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Sporadic Hemiplegic Migraine Case Study and Classification Using Machine Learning

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Abstract

Background: Sporadic hemiplegic migraine (SHM) is a rare and complex type of migraine that is characterized by temporary paralysis or weakness (hemiplegia) on one side of the body, which is estimated to affect a tiny percentage of the population and is often misdiagnosed by physicians, and is generally treated as a headache. The hemiplegia in SHM is typically reversible and usually lasts for the duration of the migraine attack, but it can cause significant concern due to its neurological nature. **Methods:** Since the number of patients suffering from this type of migraine is rare, not enough data has been collected, making diagnosis extremely difficult even for the best physicians. This often leads to misdiagnoses and delayed treatment for the patient. In this paper, we present a case study of a patient with sporadic hemiplegic migraine who has gone undiagnosed for many years by physicians. So, we discuss using Machine Learning classifiers to diagnose migraines of different types and, very specifically, the rare types of migraine, such as sporadic hemiplegic migraine, with a high degree of certainty. **Results:** We present the use of Machine Learning classifiers, such as Decision Tree (DT) and Random Forest (RF), to classify different types of migraine, specifically for diagnosing sporadic hemiplegic migraine. The classifiers' results, trained on the dataset, are verified for their performance across the overall dataset for all types of migraines, specifically for sporadic hemiplegic migraines. Given the dataset, these classifiers indicate that a high degree of precision and accuracy is achievable with Decision Trees and Random Forests for sporadic hemiplegic migraines. We find that the accuracy and precision obtained by tree-based machine learning classifiers would aid in patients' diagnoses. **Conclusion:** In this study, we present classifiers that promise to aid everyday physicians. We evaluate the classifiers' performance using classification metrics. With these classifiers, different types of migraines, specifically sporadic hemiplegic migraine, can be classified with high accuracy and reliability so that physicians can make timely clinical diagnoses of patients.

Keywords

Migraine, Familial Hemiplegic Migraine, Sporadic Hemiplegic Migraine, Decision Tree Classifier, Classification and Regression Tree, Random Forest Classifier

1. Introduction

Migraine or migraine headache is a neurological condition characterized by an intense unilateral throbbing of the head. In addition to moderate to severe head pain, migraine symptoms can include mood changes, decreased concentration, nausea, vomiting, and sensitivity to light, sounds, and odors. Migraine can be classified as either migraine with aura or migraine without aura. Migraine with aura can include flashes of light, blurred vision, blind spots, difficulty speaking, tingling, and numbness. Migraine can be further subdivided into many different categories depending on the specific set of symptoms presented. There are four phases to a migraine attack: prodrome, aura, headache, and postdrome. Prodrome occurs 24 hours before the headache begins, aura can occur five to 60 minutes before, the headache can last four to 72 hours, and postdrome lasts up to 48 hours after. While there is no exact cause for migraine, genetics is thought to play a role in some migraine types [1]-[21]. Possible migraine triggers include stress, sleep deprivation, skipping meals, dehydration, coffee, chocolate, and hormonal changes [5]. Blood testing, CT scans, and MRI cannot be used to diagnose a migraine, but they can be used to rule out other possible conditions. Healthcare providers must, therefore, rely on patient history, physical examination, and neurological examination when diagnosing migraine. While there is no cure for migraine, over-the-counter or prescription medication can be taken to help with the headache. Lifestyle modifications can be made to avoid migraine triggers [22] [23].

There are two types of hemiplegic migraines: sporadic hemiplegic migraine (SHM) and familial hemiplegic migraine (FHM). Sporadic hemiplegic migraine (SHM) is a variant of migraine with aura and headache associated with hemiplegia or motor weakness, and no first-degree or second-degree relative who has migraine aura, including motor weakness, which is estimated to affect a tiny percentage of the population. Patients with sporadic hemiplegic migraine often complain of having severe headaches, nausea, photophobia, numbness, paresthesia, dysphasia, dysarthria, and temporary muscle weakness, which can last from minutes to days. The hemiplegia in SHM is typically reversible and usually lasts for the duration of the migraine attack, but it can cause significant concern due to its neurological nature.

SHM is a rare type of migraine with an aura that causes weakness on one side of the body. People who experience FHM have a first- or second-degree relative who also has migraine with aura and motor weakness, while people who experience SHM do not. Both types of hemiplegic migraines are under the category of migraine with aura [21] [24] [25], shown in **Figure 1**.

Artificial Intelligence and machine learning techniques have shown promise in classifying and predicting different types of migraine [26]-[28]. Machine learning models, particularly decision trees, support vector machines (SVMs), and neural networks (NNs), have been utilized to analyze large datasets and identify patterns that exceed human capability [27] [28]. Machine learning models were used to distinguish episodic versus chronic migraines using patient-reported data [29]. Similar research using Random Forest models in feature selection has pinpointed key symptoms, such as photophobia, nausea, and attack frequency, as strong predictive indicators [30].

In this study, we use Machine learning classifiers to diagnose patients with different types of migraine and use the classifier as a tool to aid physicians in identifying specific types of migraine correctly, such as sporadic hemiplegic migraine, which is very rare compared to the overall population of migraineurs in the world.

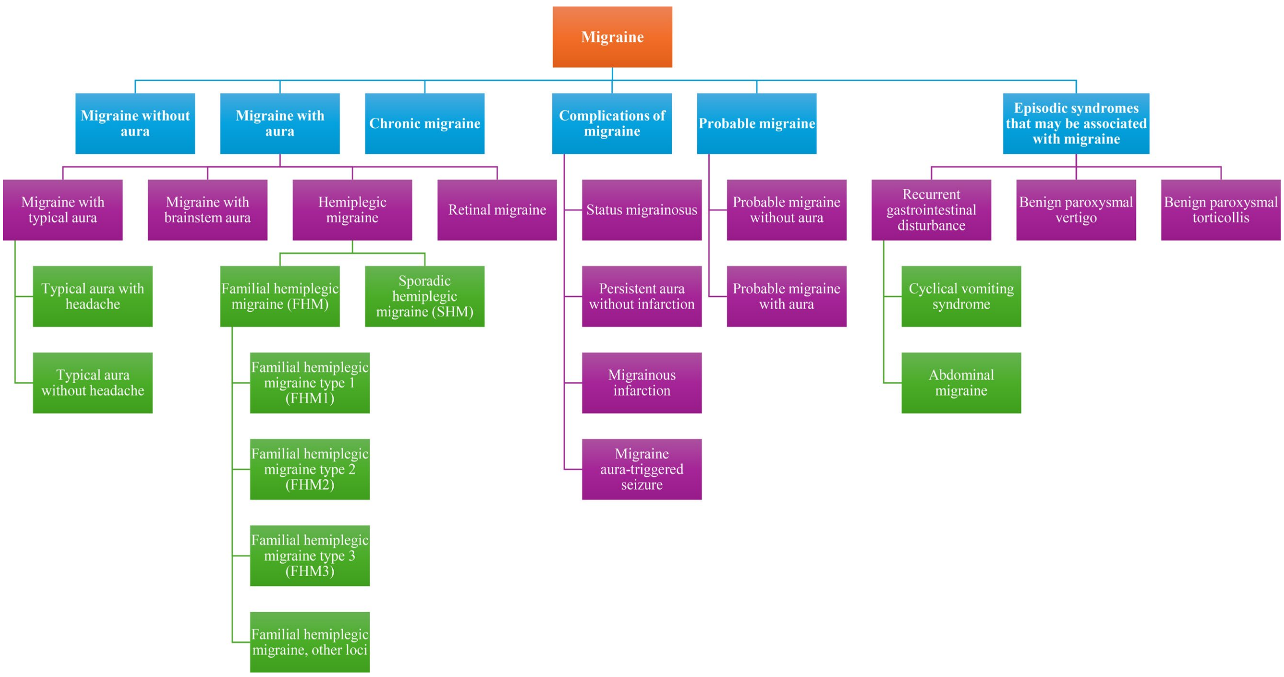

Figure 1. Third edition of international classification of headache disorders (ICHD-3).

2. Methods

2.1. Case Study

A 10-year-old female patient first presented to the pediatrician with intense pain on the right side of the head. During class at school, symptoms began as a tingling sensation in the right hand, which later progressed to complete numbness of the right hand and arm. There were no precipitating factors to explain the sudden onset of numbness. After some time, the patient began to experience pain on the right side of the head. With time, the pain increased. This was the first time the patient had experienced these symptoms. The progression of the different stages of the patient's symptoms of sporadic hemiplegic migraine is shown in Figure 2. The patient was sent to the school nurse, who tried massaging the right hand to return the sensation but was unsuccessful. The patient was then taken to the pediatrician due to severe unilateral head pain. By this time, sensation had returned to the right hand and arm. The pain on the right side of the head persisted. The pediatrician was unable to diagnose the patient's condition but prescribed Ibuprofen to help with the pain. The patient took one 200-mg ibuprofen tablet. The family physician was consulted for a diagnosis, and the patient was diagnosed with a migraine.

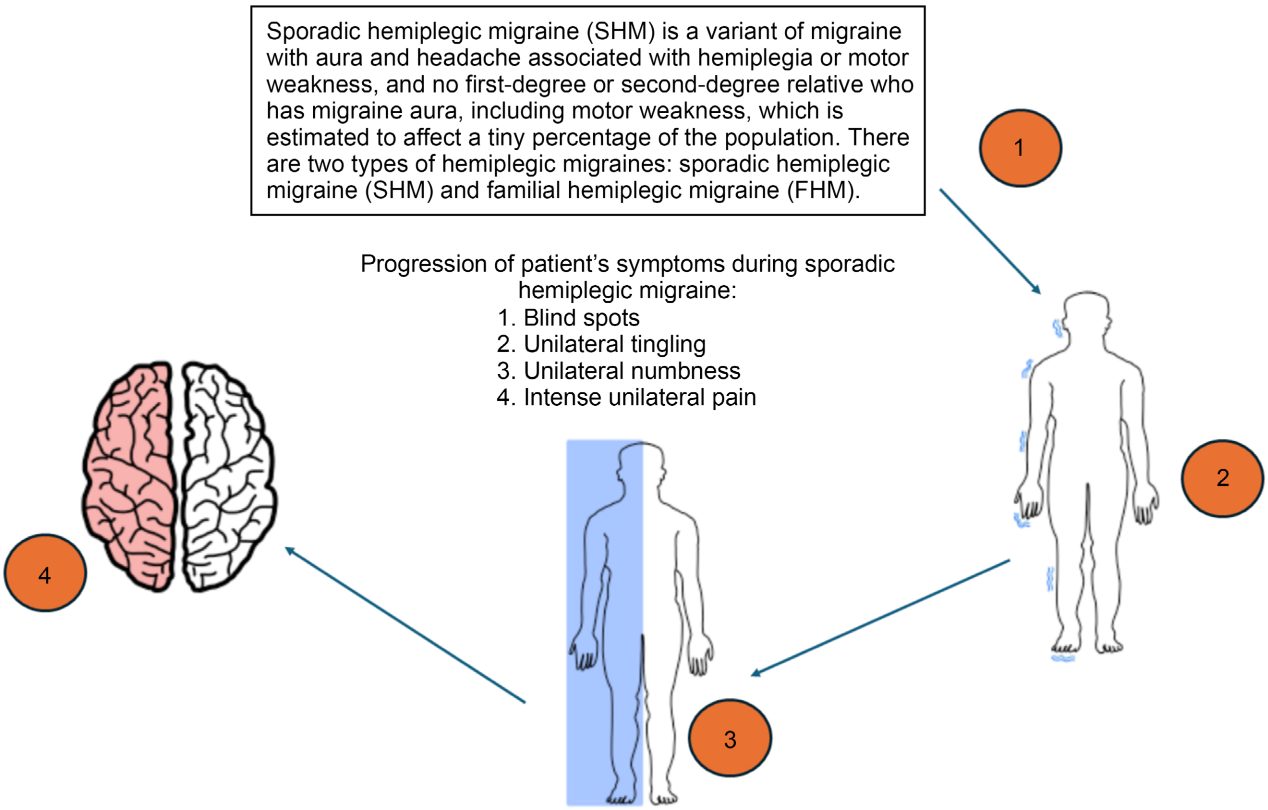

Figure 2. Progression of symptoms during sporadic hemiplegic migraine.

Over the next 13 years, the patient continued to experience migraines about once a year. For each migraine attack, symptoms first present as blind spots. Due to these blind spots, reading becomes difficult as letters seem to disappear from words, as illustrated in Figure 2. Symptoms progress to tingling and numbness limited to one side of the body, beginning at the arm or leg and moving up to the neck and face, with motor weakness in the upper and lower limbs. Due to this hemiplegia, performing activities of daily living can be challenging. The paralysis of one side of the tongue makes talking difficult (dysarthria). Symptoms culminate in a unilateral migraine headache with severe throbbing pain. This all-encompassing pain makes it quite difficult to concentrate on anything else. Alleviating factors include taking Ibuprofen to help relieve some of the pain associated with the intense headache. Aggravating factors include bright lights, loud sounds, and strong smells. Possible triggers for each migraine attack could consist of stress, sleep deprivation, skipping meals, and dehydration. The patient takes two 200-mg Ibuprofen tablets when the headache begins. This helps reduce the one-sided head pain but does not eliminate it. Additionally, the patient has noticed that if, while experiencing a migraine, a meal is had without taking Ibuprofen, emesis will result. Still, if Ibuprofen is taken while experiencing a migraine and then a meal is consumed, emesis will not result. The headache pain averages five hours. The following day, the patient experiences a mild head throbbing, reminiscent of the migraine the day prior, that can be worsened by jumping or climbing stairs. This sensation resolves by the third day [26].

The 13-year history of migraines has not caused the patient any long-term effects. The patient has no history of heart disease, diabetes mellitus, coagulation disorder, or seizures. MRI scan showed no signs of abnormal growth, inflammation, or damage. There is no family history of migraines. In the differential diagnosis, the following conditions, such as epileptic seizures and transient ischemic attack (TIA), were considered. Epileptic seizures can cause temporary weakness or paralysis following the seizure, which can mimic hemiplegia. While both TIA and SHM involve reversible neurological symptoms, TIA symptoms are typically more sudden in onset and less likely to be accompanied by other aura symptoms like nausea, vomiting, or photophobia.

2.2. Related Case Studies

Further case studies regarding sporadic hemiplegic migraine (SHM) suggest that it often takes a long time, which could be years, before the patients are correctly diagnosed with SHM.

Schwedt TJ, *et al.*, discuss a 22-year-old right-handed woman with SHM who was first evaluated for headache at the age of 15 years, which was the first attack of hemiplegic migraine (HM). Attacks consisted of severe left-sided headache, photophobia, and hemiplegia with a variable combination of confusion, mixed motor and sensory aphasia, and right hemisensory symptoms, but never with visual aura. She had no family history of HM, and it took seven years for her to be diagnosed with SHM [31].

Bhatia R, *et al.*, discuss a 30-year-old male with a history of headache and left hemiparesis of 2-day duration who had experienced bright flashes of light in both his visual fields, which was followed by severe throbbing headache accompanied by photophobia, nausea, and vomiting. Later, he became disoriented, confused, and developed weakness of his left upper and lower limbs along with slurring of speech and difficulty in swallowing. He experienced many such episodes starting at the age of 14. So, after almost 16 years, he was diagnosed with SHM [20].

Yang XY, *et al.* discuss a 46-year-old woman with weakness on the right side of her body. For about 30 minutes, she experienced flashing light in her bilateral visual fields and blurred vision. Then, she developed a left frontal throbbing headache accompanied by phonophobia, nausea, and vomiting. The motor weakness lasted 3 hours. The patient had a history of headaches preceded by a flashing light sensation starting at the age of 23 years. These symptoms presented six times yearly, with occasional abnormal sensations in her limbs. She had no first or second-degree relative who had been affected by such headaches. She was diagnosed with SHM after 23 years [32].

In these cases, patients reported throbbing headaches, photophobia, phonophobia, visual disturbances, and hemiplegia with motor and sensory weakness, heaviness, and numbness, tingling sensations accompanied by nausea and vomiting. Disorientation and confusion, accompanied by speech slurring and difficulty swallowing, were also observed [20] [25] [31]-[33]. This indicates that the correct diagnosis of SHM is not only challenging, but also that patients are often misdiagnosed and treated for some other condition. Therefore, we investigate the use of computer-aided diagnosis (CAD). This technology combines elements of artificial intelligence (AI) and machine learning to aid in the diagnosis of SHM, rather than serving as a substitute for a physician [34]. Early diagnostic methods using Artificial Intelligence (AI) were rule-based expert systems, such as MYCIN [35]. Recent use of Artificial Intelligence methods is based on Machine Learning (ML), which we tend to use for the diagnosis of SHM, wherein the model is built by feeding the system with a large amount of patient data with different types of migraine, so that the model can create an algorithm along with a set of rules to perform the required task. Once the model is completed and verified, the physician provides the system with the patient's data to facilitate diagnosis [34]. In this study, we investigate the use of machine learning models based on Machine Learning Classifiers.

Similar studies using Machine learning classifiers for diagnosing different types of migraine and tension-type headaches in patients have been discussed [26]-[30] [36]-[40], yielding promising results in terms of precision and accuracy.

3. Machine Learning Classifiers

3.1. Decision Tree Classifier

Machine Learning methods for classification adaptively split the input space into disjoint regions to construct a decision boundary. The regions are chosen based on a greedy optimization procedure, wherein, in each step, the algorithm selects the split that provides the best separation of the classes according to a specific cost function. This cost function is chosen to be compatible with the greedy optimization procedure and tends to reflect the empirical risk of miscalculation. The splitting process can be represented as a binary tree. The Classification and Regression Tree (CART) algorithm finds the best split to subset the data. Following the tree's growth, pruning occurs as a form of model selection. Most tree-based methods use growing a large tree and then pruning nodes according to pruning criteria. Empirical evidence suggests that this growing and pruning strategy provides better classification accuracy than growth alone. The pruning criteria usually include the empirical misclassification rate adjusted by some heuristic complexity penalty. The strength of the penalty is determined by cross-validation. Note that the pruning criteria provide a heuristic estimate of the prediction risk while the growing criteria roughly reflect the empirical risk. The resulting classifier has a binary tree representation where each node in the tree is a binary decision, and each leaf is assigned a class label. A classification is made by starting at the root node and descending to one of the leaves.

Search Strategy:

1) Initialization: The root node consists of the whole input space. Estimate the proportion of the classes via

$$p(j \mid t=0) = n_j(0)/n \tag{1}$$

The cost function to measure node impurity is given by,

$$Q(t) = Q(p(1 \mid t), p(2 \mid t), \cdots, p(J \mid t)) \tag{2}$$

2) Tree growing: Repeat the following until the stopping criteria have been satisfied, in which case the empirical misclassification cost reaches a threshold. The cost function for misclassification is

$$Q(t) = 1 - \max p(j \mid t) \tag{3}$$

a) Perform an exhaustive search over all valid nodes in the tree, all split variables, and all valid node points. For all these combinations, create a pair of daughters and estimate the probabilities $p_L(t)$ and $p_R(t)$, wherein $p_L(t) = p(t_L)/p(t)$ and $p_R(t) = p(t_R)/p(t)$.

b) Incorporate the daughters into the tree, resulting in the most significant impurity decrease via the Gini or entropy cost function.

Gini cost function:

$$Q(t) = \sum_j \sum_{i \neq j} p(i \mid t) p(j \mid t) = 1 - \sum_j \left[p(j \mid t)\right]^2 \tag{4}$$

Entropy cost function:

$$Q(t) = -\sum_j p(j \mid t) \ln p(j \mid t) \tag{5}$$

3) Tree pruning: Repeat the following pruning strategy until no more pruning occurs.

a) Perform an exhaustive search over all sibling leaf nodes in the tree, measuring the change in model selection criterion resulting from the recombination of each pair. Pruning is based on minimizing the penalized empirical risk:

$$R_{pen} = R_{emp} + \lambda |T| \tag{6}$$

R_{pen} is the misclassification rate for training data, and $|T|$ is the number of terminal nodes. The pruning is performed in a greedy search strategy where every pair of sibling leaf nodes is recombined to find a pair that, when recombined, reduces R_{pen}. The optimal λ Is found by minimizing the estimate of prediction risk determined via sampling.

b) Delete the pair that leads to the most significant decrease in the model selection criterion. If it never decreases, make no changes.

3.2. Random Forest Classifier

In the case of Random Forest, using multiple Decision Tree classifiers can often compensate for the bias of a single Decision Tree classifier. Multiple Decision Trees are created that generalize independently, and a discriminant function combines the classifications of the individual trees, preserving their accuracies.

The discriminant function is defined as:

$$g_c(x) = \frac{1}{t}\sum_{j=1}^{t} p(c \mid v_j(x)) \tag{7}$$

and the decision rule is to assign point *x* to class *c*, for which $g_c(x)$ is maximum and $v_j(x)$ is the terminal node [4].

Randomization has been a powerful tool for introducing differences in Decision Tree classifiers, which has been used to initialize training algorithms with different configurations that eventually yield different classifiers. Multiple trees are created in randomly selected subspaces of the feature space. For a given feature space of m dimensions, there are 2^m subspaces in which a Decision Tree can be constructed using the training dataset and the search strategy discussed. In each case, the constructed tree generalizes its classification differently by utilizing multiple subspaces in the high-dimensional feature space. The classification accuracies are related to the statistical properties of the combination function, and high accuracies can be achieved before all combinations are used.

Each Decision Tree makes the predictions by casting its vote for classification tasks or by averaging in the case of regression tasks, and the final prediction is determined by the most frequent prediction across all trees. This collaborative decision-making process, supported by multiple insights from trees, yields stable and precise results [41] [42]. We had explored the use of logistic regression, which resulted in a performance 95%. Random Forest is known for its robustness and ability to handle high-dimensional datasets, which is particularly useful for migraine research, where numerous variables often coexist. It is also less prone to overfitting, a common issue with other machine learning algorithms.

3.3. Migraine Data

The training data consists of medical records of patients diagnosed with various pathologies associated with migraines. The dataset used for training the classifier models consists of 400 medical records of patients diagnosed with multiple pathologies related to migraines. During the first quarter of 2013, trained medical personnel at the Centro Materno Infantil de Soledad, comprising medical staff and physicians, collected data on patients with various types of migraines and compiled it with the required attributes and descriptions, as shown in **Table 1**.

Table 1. Dataset attributes.

Attributes		
1) Age	9) Phonophobia	17) Hypoacusis
2) Duration	10) Photophobia	18) Diplopia
3) Frequency	11) Visual	19) Visual defect
4) Location	12) Sensory	20) Ataxia
5) Character	13) Dysphasia	21) Conscience
6) Intensity	14) Dysarthria	22) Paresthesia
7) Nausea	15) Vertigo	23) DPF
8) Vomit	16) Tinnitus	24) Type

It is acknowledged that the dataset is publicly available and has been compiled to the best of our understanding of how the data was collected, based on consultations with physicians and patients diagnosed with migraine, utilizing publicly available information. It is a retrospective study [21] [36] [43].

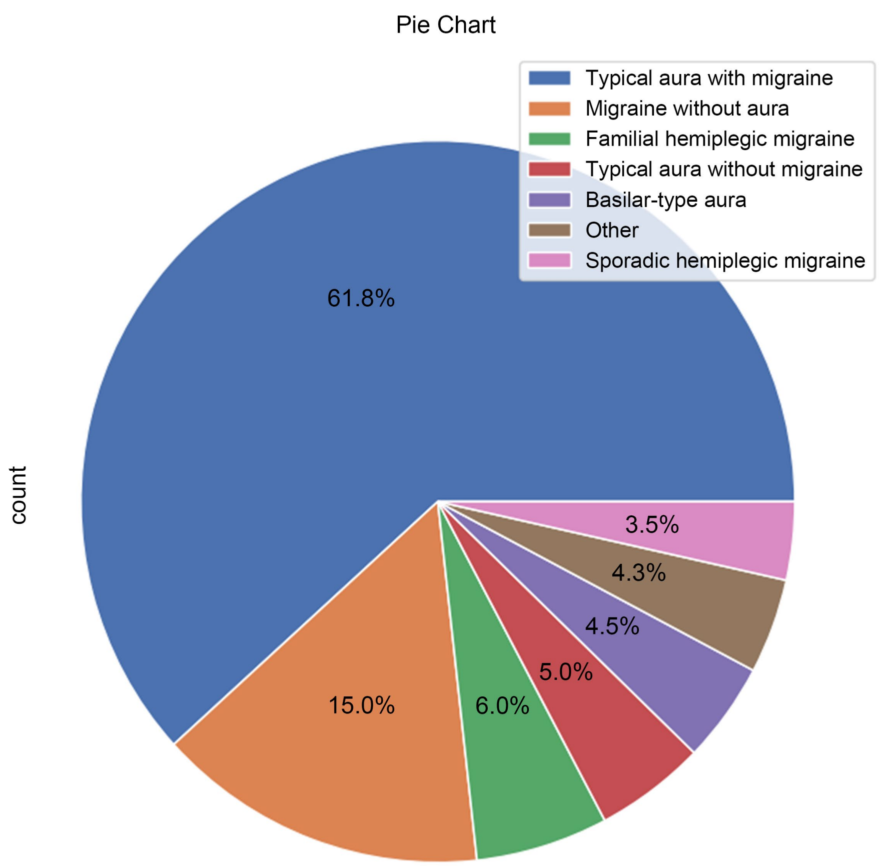

Figure 3. Distribution of migraine types in the dataset.

Based on the symptoms of the patients, the diagnosis of the type of migraine is as follows:

1) Typical aura with migraine;
2) Migraine without aura;
3) Typical aura without migraine;
4) Familial hemiplegic migraine;
5) Sporadic hemiplegic migraine;
6) Migraine with brainstem aura;
7) Other.

The distribution of various migraine types in the dataset is shown in **Figure 3**.

3.4. Pre-Processing

The data is preprocessed before being applied to the classifiers for better results. It is scanned for noise and inconsistent data, and any errors are further identified and eliminated. Since the dataset is small and the percentage of patients with sporadic hemiplegic migraine is relatively small, we address the class imbalance problem by data augmentation, which increases the dataset's volume by creating new data points from the existing data. This helps improve the performance and robustness of machine learning models by providing them with a more extensive and varied training set. Data augmentation aims to artificially expand the training dataset, which can be beneficial when the training dataset is limited or imbalanced. Data augmentation enables models to learn more robust and generalizable patterns, thereby reducing their propensity to overfit. By increasing the diversity of the training data, data augmentation helps to prevent models from memorizing the training set and becoming overly specific to it, thus reducing overfitting. Augmentation can be a cost-effective way to increase a dataset's size without collecting and labeling additional real-world data. Therefore, to obtain a balanced dataset, we use SMOTE. The generated data is further verified for correctness.

3.5. Synthetic Minority Oversampling Technique (SMOTE)

SMOTE is a data augmentation technique that addresses class imbalance in machine learning datasets. It generates synthetic samples of the minority class to balance the class distribution and enhance model performance, particularly in classification tasks. SMOTE focuses on the class that is underrepresented in the dataset, often referred to as the minority class. It is particularly effective in scenarios where the majority class significantly outnumbers the minority class, leading to biased model training. By balancing the class distribution, SMOTE can lead to more accurate and reliable models, especially in classification problems where the minority class is the target.

The initial dataset used consisted of 400 patient records with 24 attributes. After the data augmentation process, the dataset size increased to 1386 patient records, following which the training and testing data were separated. Out of a total of 1386 records, 1108 records made up the training set, and the remaining 278 records were used for testing. The dataset was significantly unbalanced before data augmentation, as shown in **Figure 3**. SMOTE was applied only to the training folds, not to the validation or test data, to prevent information leakage, as illustrated in **Figure 4**, which shows the class balance after data augmentation.

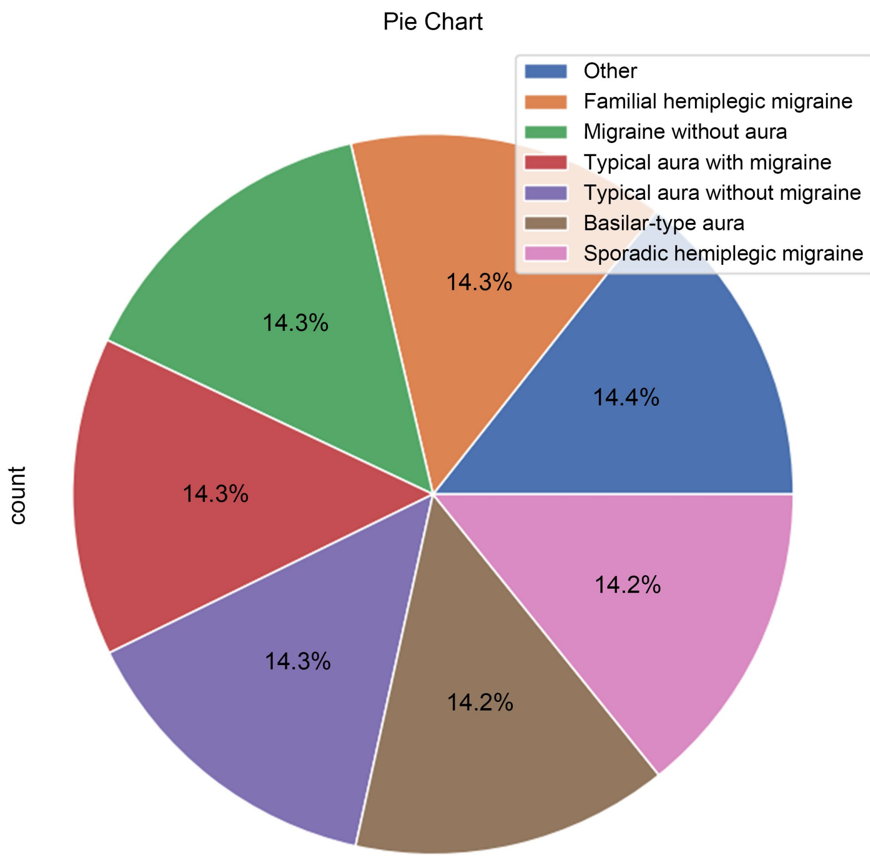

Figure 4. Distribution of migraine types in the dataset after data augmentation, showing class balance.

3.6. Machine Learning Classifiers for Migraine Diagnosis

A combination of Artificial Intelligence (AI), Machine Learning (ML), and statistics is used for the diagnosis [34] [35]. The Classification Methodology using tree-based methods discussed is used to train the machine-learning models to classify the types of migraines, as shown in **Figure 5**. First, the dataset is read, segmented, and preprocessed. We train using a Decision Tree Classifier, compare the results obtained using a Random Forest Classifier, and analyze the results using the computed metrics. The dataset is split into 80% training and 20% testing data. The classifiers are then tuned for better accuracy and precision. The various attributes in the dataset used for training and testing are presented in **Table 1**.

The following classification metrics are used to evaluate the performance of each classifier.

- The Area under the ROC Curve (AUC) represents the probability that the model will rank the positive higher than the negative if given a randomly chosen positive and negative instance.

- Classification Accuracy is the ratio of correctly predicted instances to the total number of cases in the dataset. It is useful when the class distribution is balanced.
- Precision is the proportion of accurate optimistic predictions among all positive predictions, which means it measures how accurate the optimistic predictions are.
- Recall is the proportion of true positive predictions among all actual positive instances. It measures the classifier's ability to correctly identify positive instances.
- F1-Score is the mean harmonic of Precision and Recall. It thus symmetrically represents both precision and recall in one metric. The F1-score of a classifier that always predicts the positive class converges to 1 as the probability of the positive class increases.

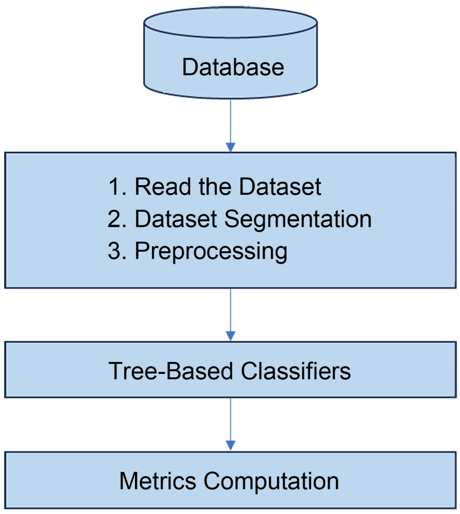

Figure 5. Classification Methodology.

4. Results

Table 2 shows the metrics for the average of all types of migraine using the Decision Tree Classifier and Random Forest Classifier.

Table 2. Overall metrics for different types of migraine.

Classifier	Area under curve	Classification accuracy	Precision	Recall	F1 score
Decision tree classifier	98.5%	92.5%	92.7%	92.5%	92.5%
Random forest classifier	99.9%	97.5%	97.6%	97.5%	97.5%

The metrics obtained for diagnosing Sporadic Hemiplegic Migraine are shown in Table 3.

Table 3. Metrics for sporadic hemiplegic migraine.

Classifier	Area under curve	Classification accuracy	Precision	Recall	F1 score
Decision tree classifier	97.4%	97.8%	77.8%	97.8%	86.6%
Random forest classifier	100%	99.3%	100%	99.3%	99.6%

The trained Random Forest Classifier was further tested based on the data of sporadic hemiplegic migraine symptoms of the patient. A patient, who was age 23, complained of severe headache, vomiting, phonophobia, photophobia, visual defect, and ataxia.

Data were gathered and written according to the patient's symptoms, as shown in Table 4. This data was then given to the trained migraine detection and classification model. Based on the attributes submitted in relation to the patient's symptoms, the classifier was able to determine with high precision and accuracy that it is sporadic hemiplegic migraine.

Table 4. Data attributes based on patient's case study.

Data attributes			
Duration (in days) = 1	Vomiting (no-0, yes-1) = 1	Dysarthria (no -0, yes-1) = 1	Ataxia (no-0, yes-1) = 1
Frequency (per month) = 1	Phonophobia (no-0, yes-1) = 1	Vertigo (no-0, yes-1) = 0	Consciousness (no-0, yes-1) =0
Location (none-0, unilateral-1, bilateral-2) = 1	Photophobia (no-0, yes-1) = 1	Tinnitus (no-0, yes-1) =0	Bilateral Paresthesia (no-0, yes-1) = 0
Character (none-0, throbbing-1, constant-2) = 1	Visual Symptoms (no-0, yes-1) = 1	Hypoacusis (no -0, yes-1) = 0	Family history = 0
Intensity (none-0, mild-1, medium-2, severe-3) = 3	Sensory Symptoms (no-0, yes-1) = 1	Diplopia (no-0, yes-1) = 0	**Type = Sporadic hemiplegic migraine**
Nausea (no-0, yes-1) = 0	Dysphasia (no-0, yes-1) = 0	Bilateral Visual Defects (no-0, yes-1) = 1	

4.1. Cross Validation

Cross-validation was used to estimate the model's performance within the same dataset, using the most common form, k-fold cross-validation, where the dataset is divided into k subsets (folds). The model is trained on k-1 folds and tested on the remaining fold. This process is repeated k times, with each fold being used as the test set once. The results are then averaged to provide an overall performance estimate. Cross-validation helps in understanding how the model performs on different subsets of the data, providing insights into its stability and variance. In this study, a 20-fold cross-validation was employed, yielding comparable results.

4.2. External Validation

External validation was also performed using an additional dataset of a smaller sample size with similar attributes to verify the model's performance. The dataset for external validation was gathered over time by various doctors, extracted retrospectively from each site's electronic health record under approved protocols. Data completeness was high, as all 24 attributes used in model development were represented in the validation set, yielding a 93% feature overlap. The results obtained were comparable to those from the present dataset used in the study. External validation evaluates a model's predictive performance using new data that were not involved in model development, providing an essential test of its applicability to real-world situations. The substantial feature overlap, large sample size, and consistent key performance metrics in this validation support the model's generalizability to similar migraine populations.

5. Limitations

With this patient's migraine data, the Random Forest model provided a high degree of precision with high accuracy for sporadic hemiplegic migraine. The results presented could vary due to several factors, depending on the dataset, size, attributes, and the training; therefore, the authors would like to point out that even though high accuracy and precision are obtained in this study for the given dataset, in real-world scenarios, we predict some divergence from the obtained results, which we see as limitations.

Furthermore, diagnostic heterogeneity itself can act as a source of bias within datasets, particularly in research studies or when developing classifiers. If a diagnostic category is applied inconsistently, samples collected for research or model training may not accurately represent the actual population of individuals with that condition, leading to biased results. Variations in how a diagnosis is arrived at can lead to misclassification of individuals within a study or dataset, particularly if different diagnostic methods are used or if observer influences data collection or recall bias. The presence of heterogeneity makes it more difficult to detect true associations or treatment effects. Findings from studies with significant diagnostic heterogeneity may not be readily generalizable to broader populations, limiting their applicability in clinical practice. By addressing diagnostic heterogeneity and potential biases, the reliability and validity of the results can be enhanced, ultimately contributing to more accurate diagnostics and effective treatments.

Additionally, the current dataset used in this study is a 2013 retrospective dataset, and the ICHD-2/3 diagnostic changes may limit its current clinical applicability. ICHD-3 tightened the rules for migraine with aura to boost specificity (up to 96% - 98% vs. ICHD-3 beta) when differentiating it from transient ischemic attacks (TIA). Tension-type headache subtypes were redefined, and the "probable migraine" categories were adjusted, potentially reclassifying cases in existing datasets. ICHD-3 introduced new entities that weren't captured or coded in earlier records. Plans for prospective data collection are currently in progress, incorporating changes as coded in ICHD-3 and anticipated future changes.

6. Differential Diagnosis

Many conditions, including transient ischemic attacks (TIAs), seizures, and even some metabolic disturbances, can produce similar transient neurological symptoms, such as weakness, sensory changes, or speech difficulties, making initial differentiation difficult. Migraine with aura, including SHM, can present with neurological deficits confined to a vascular territory, similar to stroke. While neuroimaging techniques, such as MRI and CT, can aid in differential diagnosis, their effectiveness in distinguishing between TIA and mimics, particularly in the acute phase, can be limited. Furthermore, in many countries, due to the scarcity of neuroimaging scanners, physicians often rely on alternative tools and methods for timely diagnosis, which can be challenging. The overlapping nature of symptoms, the transient nature of the episodes, potential for atypical presentations, and limitations of some diagnostic tools contribute to the complexity of distinguishing SHM from other causes of transient neurological deficits. Physicians must rely on a thorough history, a careful neurological examination, and the judicious use of appropriate investigations to arrive at an accurate diagnosis.

7. Discussion

Migraine is a debilitating health condition affecting over one billion people worldwide. Yet, despite its prevalence, diagnosing it is not always an easy task. In this patient's case, it took three healthcare providers for a diagnosis of migraine to be reached. This prolonged period causes patients to experience their symptoms for an extended period before a diagnosis can be made and a treatment suggested. More awareness should be given to its diagnosis to increase healthcare provider efficiency and decrease patient suffering. When this patient experienced the symptoms of a migraine for the first time at ten years old, the diagnosis of migraine was given. Even so, the symptoms of blind spots and hemiplegia were indicative of a specific type of migraine: sporadic hemiplegic migraine, with no first- or second-degree relative with migraine aura including motor weakness. This diagnosis, however, was not first given by any of the healthcare professionals the patient had visited. When the characteristics of the patient's migraine were input into the random forest algorithm, it gave the diagnosis of sporadic hemiplegic migraine. After 13 years, an answer was finally provided. Large Language Models (LLMs) and Deep Neural Networks (DNNs) were not considered in this study due to the small size of the dataset. Integrating this tool into clinical workflows is a multifaceted endeavor that necessitates careful planning, robust implementation, ongoing evaluation, and a commitment to ethical considerations. By addressing these factors proactively, physicians can harness the transformative potential of the tool to enhance patient care, improve efficiency, and create a more sustainable healthcare system.

8. Conclusions

There is still a long way to go in migraine research, from understanding the cause to diagnosing and curing the condition. There is no known cause for migraines, no diagnostic tool that healthcare providers can use to diagnose them effectively, and no cure has been discovered to rid patients of migraines indefinitely. To address the lack of a diagnostic tool for migraine diagnosis, healthcare professionals should utilize machine learning tools to aid in their differential diagnoses. This would aim to make the diagnostic process more efficient for everyone involved.

In this paper, we investigate the application of Machine Learning classifiers for classifying migraine types. It is seen that among the tree-based methods, the Random Forest Classifier seems to perform better in terms of accuracy and precision for the given dataset. From the results obtained, it can be stated that Random Forest is a dependable classifier that can serve as a tool for physicians to diagnose the type of migraine with certainty and reliability. Further testing of these classifiers with additional data has been conducted, and the results obtained are consistent with our study. The classifiers need to be trained with large datasets further to study the performance of classification accuracy and precision. Random Forest Classifier can also be used to classify different types of migraine headaches, such as migraine with aura and migraine without aura, and, in particular, diagnose patients with sporadic hemiplegic migraine, which can be quite challenging and therefore can be helpful for doctors to make accurate diagnoses and develop appropriate treatment plans. Again, we would like to emphasize that this study presents classifiers that can be used to classify different types of migraine, such as sporadic hemiplegic migraine, as an aid to physicians and not as a substitute for their care.

9. Clinical Implications

- The Machine Learning classifiers discussed can be used to classify different types of migraine, particularly sporadic hemiplegic migraine.
- Physicians could use these tools to diagnose and treat patients accurately.

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Data Availability Statement

The dataset used in this study is publicly available.

Ethics Statement

Consent and approval were obtained from the participant for the case study. The use of the migraine dataset in this study is based on publicly available data from a retrospective study.

Generative AI Statement

The author(s) declare that no Generative AI was used to create this manuscript.

Clinical Relevance

Machine Learning classifiers are discussed for the diagnosis of different types of migraine, serving as an aiding mechanism for physicians to diagnose and treat patients reliably.

Conflicts of Interest

The authors declare that the research was conducted independently without any outside relationships or support that could be considered a conflict of interest.

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Abbreviations

AI:	Artificial Intelligence
AUC:	Area Under the Curve
CAD:	Computer-Aided Diagnostic
CART:	Classification and Regression Tree
CT:	Computed Tomography
DNN:	Deep Neural Network
DT:	Decision Tree
FHM:	Familial Hemiplegic Migraine
LLM:	Large Language Model
ML:	Machine Learning
MRI:	Magnetic Resonance Imaging
NN:	Neural Net
RF:	Random Forest
SHM:	Sporadic Hemiplegic Migraine
SVM:	Support Vector Machine
TIA:	Transient Ischemic Attack