Advanced Machine Learning Approaches for Accurate Migraine Prediction and Classification

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Abstract*—Migraine is a neurovascular disorder with a prevalence that exceeds 1 billion individuals worldwide, but it has long been recognized to have unique diagnostic challenges due to its heterogeneous pathophysiology and dependence on subjective assessments. As has been extensively documented by a number of international law bodies, migraine in the workplace has been identified as a significant issue that requires urgent attention. Migraine defined by episodic, unilateral and debilitating symptoms including aura, nausea incurs a high socioeconomic burden in disability. Mechanisms such as altered cortical excitability and trigeminal system activation, although researched to a high extent, are still inadequately understood. Deep learning and machine learning (ML) hold tremendous potential for transforming diagnosis and classification of migraine. This study evaluates several machine learning (ML) models such as gradient boosting, decision tree, random forest, k-Nearest Neighbors (KNN), support vector machine (SVM), logistic regression, multi-layer perceptron (MLP), artificial neural network (ANN), and deep neural network (DNN) for multi-class classification of migraine. By employing advanced preprocessing techniques and publicly obtainable datasets, the study addresses the challenge of identifying different types of migraines that may share common variables. In this study, several machine learning (ML) models including gradient boosting, decision tree, random forest, k-Nearest Neighbors show that for multi-class migraine classification MLP and Gradient Boosting had good performance in most models, but did perform poorly in complex subcategories like Typical Aura with Migraine. Both attained high accuracies (96.4% and 97%, respectively). KNN and Logistic Regression, two traditional models, performed well at basic classifications but poorly at more complex situations; Neural networks (ANN and DNN) showed much flexibility towards data complexities. These results underscore how important it is to align model selection with data properties and provide avenues for improving performance through regularization and feature engineering. This strategy illustrates how AI-powered solutions can revolutionize the way we manage, treat, and prevent migraines across the globe.

***Keywords*—Headache classification; migraine; migraine diagnosis; migraine classification**

I. Introduction

Migraine is a complex and common neurovascular disease that poses many challenges to accurate diagnosis and effective treatment. More than 90% of people in the world are affected by headache disorders in general [1], but migraine stands out for its effects on the brain, body, and quality of life in particular. They are among the most common causes of neurological consultations, and treatment costs in countries such as China approach an annual 672.7 billion yuan [2]. Although migraines are not directly life-threatening, they significantly impair work performance, physical health, mental well-being, and overall quality of life [3].

The multifaceted nature of migraine, a chronic medical condition with overlapping legal and social dimensions, is well-documented. The impact of this condition on individuals' rights, professional and personal lives is significant and thus requires a comprehensive response that combines advanced healthcare, legal protection, and technological innovation. Internationally, international laws play a crucial role in regulating the treatment of chronic and complex diseases such as migraine, which have a profound impact on patients' quality of life and functioning. In this context, the International Covenant on Economic, Social and Cultural Rights (ICESCR) is a significant instrument, as it recognizes in [4] the right of individuals to health, a comprehensive right that is not limited to the provision of treatment but extends to the right to access basic healthcare services, including migraine treatment. This right is essential not only to improve the state of health of patients but also to restore the ability to lead a normal professional and social life [5, 6].

The Convention on the Rights of Persons with Disabilities (CRPD) further underscores the imperative to ensure that individuals with disabilities, including those afflicted by chronic migraine, have access to essential health services [7]. The CRPD obliges state parties to formulate comprehensive health policies that guarantee the provision of specialised medical care, taking into account individual differences in diagnosis and treatment. The utilisation of innovative technology, including machine learning techniques, has the potential to enhance the accuracy of diagnosis and personalise treatment regimens, ensuring that all patients receive the timely and optimal care they require.Legislative frameworks, such as the Americans with Disabilities Act (ADA) in the United States, play a pivotal role in safeguarding individuals with migraine from discrimination in the workplace. This legislation stipulates the provision of reasonable accommodations, such as flexible work schedules, quiet work environments, and the ability to work from home, thereby ensuring that individuals with migraine can continue to perform their professional duties in a manner that is both conducive to their well-being and effective in their roles [5,8].

Migraine, the top cause of functional disability among people aged 15 to 55, can severely hamper productivity and routine activities during episodes. The often-unpredictable nature of migraine attacks increases the anxiety and dysfunction related to them by the uncertainty of when they might occur. Conventional treatment strategies either interrupt migraine during an attack or reduce their frequency through preventative measures. Preventive medication on high-risk days, as well as abortive treatment that is most effective early in the migraine cycle, has moved from proof-of-concept studies with more promising early data. This highlights the need for prediction-based solutions in migraine management. In the International Classification of Headache Disorders (ICHD). In [9], headaches are classified into three categories: primary headaches (e.g., migraine, tension-type headaches, and trigeminal autonomic cephalalgias), secondary headaches, and cranial neuropathies or facial pain disorders.

Causes of migraines are myriad, including diet, lifestyle, genetics, and physiology (Fig. 1). The role of dietary triggers, such as caffeine, alcohol, and food additives, together with lifestyle factors, such as stress, poor sleeping patterns, and lack of exercise, cannot be underestimated in precipitating attacks. Additional risk factors include having a genetic predisposition to the condition and heightened susceptibility driven by physiological as well as biochemical factors, from hormonal fluctuations to neurotransmitter imbalances, which leads to the onset of migraines. Migraines have a multi-faceted pathophysiology, with two key components being triggers (stimuli causing attacks) and prodromal symptoms, cognitive, sensory, behavioral, or physical changes, that can occur 1 to 48 hours before an attack, and serve as critical but difficult-to-measure indicators of imminent migraines due to their highly subjective nature and methodological biases. Indeed, neurophysiological changes (e.g. changes in autonomic tone) can inform on this prodromal phase. Migraine and tension-type headaches are the most common types of primary headaches worldwide, with 10% and 40% respectively, while cluster headaches are rare, with an estimated prevalence of 0.1% [10, 11].

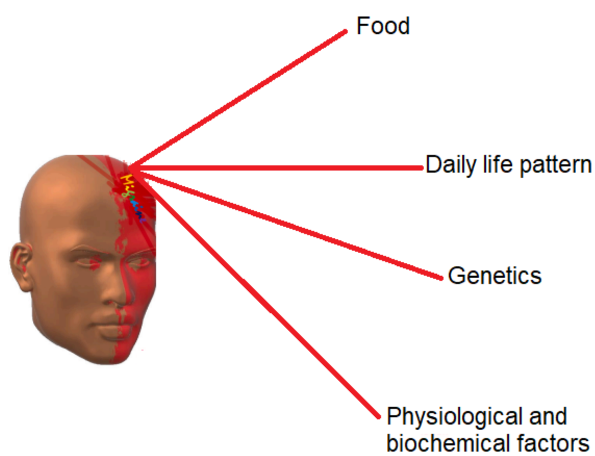

Fig. 1. Factors that trigger migraine.

Intractable migraines, with a 16% annual incidence in the general population, are the second most prevalent cerebral disease in the world and rank as the leading cause of disability worldwide, even more than all neurological diseases combined [12]. Migraines are generally divided into three categories: migraines with aura, migraines without aura, and chronic migraines. Migraines with aura occur in up to 25% of cases and are characterised by transient visual, speech, or neurological abnormalities lasting no longer than an hour [13]. Migraines without aura, on the other hand, appear as unilateral, moderate-to severe-intensity, pulsatile pain, often with accompanying nausea and vomiting, photophobia, and phonophobia, and can last from 4 to 72 h if untreated [14]. Migraine is classified into episodic (less than 15 headache days per month) and chronic types (defined as 15 or more headache days per month with eight or more headache days with features of fully developed migraine), the latter being more frequent and having an unfavorable impact on daily life [15].

Digital technologies on the rise allow new opportunities in migraine management. Direct translation can occur through wearable technology and mobile health technologies for headache characteristics, prodromic symptoms, and physiological changes. However, because so much complexity is involved in the neurobiological processes underlying migraine, prediction can be difficult. Accurate prediction requires sophisticated models capable of integrating and interpreting complex flows of biological and physiological data. Machine learning (ML) appears to be a promising solution, as it can process and analyze complex and heterogeneous data types. Machine learning could streamline migraine detection, prediction, and classification processes, enhance diagnostic accuracy, optimize treatments, and ultimately reduce the financial and societal burden associated with migraine management.

This study aims to explore the revolutionary potential of machine learning (ML) to evolve migraine attack prediction, particularly in resource-limited settings with limited access to state-of-the-art medical technology. Even when they can be valuable, conventional diagnostics such as MRI (Magnetic Resonance Imaging), PET(Positron Emission Tomography) and CT(Computed Tomography) scans are pricey and require specialist knowledge, which places them at a disadvantage in developing countries. When using ML algorithms that provide a cost-efficient and high-throughput alternative, reliable systems for diagnosing and predicting the onset of migraine are now widely available.

Many advanced machine learning techniques were evaluated in this study, such as artificial neural networks (ANN), deep neural networks (DNN), multi-layer perceptron (MLP), logistic regression, k-nearest neighbors (KNN), support vector machines (SVM), gradient boosting, decision trees, and random forests. Models showed promising results with a model accuracy of 97.12% (MLP), 96.40% (Gradient Boosting), and 96.04% (Decision Tree). Such results showcase this exciting potential for AI-powered approaches to revolutionize headache management and improve patient outcomes globally.

The remainder of the paper is organized as follows: the “Related Work” section re-views prior research, while the “Materials and Methods” section outlines the proposed methodology and dataset. The “Experiments” section details the conducted experiments and their findings. Finally, the “Conclusion and Future Work” section summarizes the key results and outlines potential directions for future research.

II. Related Work

Recent advances in artificial intelligence (AI) can yield complex predictive algorithms able to predict migraine episodes. Smith et al. For instance, [16] used supervised machine learning methods such as random forests and deep learning networks on longitudinal data collected by biometric tracking devices or mobile applications. A great example was given by the team at the National Institutes of Health, who showed that neural network models were able to predict future migraine attacks 85% of the time by including trigger factors (stress, sleep, food, etc.) into the model. This underscores the need for machine learning to pre-emptive migraine treatment, and real-time data collection.

Several studies have explored whether the combination of multimodal data (e.g. genetic, environmental, and behaviour) can augment prediction accuracy. The model of Zhang et al. [4] was able to achieve better sensitivity and specificity than using conventional methods by integrating information from genetic profiles, lifestyle surveys, and wearable sensors. The results show how combining data from multiple sources can help us learn more about and predict migraine episodes.

There has also been ongoing research regarding advancement in early detection of migraines using brain imaging techniques as well as biomarkers. For example, during the premonitory phase of migraines, Garcia and his team found cues that predicted a migraine episode was coming [17] and uncovered discrepancies in patients' levels of neurotransmitters; that is, glutamate and serotonin. Using functional magnetic resonance imaging (fMRI), their study suggested that there are different patterns of brain activity before and during migraine attacks, with encouraging potential prospects for real-time detection. Adding to this, Garcia et al. [17] conducted further research on serum biomarkers in migraine patients, including increased levels of glutamate and serotonin. This opens up the potential of diagnosis by biomolecular profile and hints at neurological mechanisms. Their techniques help ensure early intervention strategies, which become more accurate by providing a non-biassed way to identify migraines.

Continuous monitoring devices like smartwatches and fitness trackers have captured interest due to their ability in terms of potentially mitigating migraines. According to Lee et al. when physiological data (e.g. heart rate and stress) were collected in real time, they gave a 78% chance of detecting the initial symptoms for migraine [18]. These results highlight the benefits of regular physiologic monitoring in migraine therapy and may become a paving method for wearable technology-assisted preventive treatment fighting techniques.

Conventional approaches to migraine classification are based on the International Classification of Headache Disorders' (IHS) symptoms criteria. Recent studies, however, aim to improve this strategy by adding more precise clinical features. Müller et al. [19], for example, discovered a subtype of migraine associated with increased sensory sensitivities and sleep disturbances, opening the door to more individualized treatment choices.

The classification of migraines has been further transformed by genomic advancements. A meta-analysis of genetic research by Johnson et al. [20] found many genetic loci linked to heightened migraine risk. Their study suggested a genetic risk classification by combining genetic data with clinical information. This in turn permitted both patient stratification and treatment individualization to the genetic profile of each host.

The study in [21] used five different supervised machine learning methods which aimed to define group of symptoms described by participants as migraines. For classification and deployment, we used Weka data mining tool. The results indicated that, of all the models tested, naïve bayes would be more suitable and easier.

An investigation [22] used brain signals captured through an EEG and a computer-aided diagnostic (CAD) system to classify various forms of migraines. This system accomplished classification using deep learning models as follows: VGG16, ResNet101, and DenseNet121.

A method to integrate EEG in an online migraine detection tool for support of clinical decision making was also presented by a respective study [23]. The EEG dataset consisted of recordings from 21 healthy volunteers and 18 migraine patients. The results showed that the Bi-LSTM method with 128 channels outperformed other models, including Random Forests (RF), Linear Discriminant Analysis (LDA), and Support Vector Machines (SVM), with the maximum accuracy of 95.99%.

Furthermore, 400 patients' clinical data that had been annotated by domain experts was employed in a different study [24]. The 24 most pertinent factors were chosen after the researchers first collected data based on symptoms. Then, to categorize migraines, an Artificial Neural Network (ANN) and other conventional machine learning models were used. The ANN model outperformed other algorithms including SVM, Logistic Regression (LR), Decision Trees, and k-Nearest Neighbors (KNN) with a 97% classification accuracy for migraines.

In [25], different machine learning techniques were used to examine somatosensory evoked potential components in the frequency and temporal domains for migraine categorization. Among these were Logistic Regression (LR), Linear Discriminant Analysis (LDA), Random Forests (RF), k-Nearest Neighbors (KNN), Extreme Gradient Boosting (XGBoost), Support Vector Machines (SVM), and Multilayer Perceptrons (MLP). The models were able to differentiate between interictal or ictal migraine conditions and healthy controls with an accuracy of over 88%.

In detecting the two classes of headaches and differentiating between healthy controls and migraine sufferers, the CNN method based on an initiation module outperformed the conventional support vector machine, which had an accuracy of 83.67%, with a greater accuracy of 86.18% [26]. A feature selection technique was used in a different study [27] to enhance the migraine group's classification. With accuracies rising from 67% to 93%, 90% to 95%, and 93% to 94%, respectively, this method improved the performance of the Naive Bayes, SVM, and Adaboost classifiers. In a similar vein, a study by [28] that used EEG signals to diagnose migraines early revealed that the artificial neural network (ANN) outperformed logistic regression and support vector machines (SVM) with an accuracy of 88%. Hemoglobin changes in the prefrontal cortex (PFC) were observed using functional near-infrared spectroscopy (fNIRS) during a mental arithmetic (MAT) task. The specificities and sensitivities were 75% and 100% for chronic migraine (CM) and 100% and 75% for medication overuse headaches (MOH), respectively. Based on the findings, it seems that fNIRS and machine learning work better together to classify migraines [7].

In the medical industry, data mining techniques are essential. Data exploration classification methods such as Naïve Bayes, KNN, SVM, and random forests were used in the study [29]. Among these, Naïve Bayes emerged as the best classifier, with an accuracy of 0.905 and a precision of 0.475. A medical case study on hemodynamic parameter monitoring of actual patients is presented as a practical scenario to monitor real patients' life parameters using the WBSN (Wireless Body Sensor Network). N4SID models (Numerical Subspace State-Space System Identification) were built with a low false positive rate and an average forecasting horizon of 47 minutes [30]. Finally, we used one of machine learning techniques to distinguish healthy subjects with migraineurs by combining three functional measures from rs-fMRI [31].

Ufuk et al. [32] proposed the use of deep neural networks (DNN) for diagnosing migraines, achieving an accuracy of 95%. They used eight attributes to diagnose three types of migraines (with aura, without aura, and chronic migraine). Ferroni [33] suggested using a decision support system (DSS) to diagnose medication-overuse migraine, with an accuracy of 82%. In another study [34], a DSS was proposed for diagnosing primary headaches, achieving an accuracy of 80%. The authors compared four machine learning techniques: Bagging, Naïve Bayes, Boosting, and Random Forest. Rober Keight [36] proposed using decision trees (DST) to diagnose primary headache types using 9 machine learning classifiers, achieving an accuracy of 95%. Hao Yang [35] used convolutional neural networks (CNN) for migraine classification from MRI, achieving an accuracy of 99%. Akben [36] implemented an artificial neural network (ANN) for migraine diagnosis, with an accuracy of 83.3%. Akben [37] also used an SVM classifier to diagnose migraines, achieving an accuracy of 85%. Subasi [38] tested different versions of the Random Forest method for migraine diagnosis, obtaining an accuracy of 85.95%. De la Hoz [39] used an ANN for migraine diagnosis, achieving an accuracy of 88%. Yolanda Garcia [27] proposed feature selection for migraine diagnosis, achieving an accuracy of 90%. Even more recently, researchers have focused on the use of MRI and fMRI images for the detection and classification of migraines [40–42].

In [43], the study presented the design and development of an ML decision support system aimed at providing diagnosis of tension headaches and migraines. The results obtained with the logistic regression model were found to be the best among all. The accuracy level raised to 0.84 with a stand against models such as gradient boosting algorithms and random forests.

The Table I describes the parameters that were used during related works.

TABLE I. PARAMETERS USED DURING RELATED WORKS

Study	Techniques Used	Dataset/Attributes	Accuracy
[23]	Bi-LSTM, SVM, LDA, Random Forest	EEG signals from 18 migraine patients and 21 controls	95.99%
[24]	ANN, SVM, Logistic Regression, Decision Trees, KNN	Clinical data from 400 patients	97%
[25]	SVM, RF, KNN, XGBoost, LDA, MLP, Logistic Regression	Somatosensory evoked potential features	88%
[26]	CNN with initiation module	EEG signals	86.18%
[27]	Naïve Bayes, SVM, Adaboost	Feature selection applied to migraine group	Increased from 67%-94%
[28]	ANN	EEG signals, fNIRS	88%
[29]	Naïve Bayes, KNN, SVM, Random Forest	Data exploration techniques for classification	90.5% (Naïve Bayes)
[32]	DNN	8 attributes for diagnosing 3 types of migraines	95%
[33]	DSS (Decision Support System)	Medication-overuse migraine data	82%
[35]	DSS	Primary headache data	80%
[24]	DST (Decision Trees)	9 machine learning classifiers for primary headache types	95%
[36]	CNN	MRI data for migraine classification	99%
[37]	ANN	-	83.3%
[38]	SVM	-	85%
[39]	Random Forest	Different versions of Random Forest	85.95%
[40]	ANN	-	88%
[43]	Logistic Regression, Gradient Boosting, Random Forest	Symptom-based data for headache classification	84%

III. MATERIALS AND METHODS

The provision of preparation of the data takes a long time and uses relatively powerful computational resources, with the straightforward methods of deep learning/machine learning. Therefore, getting some relevant information depends on an effective machine learning system. Designing further this machine-learning architecture is therefore quite complicated. Customizing or tuning a model involves adjusting the parameters of the classifier.

In this study, different models were trained using a variety of machine-learning algorithms. These were adjusted and optimized afterward for the dataset in order to enhance the quality of classification. As shown in Fig. 2, the algorithms that have been considered include Gradient Boosting, Decision Tree, Random Forest, k-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression, Multi-Layer Perceptron (MLP), Artificial Neural Networks (ANN), and Deep Neural Networks (DNN).

A. Dataset

An in-depth examination of contributing causes and related symptoms is made possible by the migraine database that is supplied, which provides a thorough and exhaustive overview of the many components of this ailment. Individuals' ages, which range from 18 to 70 years old, are a crucial component of the demographic data since they enable investigation of the effects of migraines on various age groups. This dataset is notable for its comprehensive examination of the features of migraine episodes, recording variables like attack duration (which can vary from 30 minutes to 72 hours) and frequency (which can range from 1 to 10 attacks per month), providing a more accurate picture of symptom severity and recurrence. Additionally, a scale from 1 to 10 is used to assess the pain's intensity, with 10 being the most severe agony.

Additional information is given on where the pain may occur, which assists with spotting recurring patterns, such as

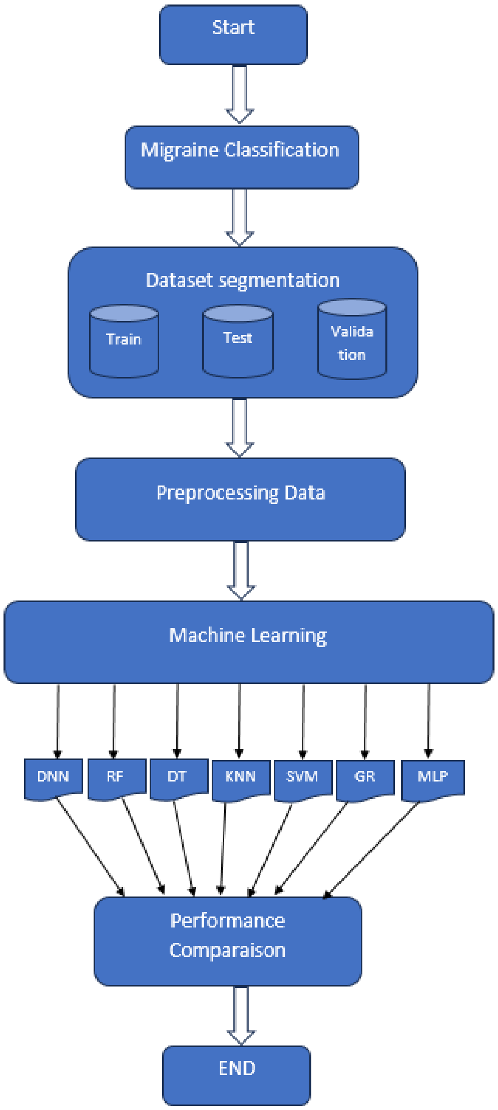

Fig. 2. Proposed system flowchart for migraine classification.

a preponderance of unilateral pain (either right or left) or pain felt on the forehead, neck, or temples. The database has also captured those associated conditions, nausea and vomiting, typical signs of migraine. The other statistic showing that 70% of migraineurs feel sick and about 50% vomit during a headache creates a more nuanced clinical impression of the side effects.

In addition to the actual pain, this database includes phenomenological and other sensory characteristics of migraines: phonophobia (hypersensitivity to sound), photophobia (hypersensitivity to light), and other visual anomalies (blurriness, aura, etc.). The extremely important features of this disease dealing with the sensory aspect are the symptoms, and about 60% of migraineurs experience photophobia and phonophobia during their attacks.

This dataset, with its rich pool of variables, affords taking a deep look into migraine research, leading to empirical observations to determine the associations among variables. Having this data will allow for extensive studies related to how age, frequency of attacks, intensity, and concomitant symptoms influence the severity of migraines. The scientific and medical community would greatly benefit from this resource, as it is of prime importance to improve diagnostics, design personalized treatments, and take more focused approaches to treatment in clinical practice.

1) Database preprocessing: Data preparation is an important step before applying machine learning models in order to obtain really reliable results. This comprises a number of crucial sub-steps in the context of our analysis of migraine data, including noise reduction, inconsistent data repair, error detection, and data conversion into useful numerical variables.

We began our efforts by doing much cleaning of the data: extreme values and missing information were removed, mismatches resolved, and missing numbers imputed. For example, any rows where there was missing data on features such as age, severity of pain, or frequency of attack were either deleted or imputed. To further ensure data validity and consistency, problematic cases of data entry (like somewhat unbelievable values of negative ages and migraine attacks lasting more than 72 hours) were fixed.

The input was then transformed into numerical variables so that machine learning algorithms could process it more easily. To make the data interpretable for the analytic models, some variables, such as pain intensity, were left on a numeric scale (from 1 to 10), while other variables, like related symptoms (nausea, vomiting, phonophobia), were converted into binary variables.

These methods have strengthened data quality and made our dataset a better candidate for machine learning models while simultaneously guaranteeing a balanced representation of the various classes (such as severe and non-severe migraines). This pre-emphasis technique is what allows a model to achieve the highest performance possible during training and yield analyses that are more reliable and precise of variables linked to migraines.

The study relied on an initial corpus of 1,386 clinical records of Tunisian patients suffering from various pathologies associated with migraines. Several machine learning classifiers, including KNN, SVM, RF, DT, LG, MLP, ANN, and DNN, were applied. The proposed analysis used the diagnosed condition and migraine symptoms as input data.

This analysis focused on 23 variables, including age, visual disturbances, dizziness, and vomiting that represent the common clinical symptomology during an acute headache. In addition, the variable identified as diagnostic was included to signify the type of migraine classically referred to. This variable is the diagnosis of the migraine type that was made by the doctor on the basis of the patient's medical history and reported symptoms. The symptomatic variables record the manifestations such as nausea or lightheadedness.

The Feature Importance Analysis is shown in Fig. 3, with enrolling age, visual disturbances, intensity of pain, and phonophobia among the class-leading features in migraine classification. On the contrary, there are worthless factors such as ataxia, diplopia, and dysarthria that have little influence on classification and could be disregarded; this would increase efficiency and thereby help simplify the model. This procedure emphasizes the priority of emphasizing the necessary components while eliminating the least important ones to boost the performance of classifications.

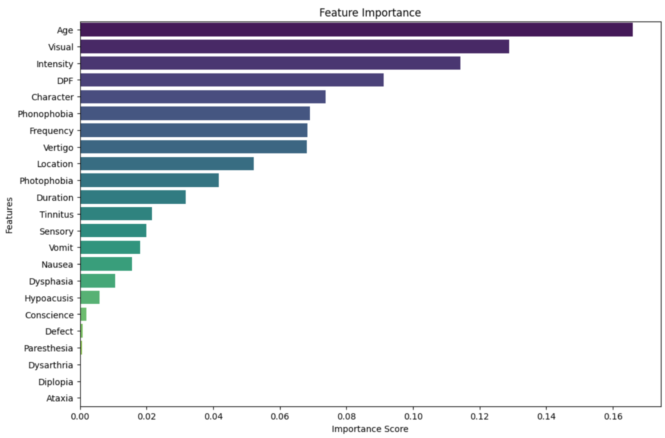

Fig. 3. Feature importance analysis for migraine classification.

B. Classification Models

The algorithms testing on the migraine classification dataset after applying the basic preprocessing methods, various machine learning methods including GB, LG, SVM, KNN, DT, RF, MLP, ANN as well as deep neural network DNN were applied to the dataset.

The parameters utilized in the experiment are described in Table II.

TABLE II. Hyper-parameters for Different Models

Model	Hyper-parameter	Value
multirow DNN	Number of epochs	100
	Activation function	relu
	Optimizer	Adam
	Model	Sequential (first layer)
	Number of neurons at first dense layer	512
	Hidden layer	2
	Classification function	softmax
	Loss function	categorical-cross entropy
SVM	Kernel	Linear
	Class	sklearn.svm.SVC
	Regularization parameters C	1
	Probability	True
KNN	Neighbors range	(1,15,1)
	Weights	Uniform
	Metric distance	Euclidean
RF	n_estimators	100
	max_depth	50
	min_samples_split	5
	min_samples_leaf	2
	max_features	sqrt
	random_state	42

IV. Experiments and Results

The outcomes for migraine classification using various machine learning models are presented in this section. Specifically, we focus the assessment on the classifiers of complexity namely Multi-Layer Perceptron (MLP), Deep Neural Networks (DNN), and Artificial Neural Networks (ANN). These classifiers were examined in detail with a view that performance assessment based on a variety of training sets would reveal their capability in maintaining accuracy, robustness, applicability in migraine diagnosis and attacks management with a large dataset. In-person examination and assessment reveal to a great degree the applicability of such techniques in real life including the merits and demerits.

A. ANN Model

Despite the fact that both belong to the same family of neural networks, ANN and DNN stand separated by layers-of-Depth and complexity, which will influence their efficiency in predicting, detecting, and classifying migraines. ANN, having just one or two hidden layers, is more preferred in classification, such as classifying migraineurs from clinical tabular data, because ANN works better with small datasets due to its lesser training data requirements and resistance to overfitting. Fig. 4 illustrates the basic architecture of ANN.

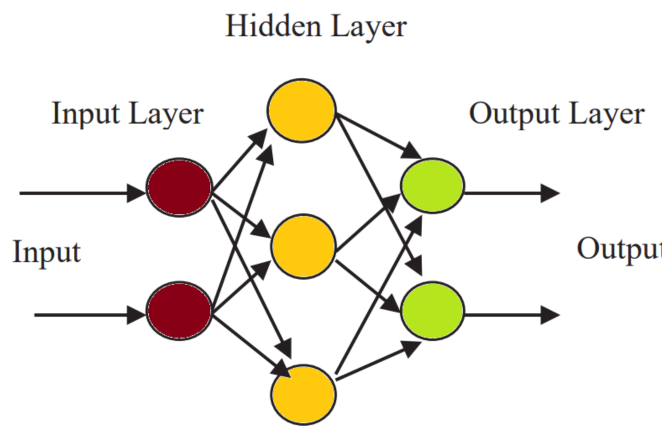

Fig. 4. Basic model of ANN.

The accuracy curves (Fig. 5) show a steady improvement in performance over the 100 epochs, reaching a high level and stabilizing around 95% for both the training and validation sets. The model does not exhibit significant signs of overfitting, as the validation accuracy closely follows the training accuracy. This indicates that the dense neural network (ANN) has effectively learned to generalize without being restricted solely to the training data.

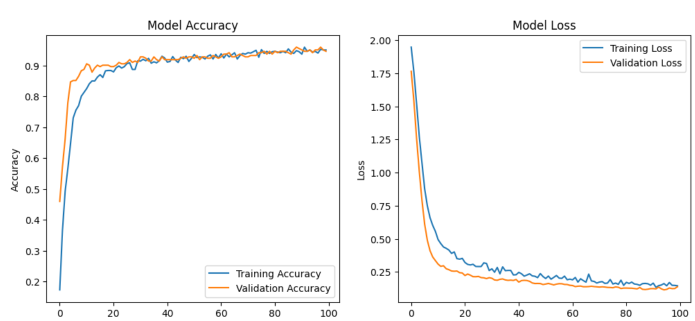

Fig. 5. Accuracy and loss graph of ANN model.

The loss curve (Fig. 5) demonstrates a steady decline, converging toward a low value, indicating the effective training of the ANN model. The validation loss closely mirrors the training loss, confirming good generalization without noticeable overfitting or underfitting.

The confusion matrix (Fig. 6) provides a detailed assessment of the model's classification performance across different categories. Correct predictions are highlighted along the main diagonal, with most classes, including Basilar-type aura, Familial hemiplegic migraine, Migraine without aura, Other, and Typical aura without migraine, exhibiting near-perfect accuracy. However, some misclassifications are noted, particularly for Sporadic hemiplegic migraine, which shows moderate confusion with the Other category, and for Typical aura with migraine, where a few samples are incorrectly classified as Basilar-type aura or Familial hemiplegic migraine.

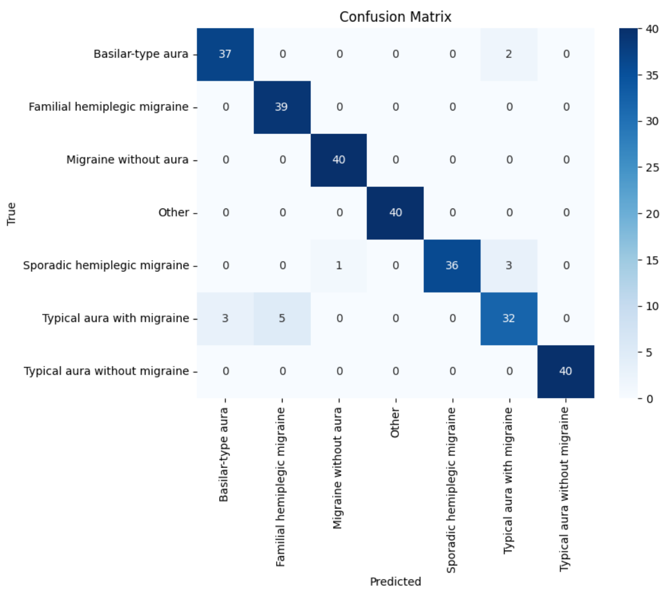

Fig. 6. Confusion matrix of ANN model.

The ANN model provides relatively good performance, and that can be seen by clear separability among most of the classes and fewer misclassifications there. Additional support for effective learning and generalization is provided by accuracy and loss curves. However, remaining challenges relate more to classes with overlapping characteristics, such as migraines with or without aura and the different types of hemiplegic migraine. Class imbalances or an insufficient distinction among classes in the dataset could be responsible for the said problems.

B. DNN Model

Deep neural networks (DNN) become particularly suited for such works because of their more comprehensive and deeper architecture and their capability to furnish complex information, for instance, time-series information collected by Internet of Things sensors for other physiological signals (ECG, vectorcardiogram), or functional MRI images. The ability of these models to perform well in complex tasks-such as discerning migraine types (e.g. aura versus non-aura) and amalgamating data from various sources to give timely warning of migraine attacks-is astonishing. An ability to capture complex interactions proves helpful to tackling migraine classification's different challenging problems. However, the efficiency of DNN usually depends on the availability of large datasets and the employment of complex regularization techniques to minimize the risks of overfitting. Thus, this emphasizes how critical it is to have proper data preparation and model optimization to fully leverage the advantage of DNN in this field.

The architecture of the DNN model used in the classification of migraine types is described in its Fig. 7. It has four layers-an input layer, two hidden layers, and an output layer. This architecture can manage the complexity of the migraine-related datasets and give extremely high classification results.

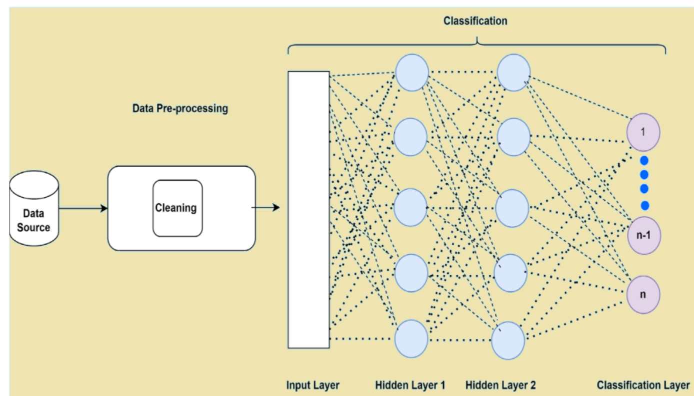

Fig. 7. Fundamental architectural design of a deep neural network applied to migraine classification.

The DNN model showed a fast improvement of performances within the first epochs, after which the accuracy curve was stable at above 95% up to the end of 100 iterations, as seen in Fig. 8. This behavior shows the ability of the model to form these important data features and learn them. The training accuracy matched close to the validation accuracy, which shows good generalization capability. The two curves diverge only mildly, indicating that the model avoids overfitting and can keep providing high performance on unseen data.

The loss curve, also shown in Fig. 8, drops swiftly in the first few epochs, indicating a decent learning process that reduces errors. The optimization is seen to be successful when the curve plateaus at a low value. The same pattern occurs in the validation loss, which indicates that the model was well-regularized and neither overfit nor underfit. Lastly, an additional line indicates the test loss, which tells the generalization of this model to independent data, lying very close to the training and validation losses.

This robustness of the model has also been corroborated by the recall and F1-score metrics, assessing its capacity to classify each class correctly and strike a balance between precision and recall. All average values for these metrics exceed 0.95.

The confusion matrix in Fig. 9 provides a detailed treatment of misclassifications. The great clustering of values along the diagonal illustrates that most samples have been correctly assigned. There are, however, slight misclassifications, including

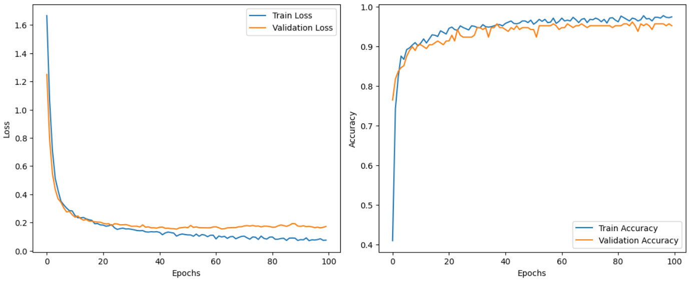

Fig. 8. Accuracy and loss graph of DNN model.

the assignment of four sporadic hemiplegic migraine samples to other categories and the wrong assignment of two Basilar-type Aura samples as Typical Aura along with migraine. These unintentional errors are common in any multi-class classification problem; being rare, they barely dent the overall efficacy of the model.

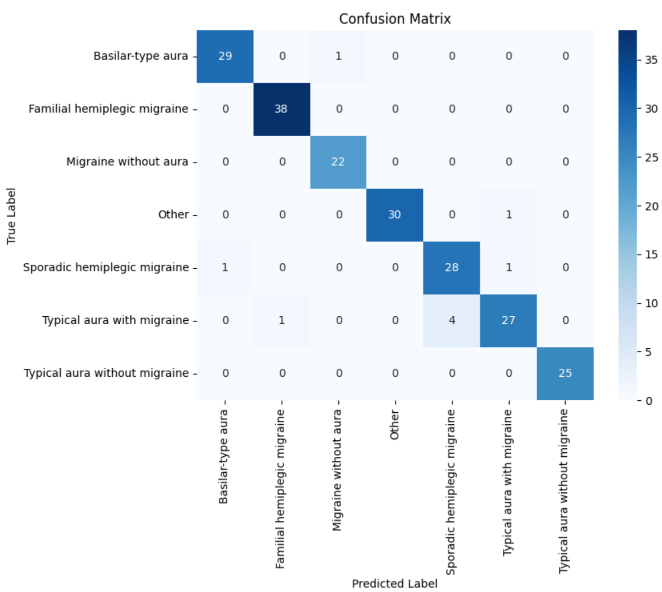

Fig. 9. Confusion matrix of DNN model.

The findings reveal the successful classification of migraines by the DNN model and its high generalization capability for fresh data. The resilience of the model is evidenced by the almost-perfect results in numerous categories and overall high accuracy. These encouraging results suggest that DNN can support the diagnoses and categorizations of different types of migraine while maintaining a strong balance between learning and generalization.

C. Multi-Layer Perception Model

The architecture of the Multi-Layer Perceptron (MLP) model, presented in Fig. 10, is essential for classification tasks, particularly in predicting migraine types.Taking factors such as age, migraine severity, or symptom frequency as inputs, the architecture comprises three main modules: the input layer, hidden layer(s), and the output layer. The hidden neurons nest in various buried layers, using activation functions and weight computations to identify complex patterns in the data. The output layer gives predictions like Migraine with Aura or Migraine without Aura. Every neuron uniformly influences the neurons in the downstream layers, thus enabling the MLP to model complex and intricate non-linear relations while analyzing clinical migraine data.

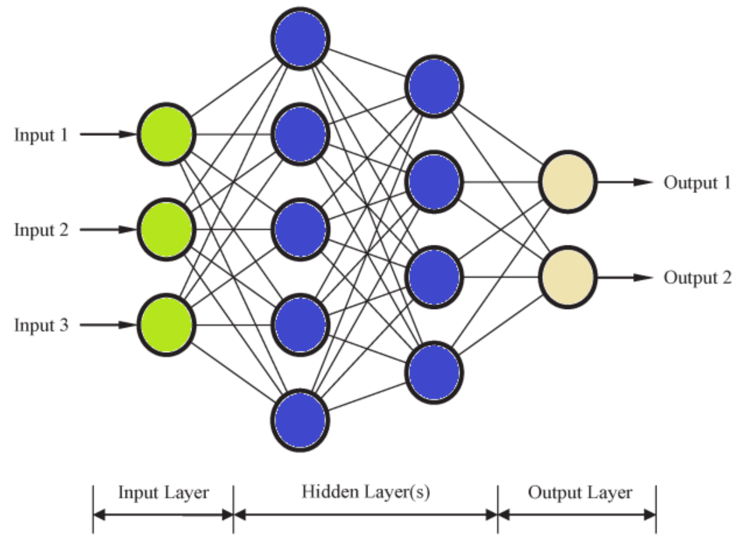

Fig. 10. MLP Model architecture.

How well the Multi-Layer Perceptron (MLP) model have performed in migraine prediction, detection, and classification is validated by the learning curves (Fig. 11). The loss curve which is an insight into learning, shows a very high decrease from 1.75 to around 0.2 during the initial 20 epochs, thereby it rapidly develops. It then stabilizes between 0.1 and 0.2, which indicates the model has been successfully trained and has effectively converged. Notably, when the training and validation loss curves are in close proximity it implies a lack of overfitting and high generalization to new data by the model which is another way of saying its accuracy is high hence.

The accuracy curves (Fig. 11) further underscore the model's success, showing a swift increase in performance, reaching 95 to 97% accuracy within the first 20 epochs and maintaining stability afterward. Although slight fluctuations in the validation curve occur likely due to mini-batch variations or sample differences they do not compromise the overall robustness of the results. The consistency observed between the training and validation curves for both accuracy and loss demonstrate that the model is well-regularized and capable of generalizing effectively.

These results support the MLP model's dependability in accurately diagnosing migraines while striking the ideal balance between generalization and learning.

The results gathered by the model are quite promising and reassuring in finding which kind of migraines types is dissimilar, even in the case of a multi-class scenario, when things are much more complicated. As the confusion matrix (Fig. 12) is quite detailed, we can witness the model's performance within different migraine categories.

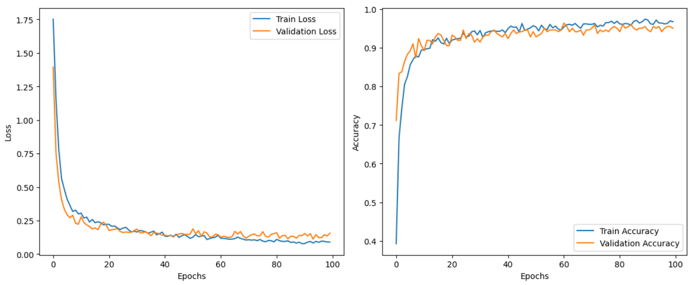

Fig. 11. Accuracy and loss graph of MLP model.

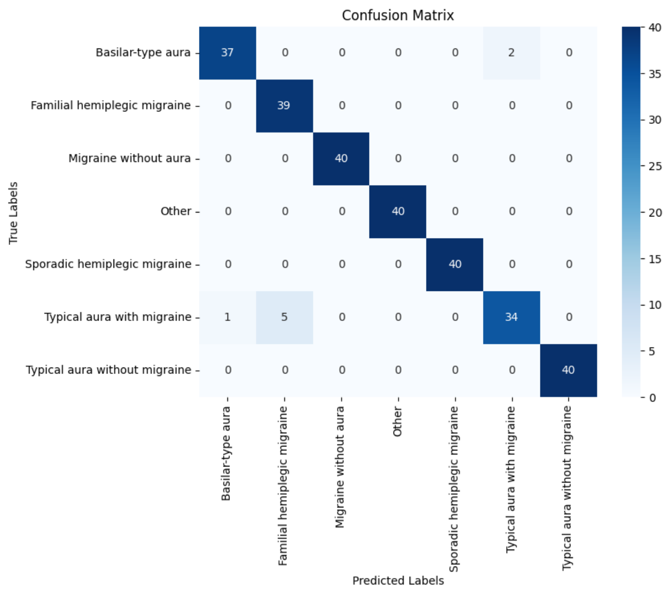

Fig. 12. Confusion matrix of MLP model.

The performance of classes demonstrates very high precision in a small number of categories. Notably, Migraine without aura, Other, Sporadic hemiplegic migraine, and Typical aura without migraine are the best ones with precision, recall, and F1-score equal to 1.00. These facts are evidence for the model's ability to practically learn to correctly classify different types of migraines according to specific characteristics among other features by the time the model is finished.

For Basilar-type aura, the model achieved a precision of 97% and a recall of 95%, resulting in an F1-score of 96%. Although these results are outstanding, they indicate that a small number of samples were misclassified. Similarly, for familial hemiplegic migraine, while the model achieved a perfect recall of 100% indicating all instances of this class were identified, its precision was 89%, suggesting some degree of misclassification with other classes.

Performance was somewhat worse in the event of a typical aura with migraine, with an F1-score of 89% (precision of 94% and recall of 85%). Overlapping characteristics with different migraine kinds are probably to blame for this, which could make classification difficult.

97% accuracy was achieved in the experiment of experimenting with errors with a particular reason by the model and the training data, and the precision is 0.9915, recall is 0.5926, and F1-score is 0.7321. In multi-class tasks that complicate the problem well, such as difficulty in distinguishing the boundary between the two classes or the presence of overlapping behaviors, the ability of this model to maintain balance is more than necessary. Together, these results establish that the model is not only able to learn from a variety of types of data but also to classify properly into many classes in general.

V. Discussion

The research compared the supervisory learning models: Gradient Boosting, Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression, Multi-Layer Perceptron (MLP), Artificial Neural Networks (ANN), and Deep Neural Networks (DNN) for migraine prediction and classification. Interesting information about the strengths and weaknesses of the models' related to the multi-class classification of migraine was exposed by the comparison.

The Gradient Boosting model exhibited impressive performance in classes such as Migraine Without Aura and Typical Aura Without Migraine, yielding an accuracy rate of 96.4%. But it struggled with complex types like Migraine with Typical Aura. The Decision Tree model exhibited stellar performance at 96.04% accuracy; yet, it faced challenges with Basilar-Type Aura, shown by an F1-score of 0.90.

In a number of classes, including Migraine Without Aura, Other, and Sporadic Hemiplegic Migraine, the Multi-Layer Perceptron (MLP) demonstrated the maximum accuracy of 97%, with flawless precision and recall. However, MLP performed worse for Typical Aura with Migraine (F1-score of 89%), most likely as a result of category overlap.

The Random Forest model had a very good accuracy at 95%, but exhibited signs of overfitting, particularly in certain categories. It performed well in less complex classes, such as Other and Typical Aura Without Migraine. With corresponding accuracies of 93.17% and 92.09%, KNN performed better than SVM. KNN proved effective in distinguishing Basilar-Type Aura and Migraine Without Aura but faced similar challenges in complex categories. Logistic Regression performed at a baseline with an accuracy of 89%, excelling in simpler classifications but struggling with nuanced categories, such as Typical Aura with Migraine, where its F1-score dropped to 70%.

The ANN model performance was robust in terms of accuracy with 95% on overlapping class problems as long as the scope of the clinical dataset was limited and well defined. It was a bit challenging for the ANN to manage overlapping classes. On the other hand, DNN performed slightly better at 95.19%, leveraging its deeper architecture to model more complex patterns, especially for challenging classes like Sporadic Hemiplegic Migraine. However, the DNN had high computational cost and also extensive regularization requirements which are its main downsides.

In conclusion, the best models overall were the Gradient Boosting and MLP as they gave consistently high accuracy. Both ANN and DNN also had their advantages, ANN was optimal for less complicated datasets which use One Dimensional representations and DNN was optimal for multidimensional and complex datasets. All these findings stress the need to be selective on the choice of model to be developed, with respect to the complexity of the data and the nature of the task. For the future research, better performance may be obtained from harnessing class imbalance, better feature engineering, fine-tuning the regularization and adding ensemble methods.

In Table III, the results of existing work for migraine classification are equated with the accuracy of the classification produced by our proposed model.

TABLE III. COMPARATIVE RESULTS

Model	Accuracy (%)	F1-score (%)	Sensitivity (%)	precision (%)
Gradient Boosting	96.4	96	96	97
Random Forest	95	71.8	73.2	70.8
SVM	92.09	91.64	91.63	91.64
KNN	93.17	92.63	92.74	93.08
Decision Tree	96.04	95.87	95.84	96.03
Logistic Regression	89.21	89.2	89	89.8
MLP	97.12	94.14	94.25	94.32
ANN	95.86	95.4	95.7	95.7
DNN	95.19	95.15	95.08	95.18

VI. CONCLUSION

This study highlights the ability of machine learning to correctly define attacks of migraines through classification models. Gradient Boosting achieved an accuracy of 96.4%, excelling in classes like Migraine Without Aura, while MLP stood out as the best performer with 97% accuracy and perfect scores in several classes. Artificial Neural Network also performed well with ANN at 95% accuracy and DNN at 95.19%, although computational demands were notable. Other models such as Logistic Regression (89%) struggled with nuanced categories, while Random Forest (95%), KNN (93.17%), and SVM (92.09%) performed moderately. Finally, MLP and Gradient boosting were the outstanding models emphasizing the importance of model selection which depends on the complexity of the data set in improving clinical practice.

The implications of improving our understanding of how algorithm choice affects performance in classification and providing a way forward in performing more efficient migraine diagnosis are crucial for future research through feature engineering and model optimization. Future studies may incorporate ensemble methods, refine how complex models overfit and improve procedures for more detailed and specific types of migraines.

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