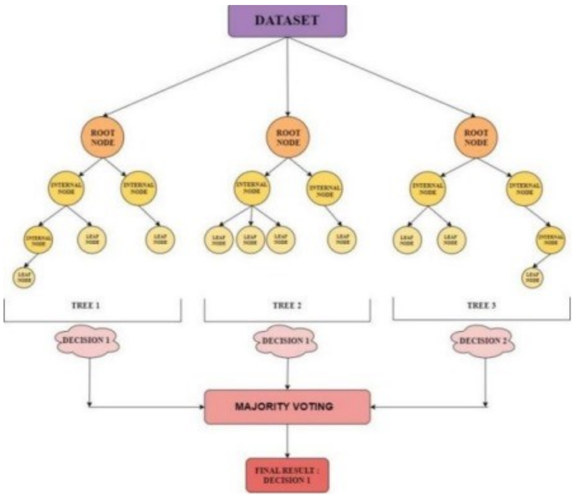

Fig. 4. Random Forest

G. Software and Hardware

All the above-mentioned algorithms of machine learning were trained and tested through Python 3.10 using the sklearn library. The codes were employed using the Jupyter Notebook through Anaconda. The hardware used for the execution of programs is an Intel i7 11th Generation x64-based processor, 16 GB RAM operating on Windows 11 OS.

IV. Experimentation and Results

This section discusses the implementation of the six machine learning algorithms discussed in section 3 on the Migraine dataset. It shows which algorithm has the best accuracy and thus selects the most ideal one for classification. This section has two subsections: A. Implementation and analysis, and B. Results.

A. Implementation and Analysis

In this section, the outcomes are measured using various metrics or evaluation measures to select the best classifiers for the Migraine data set. The predictions are made based on the different parameters given in the dataset. The parameters involve age, duration, and symptoms of migraine. The evaluation measures and their acronyms used, in this paper, are given in Table II.

TABLE II. Metrics Used and Their Acronyms

Sl. No.	Evaluation Measures	Acronyms
1.	True Positive	TP
2.	True Negative	TN
3.	False Positive	FP
4.	False Negative	FN
5.	Accuracy	ACC
6.	Negative Predictive Value	NPV
7.	Confusion Matrix	CM
8.	Mathews Correlation Coefficient	MCC
9.	Specificity	SPEC
10.	F1 Score	
11.	Sensitivity	
12.	Precision	
13.	False Negative Rate	FNR

$$ACC = (TP + TN)/(TN + FP + FN + T) \tag{2}$$

$$NPV = TN/(TN + FN) \tag{3}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)\times(TP+FN)\times(TN+FP)\times(TN+FN)}} \tag{4}$$

$$SPEC = TN/(FP + TN) \tag{5}$$

$$F1\ SCORE = 2TP/(2TP + FP + FN) \tag{6}$$

$$SENSITIVITY = TP/(TP + FN) \tag{7}$$

$$PRECISION = TP/(FP + TN) \tag{8}$$

$$FNR = FN/(FN + TP) \tag{9}$$

Proceedings of the 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT-2024)
IEEE Xplore Part Number: CFP24CV1-ART; ISBN: 979-8-3503-2753-3

TABLE III. METRICS EVALUATION TABLE

Model	Accuracy	Precision	Sensitivity	F1	MCC	SPEC	NPV	FNR	CM	
									TP	FP
									TN	FN
Decision Tree	0.7138	0.7138	0.5094	0.7138	0.4663	0.9909	0.9909	0.4905	27	2
									7	26
Random Forest	0.8138	0.8138	0.7636	0.8138	0.6627	0.9912	0.9912	0.2363	42	1
									6	13
SVM	0.8125	0.8125	0.8125	0.8125	0.7170	0.9756	0.9756	0.1875	13	1
									45	3
Naive Bayes	0.6752	0.6758	0.08	0.6752	0.4501	0.9958	0.9958	0.92	2	1
									36	23
KNN	**0.85**	**0.9622**	**0.555**	**0.85**	**0.7040**	**0.9622**	**0.9622**	**0.444**	**5**	**2**
									51	**4**
Gradient Boosting	0.8221	0.9916	0.7627	0.8221	0.6795	0.9916	0.9622	0.2373	45	2
									1	14

B. *Results*

Table III shows the results of different metrics used and the estimation errors obtained in each model. The results show that KNN is the best-performing algorithm that has given the best results with an accuracy of 0.85. The superior accuracy of KNN is achieved as it can work well with limited data and is not sensitive to outliers. It has also achieved a good Negative Predictive value which shows that the algorithm is good at correctly identifying the negative conditions. KNN also acquires the highest f1 score and precision across the dataset which means that it is good at correctly classifying positive and negative cases. Following KNN is the Random Forest classifier algorithm exhibiting an accuracy of 0.8138 and the highest NPV of 0.9912.

The Naive Bayes algorithm has the lowest performance with an accuracy of 0.6752. Although the Naive Bayes algorithm gives a good specificity, the other algorithms outperform it on all other metrics. It has the highest FNR which means that it incorrectly predicts the positive cases. The algorithm is predicting a lot of false negatives, which is not ideal. The algorithm also shows a low sensitivity which indicates that the classifier is underperforming in identifying true positives. This leads to errors in the prediction of the type of migraine. The reason for such poor performance could be the small size of the data set, which prevented The Naive Bayes model from being able to identify the underlying patterns in the data.

Figure 5 shows a real time graphical representation of Table III for a better comparison of the classifiers and their performances.

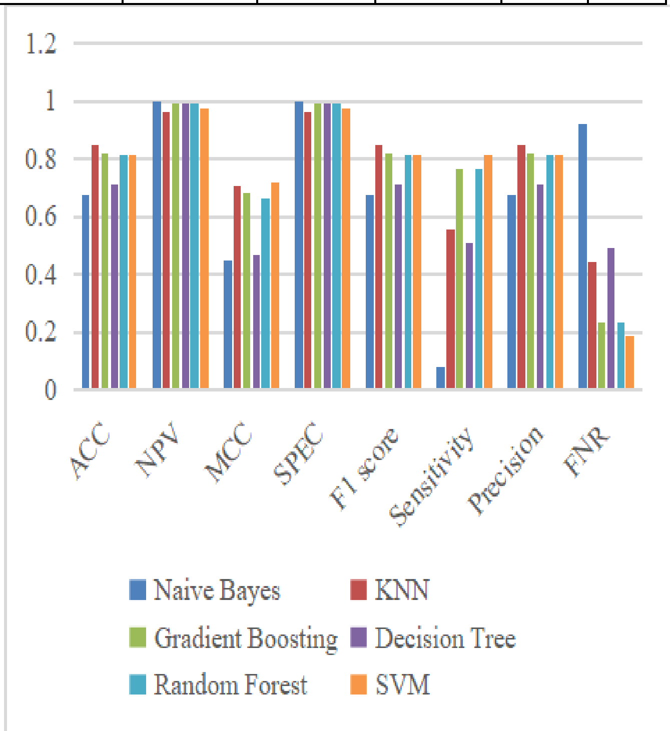

Fig. 5. Graphical Analysis of Table III

Fig 6 illustrates the confusion matrix of the best-performing algorithms.

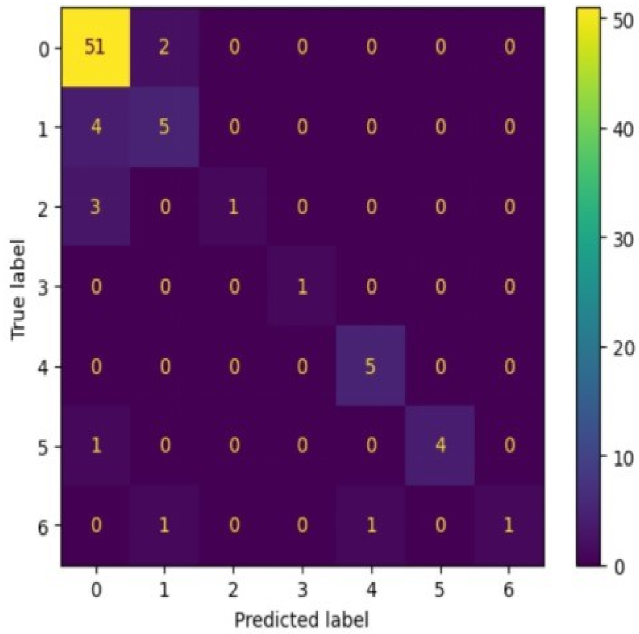

Fig. 6. Confusion Matrix of KNN

V. CONCLUSION AND FUTURE SCOPE

To correctly predict the type of migraine a patient suffers from, a variety of machine learning models have been used here, namely Decision Tree, Random Forest, SVM, Gradient Boosting, Naive Bayes, and KNN. On implementing these algorithms on different metrics, it was seen that the KNN algorithm outperforms all others with an accuracy of 0.85. The Naive Bayes model appeared to have the lowest accuracy of 0.6752.

Thus, the KNN model is the most effective way for predicting the type of migraine. This paper aims to identify the optimal Machine Learning model for identifying the type of migraine based on age, duration, symptoms, and additional parameters by comparing the results of various models. The KNN model shows great accuracy and outperforms all other models while remaining steady and precise.

In future works, advanced techniques such as Natural Language Processing (NLP) and Deep Learning may be used to predict the type of Migraine. These techniques can be applied to real-world data sets to have a more practical use of AI in this field. Natural Language Processing can be used in programs requiring input from the user to predict the type of Migraine the user suffers from. The ML algorithms used in this paper are quite simple and their practical use on a real-world dataset may generate a lower accuracy and precision. However, in the future, Deep Learning Algorithms such as ANN will be implemented on real-world data sets to achieve more accurate AI-based diagnosis.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to their guide Prof. M. K. Gourisaria Sir for providing them with this golden opportunity of working on this research paper and for the tremendous assistance and help in making this endeavor possible.

REFERENCE

[1] A. K. Eigenbrodt, H. Ashina, S. Khan, H. C. Diener, D. D. Mitsikostas, A. J. Sinclair, ... and M. Ashina. “Diagnosis and management of migraine in ten steps,” Nature Reviews Neurology, vol. 17, no. 8, pp. 501-514, 2021.

[2] M. Ashina, “Migraine,” The New England Journal of Medicine, vol. 383, no. 19, pp. 1866-1876, 2020.

[3] F. Liu, G. Bao, M. Yan, and G. Lin., “A decision support system for primary headache developed through machine learning,” PeerJ, vol. 10, pp. e12743, 2022.

[4] C. Lucas, “Migraine with aura,” Revue neurologique, vol. 177, no. 7, pp. 779-784, 2021.

[5] M. A. P. Ruschel and O. De Jesus, “Migraine headache”, StatPearls Publishing, pp. 3, 2023.

[6] G. Ying, W. Fan, N. Li, J. Wang, W. Li, G. Tan, and J. Zhou., “Clinical characteristics of basilar-type migraine in the neurological clinic of a university hospital,” Pain Medicine, vol. 15, no. 7, pp. 1230-1235, 2014.

[7] N. Pelzer, A. H. Stam, J. Haan, M. D. Ferrari, and G. M. Terwindt., “Familial and sporadic hemiplegic migraine: Diagnosis and treatment,” Current treatment options in neurology, vol. 15, no. 1, pp. 13-27, 2013.

[8] J. C. Jen, Familial Hemiplegic Migraine, 2021.

[9] Y. He, Y. Li, and Z. Nie ., “Typical aura without headache: A case report and review of the literature,” Journal of medical case reports, vol. 9, no. 1, pp. 1, 2015.

[10] M. Tanveer, B. Richhariya, R. U. Khan, A. H. Rashid, P. Khanna, M. Prasad, and C. T. Lin, “Machine learning techniques for the diagnosis of Alzheimer’s disease: A review,” ACM Transactions Multimedia Computing Communications and Applications, vol. 16, no. 1s, pp. 1-35, 2020.

[11] M. K. Gourisaria, P. Jain, V. Singh, and T. Choudhury., “A duplex method for classification of Parkinson’s disease using data reduction techniques” in Advances in Distributed Computing and Machine Learning: Proceedings of ICADCML. Singapore: Springer Nature Singapore, pp. 555-565, 2022.

[12] S. Aleem, N. U. Huda, R. Amin, S. Khalid, S. S. Alshamrani, and A. Alshehri., “Machine learning algorithms for depression: Diagnosis, insights, and research directions,” Electronics, vol. 11, no. 7, pp. 1111, 2022.

[13] J. Qin, L. Chen, Y. Liu, C. Liu, C. Feng, and B. Chen., “A machine learning methodology for diagnosing chronic kidney disease,” IEEE Access, vol. 8, pp. 20991-21002, 2019.

[14] M. K. Gourisaria, S. Das, R. Sharma, S. S. Rautaray, and M. Pandey., “A deep learning model for malaria disease detection and analysis using deep convolutional neural networks,” International Journal of Emerging Technologies, vol. 11, no. 2, pp. 699-704, 2020.

[15] W. T. Li, J. Ma, N. Shende, G. Castaneda, J. Chakladar, J. C. Tsai, ... and W. M. Ongkeko ., “Using machine learning of clinical data to diagnose COVID-19: A systematic review and meta-analysis,” BMC medical informatics and decision making, vol. 20, no. 1, pp. 247, 2020.

[16] B. Krawczyk, D. Simić, S. Simić, and M. Woźniak ., “Automatic diagnosis of primary headaches by machine learning methods,” Central European Journal of Medicine, vol. 8, no. 2, pp. 157-165, 2013.

[17] C. D. Chong, N. Gaw, Y. Fu, J. Li, T. Wu, and T. J. Schwedt., “Migraine classification using magnetic resonance imaging resting-state functional connectivity data,” Cephalalgia, vol. 37, no. 9, pp. 828-844, 2017.

[18] G. Vandewiele, F. De Backere, K. Lannoye, M. Vanden Berghe, O. Janssens, S. Van Hoecke, ... and F. De Turck, ., “A decision support system to follow up and diagnose primary headache patients using semantically enriched data,” BMC Medicine Informatics and Decision Making, vol. 18, no. 1, pp. 98, 2018.

[19] R. Messina and M. Filippi, “What we gain from machine learning studies in headache patients,” Frontiers in Neurology, vol. 11, pp. 221, 2020.

[20] F. J. Hsiao, W. T. Chen, L. L. H. Pan, H. Y. Liu, Y. F. Wang, S. P. Chen, ... and S. J. Wang., “Resting-state magnetoencephalographic oscillatory connectivity to identify patients with chronic migraine

using machine learning," Journal of Headache Pain, vol. 23, no. 1, pp. 130, 2022

[21] R. Raut, (2023, October). Migraine Dataset, Version 1. Retrieved September 18, 2023 from https://www.kaggle.com/datasets/ranzeet013/migraine-dataset/data.

[22] N. Salari, A. Hosseinian-Far, M. Mohammadi, H. Ghasemi, H. Khazaie, A. Daneshkhah, and A. Ahmadi., "Detection of sleep apnea using Machine learning algorithms based on ECG Signals: A comprehensive systematic review," Expert Systems with Applications, vol. 187, pp. 115950, 2022.

[23] M. K. Gourisaria, U. Singh, A. Arora, and R. Chatterjee., "Keppler Red Giants Classification using a Machine learning approach" in 2022 OPJU International Technology Conference on Emerging Technologies for Sustainable Development (OTCON), IEEE, pp. 1-6, 2023.

[24] A. Arora, M. K. Gourisaria, and R. Chatterjee., "Classification and analysis of dementia using machine learning algorithms" in IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), vol. 2022. IEEE, 2022, Jul., pp. 1-6, 2022.

[25] S. Sarah, M. K. Gourisaria, S. Khare, and H. Das., "Heart disease prediction using core machine learning techniques—A comparative study" in Advances in Data and Information Sciences: Proceedings of ICDIS. Singapore: Springer, pp. 247-260, 2022.