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Research Article

Deciphering the Symptom Spectrum: A Comprehensive Analysis of Migraine Patterns and Types

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Abstract

Complex neurological diseases like migraine migraine affect a large section of the global population, causing health, social, and economic issues. Migraine causes intense, painful headaches that are usually one-sided and pulsing. Auras, nausea, vomiting, and excessive light and sound sensitivity may precede these episodes. Migraine affect millions worldwide and can be intermittent or persistent, impairing function. Diet and stress may induce it, but the cause is unknown. Prevention and symptom treatment drugs and lifestyle changes are used. Debilitating migraines are hard to diagnose due to their varied presentation and subjective symptom reporting. Traditional migraine diagnosis, based on clinical evaluation, typically fails to classify migraine types, requiring more objective and rigorous instruments. This study proposes a machine learning-based migraine categorization method to address this issue. The dataset includes different patient demographics and clinical variables; thus, we use complex algorithms like Random for Forest, XGBoost, and Extra Trees. These algorithms are great for deciphering migraine patterns because they excel at evaluating complex datasets. The research seeks to close this gap to improve migraine classification accuracy, objectivity, and reliability, enabling tailored migraine management and treatment. This neurology study could improve migraine diagnosis and treatment with more effective and personalized plans.

Keywords

Migraine, Epidemiology, Risk Factors, Migraine Pattern and Machine Learning

1. Introduction

Migraine, a sickness that impacts around one billion individuals globally, are a substantial neurological disorder that surpasses the ordinary headaches commonly encountered by people. Common symptoms accompanying these episodes consist of light or sound sensitivity (phonophobia), nausea, vomiting, and photophobia. These episodes are characterized by intense and overwhelming agony Patrizia et al. [1]. Due to the significant influence on daily activities, such as hindering routine tasks and greatly affecting general well-being, it is crucial to promptly seek accurate diagnosis and appropriate therapy. Traditional diagnostic methods for migraine, which rely on subjective symptomatic assessment, have inherent limits in terms of accuracy. This can lead to erroneous diagnosis and less successful treatment strategies. The paper seeks

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to address this difficulty by providing a novel approach that employs sophisticated comprise computer learning formulas, like Random Forest, XGBoost, and Extra Trees. The selection of these algorithms was based on their extraordinary ability to handle complex datasets and their resistance against over fitting. The ensemble learning method known as Random Forest is particularly useful for medical data analysis due to its robustness and capacity to handle over fitting Bing Zhao et al. [7]. Due to its efficacy in handling non-linear interactions and swiftly processing large datasets, XGBoost can effectively manage the diverse manifestations of migraine symptoms. Extra Trees is highly proficient in detecting subtle patterns that are crucial for differentiating between various types of migraines due to its use of increased randomness [11]. The purpose of using these algorithms is to enhance the precision and reliability of migraine classification, hence facilitating the advancement of treatment options that are tailored and effective. This study not only enhances the precision of classifying migraines, but it also explores wider implications, showcasing the transformative capabilities of machine learning for diagnosing medical conditions.

Migraine, a neurological condition characterized by intense, debilitating headaches, is a common ailment that significantly impacts the quality of life [16]. It often presents with a throbbing or pulsating pain, typically usually on one side of the head, and is often accompanied with acute light and sound sensitivity (photophobia and phonophobia), nausea, and vomiting. Some individuals experience aura - sensory disturbances like visual flashes or tingling sensations preceding the headache. The dataset provided indicates the inclusion of additional symptoms like vertigo, tinnitus, hypoacusis, diplopia, and other neurological deficits, suggesting a comprehensive approach to understanding migraine patterns. Migraine episodes vary in duration and frequency, influenced by factors like stress, hormonal changes, dietary triggers, and environmental stimuli [17]. Treatment strategies include both preventive measures and pain-relief interventions, tailored to individual needs. Migraines are typically diagnosed based on clinical history and symptomatology, as detailed in the dataset. This condition, more prevalent in females, often begins in early adulthood and can be debilitating, affecting daily functioning and overall well-being. The dataset's focus on a broad spectrum of symptoms, including specific migraine types like 'typical aura with migraine,' underscores the complexity and variability of this condition. The intricacy of migraine lies in their ability to manifest in diverse ways and for individuals to encounter symptoms that differ from one another [13]. This poses a substantial challenge in terms of diagnosis and categorization. The World Health Organization (WHO) and other neurological organizations have extensively documented the various types of migraines, categorizing them based on specific symptom patterns, the frequency of episodes, and the intensity of the attacks Zain et al. [15]. Due to the subjective nature of symptom reporting and the overlapping symptoms with other headache illnesses, accurately identifying certain forms of headaches can be challenging. The proposed research offers a novel approach to this challenge by leveraging machine learning techniques, including the Random Forest, XGBoost, and Extra Trees algorithms. This method's goal is to establish a system that is more impartial and reliable in detecting different types of migraine. The selection of these algorithms is based on two factors: firstly, their proven track record in effectively handling complex data patterns, and secondly, their ability to resist over fitting.

2. Previous Work

The Migraines are terrible headaches that happen over and over again. They often come with dizziness, photophobia (aversion to light), and phonophobia (iraphobia of sound). An aura, which is a series of sensory changes that come before the headache, may or may not go along with a migraine. The cause of migraines is made up of complex neurological processes, including neural and vascular parts that we don't fully understand yet. The process of classification involves using machine learning methods and a dataset of already labeled observations to figure out which category a new observation fits into. Random Forest, XGBoost, and ExtraTrees are some ensembles learning methods that are used for classification problems [14]. The way these methods work is by making a lot of decision trees and finding the class that is the average of the classes in each tree. Data preprocessing is an important part of machine learning that involves cleaning and sorting raw data in order to make models more accurate. The ideas listed above form the basis for the method and evaluation described in this work.

This extensive, long-term, web-based panel study is called the Migraine in America Symptoms and Treatment (MAST) study in the U.S., focusing on migraine symptoms, man-agement approaches, and unmet treatment needs. Utilizing a stratified random sample of adults, the study employed a verified diagnostic screener built using adjusted standard scale for migraine identification. It revealed significant gender disparities in the characteristics of headaches, patterns of consultation and diagnosis, and the use of acute and preventative drugs. The study highlights migraine status a public health concern that is underdiagnosed and undertreated, emphasizing the need for improved diagnosis and treatment strategies. [1]

This study uses dynamic contrast-enhanced magnetic resonance imaging (DCE MRI) to examine increased vascular permeability in brain areas linked with migraine. The purpose of the study is to comprehend how migraine and the permeability of the blood-brain barrier (BBB) in these regions. Participants included both migraine sufferers and healthy controls. Key findings demonstrate lower left amygdala fractional plasma volume of migraine sufferers, suggesting BBB impairment in these individuals. This lower plasma volume was inversely correlated with the intensity of migraine attacks. The method-ology employed provides a new perspective on the pathophysiology of migraine, offering potential for diagnostic imaging markers. [2]

This paper reviews migraine pathophysiology, focusing on animal models, pharmacological targets, and new therapeutic strategies. It discusses migraine's debilitating effects and examines murine models for understanding migraine mechanisms, highlighting 5-HT and CGRP receptors as key pharmacological targets. The paper also explores the use of nanoparticles for drug delivery, enhancing the efficacy of traditional migraine treatments. The purpose of this review is to give a summary of the present understanding and advancements in migraine treatment, underlining the need for more effective therapies. [3]

The paper" Application of EEG in Migraine" explores electroencephalography (EEG) in studying migraine. It devarious EEG signal processing and analysis methods, including preprocessing, feature extraction, functional connectivity, brain network analysis, source localization, and microstate analysis. The study also incorporates machine learning and deep learning techniques to analyze EEG data. The paper aims to deepen understanding of migraine pathophysiology and suggests potential clinical applications for diagnosis and treatment, highlighting the complex neurophysiology of mi-graine and its phases. [4]

The research paper conducts a comprehensive genetic correlation analysis on migraine, linking it with various traits like blood pressure, cholesterol, neuroticism, asthma, autoimmune diseases, education, white blood cell count, platelet count, and smoking status are all associated with cardiovascular disease. It utilizes cross trait linkage disequilibrium score regression and Mendelian randomization, revealing widespread pleiotropy at loci linked to migraine. The paper significantly advances understanding of migraine shared genetic basis with numerous traits, underscoring its complex nature and potential avenues for therapeutic intervention. [5]

This research paper analyzes the frequency, effects, and severity of migraine and severe headaches in the United focusing on updated figures from official health surveys that are specific to age, sex, and socioeconomic status. It emphasizes the consistent age-adjusted prevalence of these conditions and their higher impact on women and individuals with lower socioeconomic status. The study highlights the importance of addressing these health disparities and improving access to mi-graine treatment for disadvantaged groups, especially in light of the socioeconomic challenges posed by coronavirus pandemic. [6]

Latent Class Analysis (LCA) is used in this study to determine natural subgroups of migraine sufferers based on comorbidity profiles derived from the Chronic Migraine Epidemiology and Outcomes (CaMEO) study. It aims to understand migraine heterogeneity and facilitate personalized treatment strategies. The study identified eight distinct migraine subgroups, each characterized by specific comorbidity patterns. This classification not only sheds light on the dinature of migraine but also highlights significant differences in demographic and headache features across the subgroups, enhancing our understanding of migraine complexity. [7]

This paper presents a novel machine learning approach, RO-MO, for predicting medication overuse in migraine patients. Utilizing a support vector machine algorithm and Random Optimization, the study analyzed a database with 777 migraine sufferers. The RO-MO system showed high accuracy, with a c-statistic of 0.83 and a sensitivity and specificity of and 0.87, respectively. The research highlights the potential of combining machine learning with clinical and biochemical to improve medication overuse prediction in migraine, significantly contributing to personalized patient care. [8] This research paper focuses on using neuroimaging, specifically MRI and CT scans, in diagnosing migraine in adult patients. It systematically reviews existing studies, assessing the utility and necessity of neuroimaging in migraine diagnosis. The paper evaluates various studies to determine the frequency and significance of neuroimaging findings in this context. It that neuroimaging is generally not required in typical migraine cases without atypical features or red flags, as significant abnormalities are rare in such patients in contrast to people in general. The paper aims to provide evidence-based recommendations for clinicians on when to use neuroimaging in migraine diagnosis. [9]

The paper explores the relationship between migraine and epilepsy, chronic disorders marked by neurologic attacks. It reviews diagnosis criteria, mainly focusing on migraine variants commonly mistaken for epilepsy. The paper highlights the epidemiologic evidence of an association between migraine and epilepsy, discussing specific interrelationships. It also covers the differential diagnosis of both conditions, considering clinical and EEG features, and suggests implications for diagnosis and treatment. The study aims to enhance understanding of these conditions, their overlap, and their distinct characteristics, guiding better diagnosis and managestrategies. [10]

The comparative analysis of various studies in migraine prediction using machine learning techniques reveals a diverse range of approaches and outcomes. Amir et al. [8] utilized a small dataset of 47 patients with an SVM-based method, achieving 87% accuracy, showcasing effectiveness even with limited data. In contrast, Daniel et al. [12] applied advanced algorithms like Random Forest and XGB on a larger dataset involving over 18,000 participants, reaching a higher accuracy of 89.7%.

Our proposed model stands out by employing an ensemble technique (RF, XGB, ET) on a dataset of 400 patients, achieving the highest accuracy of 99.42%, indicating the potential superiority of ensemble methods in handling complex migraine data. This comparative analysis underscores significance of both dataset size and methodological sophistication in enhancing predictive accuracy in migraine research.

Figure 1. Heat Map of Data frame.

3. Methodology

3.1. Dataset

We present an in-depth study of a large dataset that carefully records many aspects of migraine and related neurological conditions in this research paper. The dataset has several important factors, such as the subjects'" Age," which gives useful information about the age range of migraine sufferers;" Duration" and" Frequency," which measure how long and how often migraine happen. Symptom-specific metrics like" Location,"" Character," and" Intensity" are described in great depth, giving you a full picture of what migraine pain is and how bad it is. Some typical migraine symptoms are" Nausea,"" Vomiting,"" Phonophobia" (sensitivity to sound), and" Photophobia" (sensitivity to light). These indicators show whether the symptoms are present or absent. The list also includes less common migraine symptoms like" Vertigo,"" Tinnitus,"" Hypoacusis" (loss of hearing), and" Diplopia" (double vision), as well as more serious neurological signs like" Defect,"" Ataxia,"" Conscience Disturbances," and" Paresthesia." There is also a binary variable which doesn't instantly make sense in terms of what it means. The" Type" column sorts the condition into specific groups, such as" Typical aura with migraine," which shows a full list of migraine kinds. The goal of this dataset's in-depth analysis and explanation is to find the complex 26 patterns, symptom correlations, and categorizations across the wide range of migraine and related conditions. We have collected our dataset from Kaggle. The count values of each type of migraine are shown in Figure 2. Here we define the classes in numerical order. Typical aura with migraine as 0, Migraine without aura as 1, Basilar-type aura as 2, Sporadic hemiplegic migraine as 3, Familial hemiplegic migraine as 4, Others as 5 and Typical aura without migraine as 6. Headaches that happen less than fifteen days a month are referred to as episodic migraine. Individuals who suffer from episodic migraines have less frequent but possibly incapacitating headaches that are spaced out by periods without a headache.

Migraine with Aura: Aura migraine comprises extra neurological symptoms that usually appear prior to the headache. These symptoms, which can include problems speaking, changes in sensation (like tingling or numbness), and visual disturbances (such seeing flashing lights or blind areas), can last for 20 to 60 minutes.

Migraine without Aura: The most prevalent kind of migraine headache is known as an aura-free migraine, in which there are no prior neurological symptoms. The classic migraine symptoms—such as throbbing pain, nausea, and light-and sound-sensitivity—remain persistent.

3.2. Dataset Processing

This research employed a systematic approach to refine the dataset for optimal analysis and model training. Initially, we addressed data quality by removing all null values, ensuring the dataset's completeness. Subsequent focus was on feature selection, where we utilized iloc to segregate features from the target variable and applied label encoding to transform categorical data into a machine-readable format. A critical step involved assessing data skewness to identify and remove non-informative features, such as 'Ataxia', which exhibited no skewness. To visually explore and understand the correlations between different features, a heatmap was generated. (Figure 3) Finally, we implemented the Standard Scaler method to normalize the data, standardizing the feature set to have a mean of zero and a standard deviation of one, which is particularly crucial for models sensitive to feature scaling. This thorough data processing regimen laid a robust foundation for the subsequent stages of machine learning model development. Removal of null values for data completeness. Feature selection using iloc and transformation via label encoding. Assessment and removal of features with no data skewness, enhancing data relevance. Generation of a heatmap for visual correlation analysis. Standardization of data using Standard Scaler, ensuring uniformity across features for model training.

3.3. Statistical Analysis

We used easy-to-understand methods for this. For example, we compared the model's guess about the type of migraine with the actual type to see if it was correct. We tried several models, including one called K-Nearest Neighbors and another special model that we created by combining different techniques like Random Forest, XGBoost, and Extra Trees classifiers.

We have presented a visual representation illustrating the impact of the dataset's characters on the classification of migraines. Our visualization encompasses many types of plots, including scatter plots, bar plots, box plots, and point plots. Figure 2 presents visualizations of the duration, intensity, and frequency of each form of migraine, as well as the classification of types based on their frequency. Figure 4 displays the categorization of individuals into various age groups according to the type of migraine they experience. DPF, Tinnitus and Dysphasia shows in Figure 4.

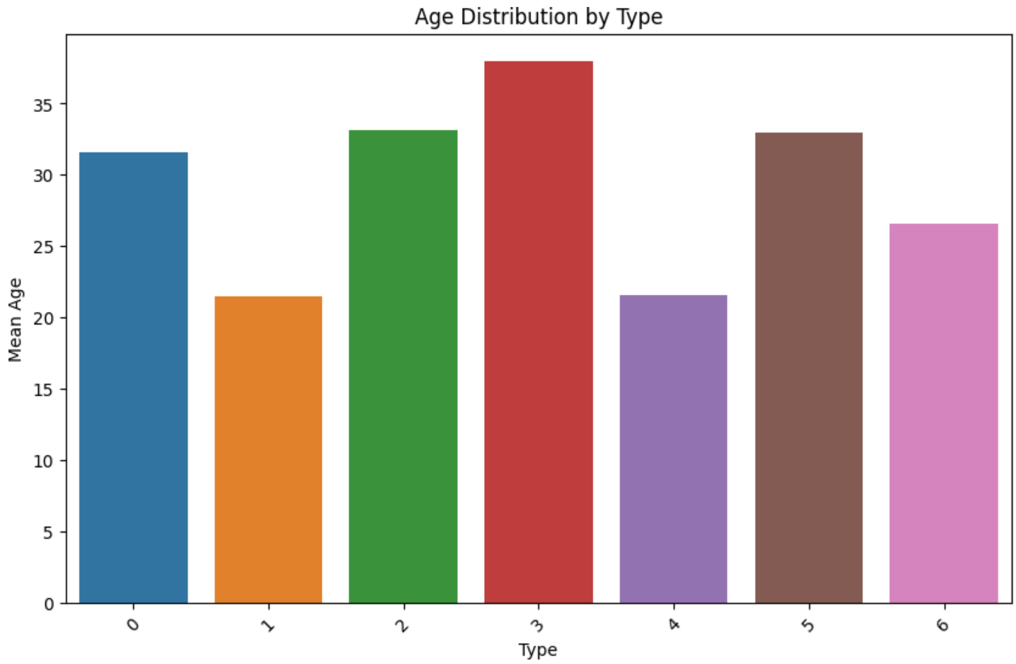

Figure 2. *Migraine type vs. Age.*

Figure 3 of this study paper shows a joint plot that clearly shows how Age and Duration of Migraines are related. This picture shows how the duration of migraines varies between people of different ages, pointing out possible patterns or trends linked to age. Scatterplot of Age versus Migraine Type, which shows in more detail how different types of headaches are spread out among different ages. We need this scatterplot to find out if different types of migraines are more common in certain age groups. This will help us get a better picture of the people who get migraine. These visual studies are very helpful for helping us learn more about migraine and what they mean for people of all ages.

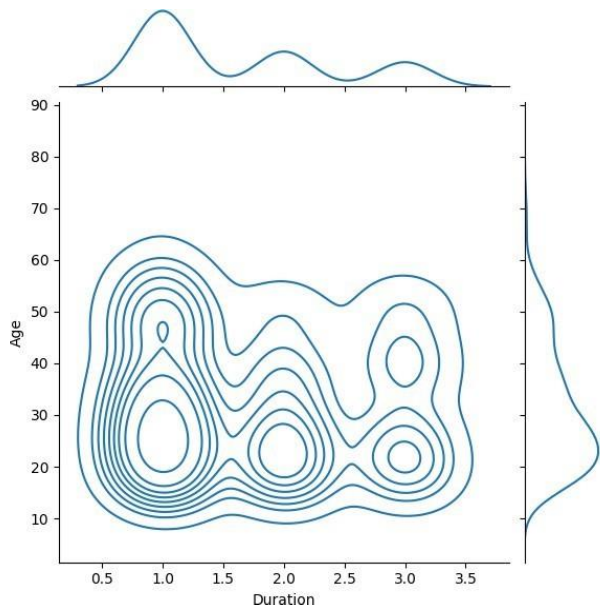

Figure 3. *Joint Plot of Age Vs Duration.*

We need this scatterplot to find out if different types of migraines are more common in certain age groups. This will help us get a better picture of the people who get migraine. These visual studies are very helpful for helping us learn more about migraine and what they mean for people of all ages.

We use joint plots and box plots as it helps us to visualize and comprehend our data very well. The joint plot, especially when Age is compared to Duration, helps us see how these two important factors are related and how they are spread out.

Box plots are also used to find statistical outliers and figure out the spread and central trend in our data. For example, we can use them to find out how long or how intense migraines usually are for different patient groups. Together, these plots help show the underlying patterns and differences in the migraine data, which is important for correct analysis and model building.

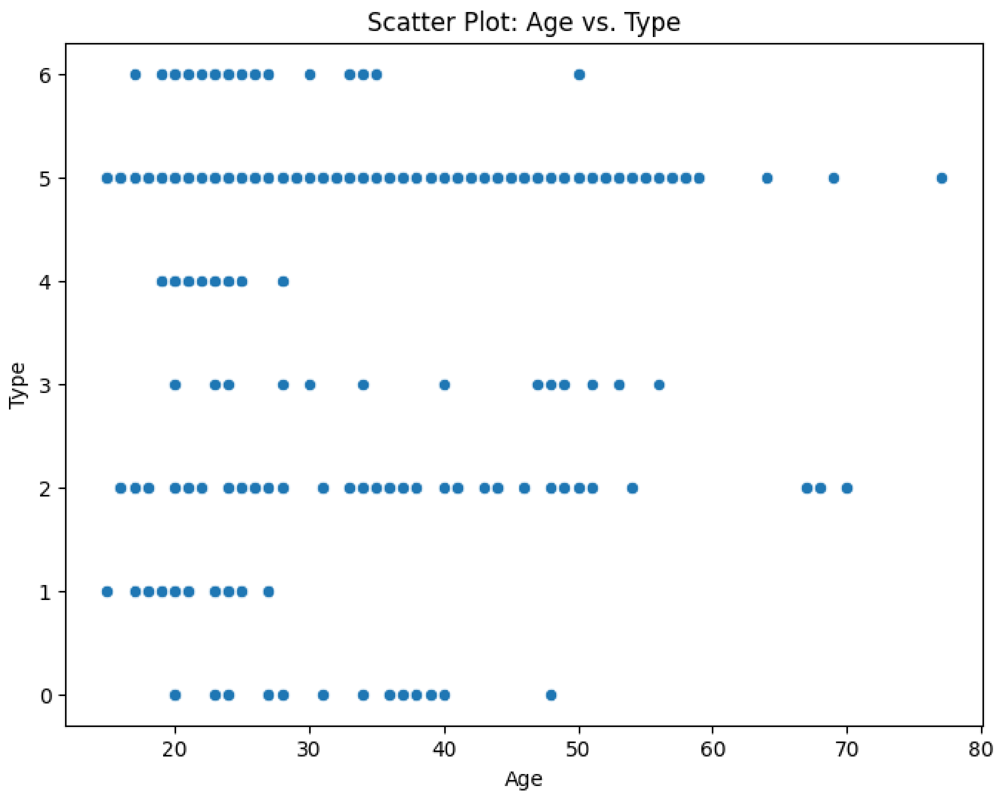

Figure 4. *Scatter Plot of Age Vs Duration.*

3.4. Methodology

In our research on migraine prediction, we initiated the process by combining data from multiple sources, ensuring a comprehensive dataset. This dataset comprised various migraine types, which were encoded numerically for clarity and ease of analysis. The types were categorized as follows: basilar-type aura as 0, familial hemiplegic migraine as 1, migraine without aura as 2, and so forth, providing a structured framework for our analysis.

The next critical step involved preprocessing the data. This included the removal of null values to enhance data quality and the application of label encoding to transform categorical variables into a machine-readable format. An essential aspect of our preprocessing was assessing the skewness of the data, leading to the removal of features that did not significantly contribute to migraine prediction. We adopted a dual approach in our methodology. The first approach utilized advanced machine learning algorithms – specifically, Random Forest (RF), K-Nearest Neighbors (KNN), and Na¨ıve Bayes (NB).

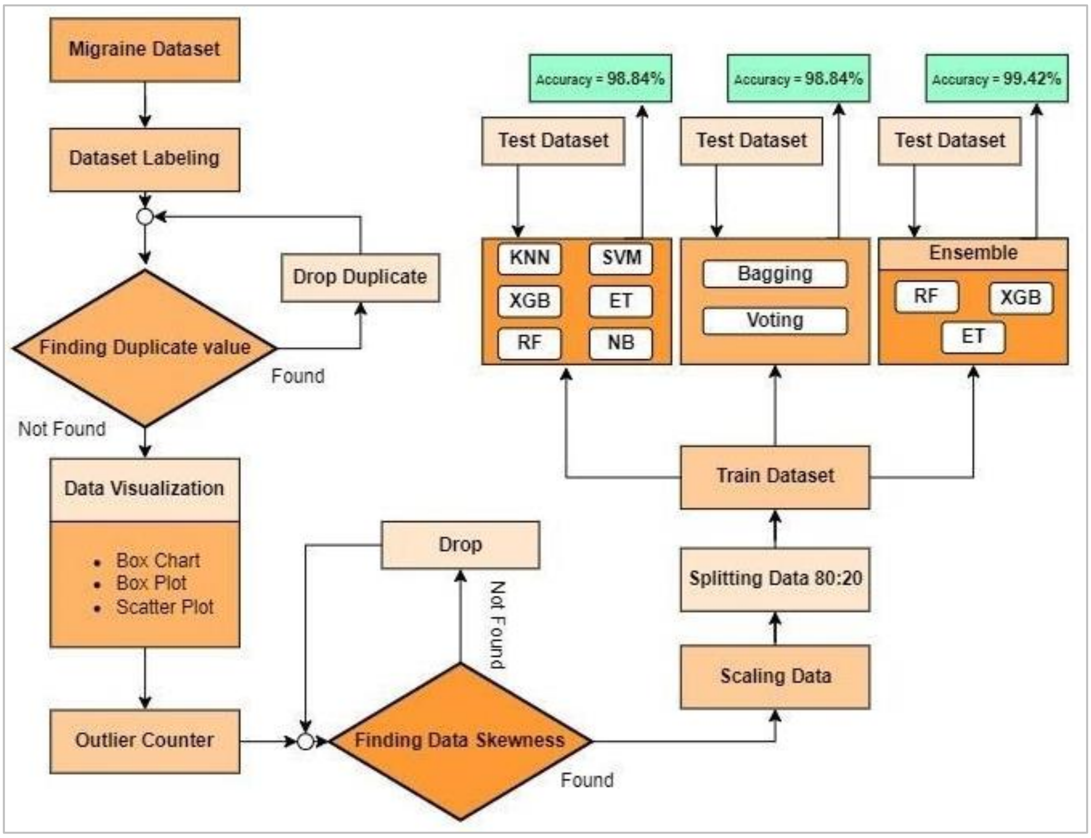

Figure 5. *Flow chart of the methodology.*

After splitting the dataset into an 80:20 ratio for training and testing, these models were rigorously trained and evaluated.

Our second approach focused on the implementation of an ensemble model, integrating the strengths of Random Forest (RF), XGBoost (XGB), and Extra Trees (ET) classifiers. This ensemble model was fine-tuned and optimized, resulting in a highly accurate predictive tool. The combination of these diverse algorithms in the ensemble model allowed us to achieve an impressive accuracy rate of 99.42%, surpassing the individual models. This methodology, particularly our ensemble model, proved to be highly effective in predicting migraine episodes. The ensemble's success lies in its ability to aggregate insights from various models, thereby enhancing the overall predictive accuracy and robustness.

The remarkable performance of this model underscores the potential of machine learning in revolutionizing migraine prediction and management. The working process of our proposed method is shown in Figure 5. Figure 5 in this study shows a detailed flow chart that shows the whole research process and the order in which the steps were taken. Providing a clear overview of the study's structure, this visual guide covers everything from gathering data to the end analysis. Figure 6 shows the ensemble diagram, which shows how the different machine learning models we used in our study work together in a complex way. This diagram is very important for understanding how different methods were combined to make our predictive model more accurate and useful.

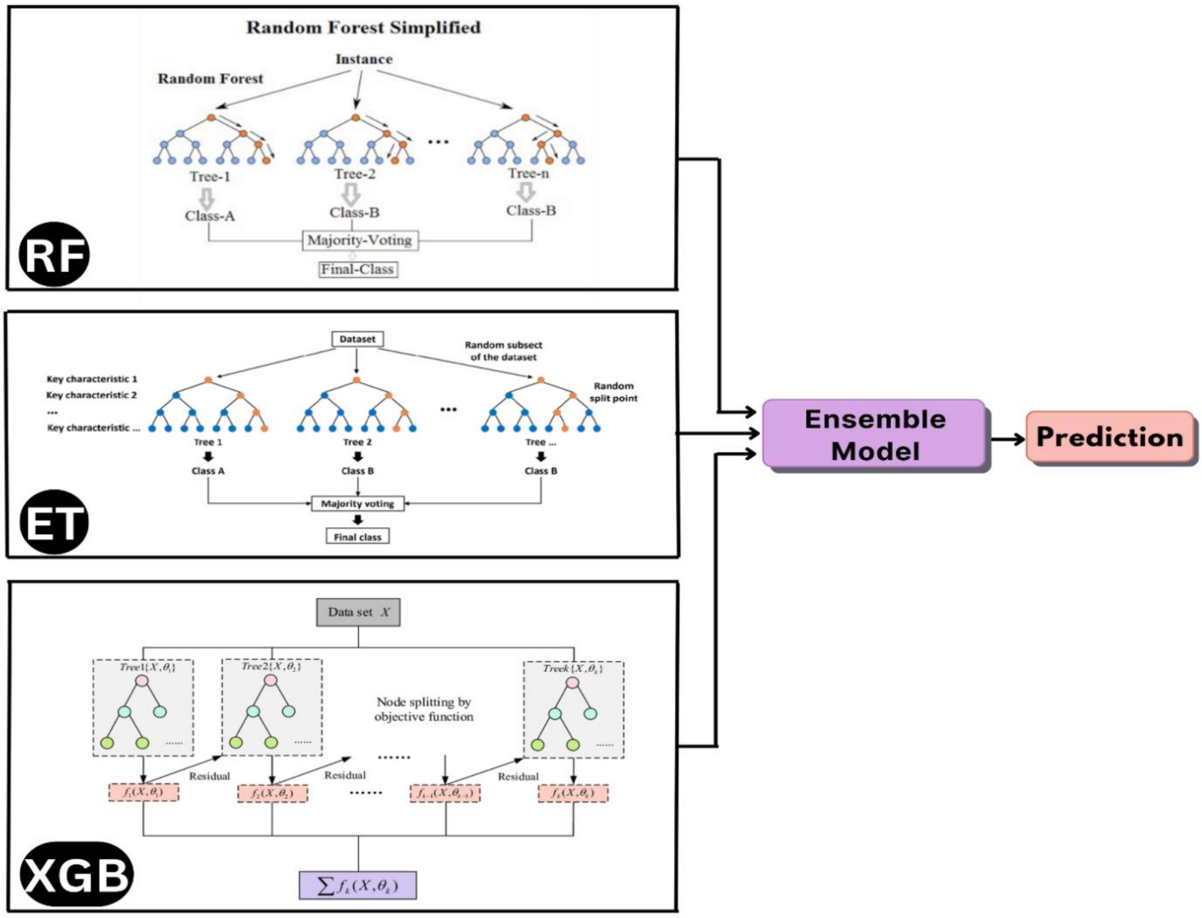

Figure 6. *Flow chart of proposed method.*

The ensemble model from our study is shown in Figure 6. It includes the Random Forest (RF), Extra Trees (ET), and XGBoost (XGB) algorithms in a useful way. Each method brings something special to the ensemble. For example, RF deals with variance, ET adds randomness, and XGB improves gradient boosting. The ensemble model combines different decision-making processes to come up with a final, highly accurate classification result for migraine types. This strategic combination makes for a strong prediction mechanism. The diagram makes it easy to understand how the ensemble works, from the separate algorithmic inputs to the predictive power of the whole model.

4. Experimental Analysis

In this study, we embarked on an exhaustive exploration of multiple machines learning models, culminating in the creation of an exceptionally accurate ensemble model. Our investigation began with the K-Nearest Neighbors (KNN) algorithm, which demonstrated a commendable accuracy of 93.93%. KNN's strength in capturing the intricate local pat-terns within our dataset was notable, although its performance was somewhat constrained by the sensitivity to the choice of neighbors and distance metrics, which are crucial parameters in this algorithm. The Support Vector Machine (SVM), a model renowned for its effectiveness in high-dimensional spaces, surprisingly achieved a lower accuracy of 62.56%. This could be attributed to SVM's potential challenges in managing the size and complexity of our migraine dataset, possibly leading to difficulties in finding an optimal hyperplane for classification. Also, the Random Forest (RF) and Extra Trees (ET) classifiers exhibited remarkable performances, achieving accuracies of 98.55% and 98.84%, respectively. These models, both ensemble methods themselves, utilize multiple decision trees to create a more robust and less biased prediction. Their success in our study can be ascribed to their ability to handle the dataset's non-linear characteristics and their effectiveness in reducing variance, which is a common issue in decision-tree-based models. The Naive Bayes model, with its fundamental assumption of feature independence and its inherent simplicity, scored an accuracy of 84.68%. This was a respectable outcome, yet it reflected the limitations of this model in capturing the complex relationships often present in intricate datasets like ours. XGBoost (XGB) also featured prominently in our experiments, attaining a 92.77% accuracy. XGB's gradient boosting framework, known for its efficiency and performance, was evidently effective, although it still did not reach the peak performance of our ensemble methods. This study further delved into the realm of ensemble techniques, where we combined different models to harness their collective strengths. The ensemble of KNN and SVM gives a lower accuracy of 68.78%, suggesting that the combination did not synergize as effectively as anticipated. However, the ensemble comprising RF, KNN, and Naive Bayes marked a significant improvement, achieving an accuracy of 98.26%. This combination benefitted from the diverse approaches of each algorithm, leading to a more balanced and accurate prediction model.

A bagging technique was also employed, which paralleled the accuracy of the ET model at 98.84%. This approach underlined the advantages of using ensemble learning to improve the stability and accuracy of machine learning algorithms. The Table 1 shows the confusion matrix report of KNN with 94% accuracy. Table 2 shows about XGBoost's performance. And in Table 4 it shown our proposed ensemble model with Random Forest, Extra Trees and XGBoost. The final result of our research was the proposed ensemble model, with RF, XGB, and ET. This model achieved a re-markable accuracy of 99.42%, setting a new benchmark in our migraine classification study. The exceptional performance of this ensemble model is a testament to the power of combining multiple advanced machine learning techniques. By effectively amalgamating the distinct strengths of RF, XGB, and ET, we mitigated the weaknesses inherent in each individual model. This not only resulted in a highly accurate classifier but also demonstrated a robust approach to handling the complexities and variabilities inherent in migraine data. In this Study we applied multiple models to find the best accuracy. Here we applied KNN which performs 94% accuracy, SVM didn't perform that well, the performance of SVM is 63%. Random Forest and Extra Trees performs very well here with 98.5% and 98.84% accuracy. Naive Bayes and XGB also performs 84.68% and 92.77. We applied an ensemble model with KNN and SVM which perform 68%. It doesn't give proper result so we applied another ensemble RF, KNN and NB which perform 98.26%. And applied another Bagging method which results 98.84%. Then we got our proposed model where we ensemble RF, XGB and ET which scores 99.42%. In the Figure 7 it shows the compare result analysis of all models.

Table 1. *Performance report for KNN.*

KNN	Precision	Recall	F1-Score	Support
Basilar-type aura (0)	1.00	1.00	1.00	50
Familial hemiplegic mi-graine (1)	0.89	1.00	0.94	49
Migraine without aura (2)	0.90	0.94	0.92	49
Other (3)	0.96	1.00	0.98	50
Sporadic hemiplegic mi-graine (4)	0.91	1.00	0.95	49
Typical aura with mi-graine (5)	0.91	0.63	0.75	49
Typical aura without mi-graine (6)	1.00	1.00	1.00	50
Accuracy			0.94	346
Macro Avg	0.94	0.94	0.93	346
Weighted Avg	0.94	0.94	0.93	346

Table 2. *Performance report for XGBoost.*

XGBoost	Precision	Recall	F1-Score	Support
Basilar-type aura (0)	0.98	0.82	0.89	50
Familial hemiplegic mi-graine (1)	0.94	1.00	0.97	49
Migraine without aura (2)	0.94	1.00	0.97	49
Other (3)	1.00	0.94	0.97	50
Sporadic hemiplegic mi-graine (4)	0.80	0.84	0.82	49
Typical aura with mi-graine (5)	0.77	0.82	0.79	49

XGBoost	Precision	Recall	F1-Score	Support
Typical aura without mi-graine (6)	1.00	1.00	1.00	50
Accuracy			0.92	346
Macro Avg	0.92	0.92	0.92	346
Weighted Avg	0.92	0.92	0.92	346

Table 3. Performance report for Proposed Ensemble Model (Random Forest, XGB and ET).

XGBoost	Precision	Recall	F1-Score	Support
Basilar-type aura (0)	0.98	1.00	0.99	50
Familial hemiplegic mi-graine (1)	0.96	1.00	0.98	49
Migraine without aura (2)	1.00	1.00	1.00	49
Other (3)	1.00	1.00	1.00	50
Sporadic hemiplegic mi-graine (4)	1.00	1.00	1.00	49
Typical aura with mi-graine (5)	1.00	0.94	0.97	49
Typical aura without mi-graine (6)	1.00	1.00	1.00	50
Accuracy			0.99	346
Macro Avg	0.99	0.99	0.99	346
Weighted Avg	0.99	0.99	0.99	346

In our discussion on the study of migraine classification using machine learning, we found that different models have varying success rates. The most effective model was our spe-cially designed ensemble model, combining Random Forest, XGBoost, and Extra Trees classifiers, which showed an impressive accuracy of 99.42%. This high accuracy sug-gests that this model is very good at correctly identifying different types of migraines. However, simpler models like the K-Nearest Neighbors and Support Vector Machines didn't perform as well, which might be because these models are less capable of handling the complex patterns found in migraine data. What's interesting is how combining different models into one, like we did with our ensemble model, can work better than using a single model. This research is im-portant because it can help doctors and healthcare profes-sionals better understand and diagnose migraine, leading to better care for patients. However, it's also important to re-member that our study has some limitations, like how well our model would work with different types of patients not in our study, and the model's complexity might make it hard for some doctors to use without special training.

Table 4. Performance report for Proposed Ensemble Model (Random Forest, XGB and ET).

Model Name	Actual Type	Prediction Value	Accuracy
KNN	4 4 4 0 0 2 0 1	4 4 4 0 3 2 0 1	93.93
SVM	4 4 4 0 0 2 0 1	4 4 4 1 0 2 0 1	62.56
Random Forest (RF)	4 4 4 0 0 2 0 1	4 4 4 0 1 2 0 1	98.55
ET	4 4 4 0 0 2 0 1	4 4 4 0 1 2 0 1	98.84
NB	4 4 4 0 0 2 0 1	4 4 4 4 1 2 0 5	84.68
XGB	4 4 4 0 0 2 0 1	4 4 4 4 0 2 0 1	92.77

Model Name	Actual Type	Prediction Value	Accuracy
Ensemble (KNN, SVM)	4 4 4 0 0 2 0 1	4 4 4 0 0 2 0 1	68.78
Ensemble (RF, KNN, NB)	4 4 4 0 0 2 0 1	4 4 4 0 0 2 0 1	98.26
Bagging	4 4 4 0 0 2 0 1	4 4 4 0 0 2 0 1	98.84
Proposed Model	4 4 4 0 0 2 0 1	4 4 4 0 0 2 0 1	99.42

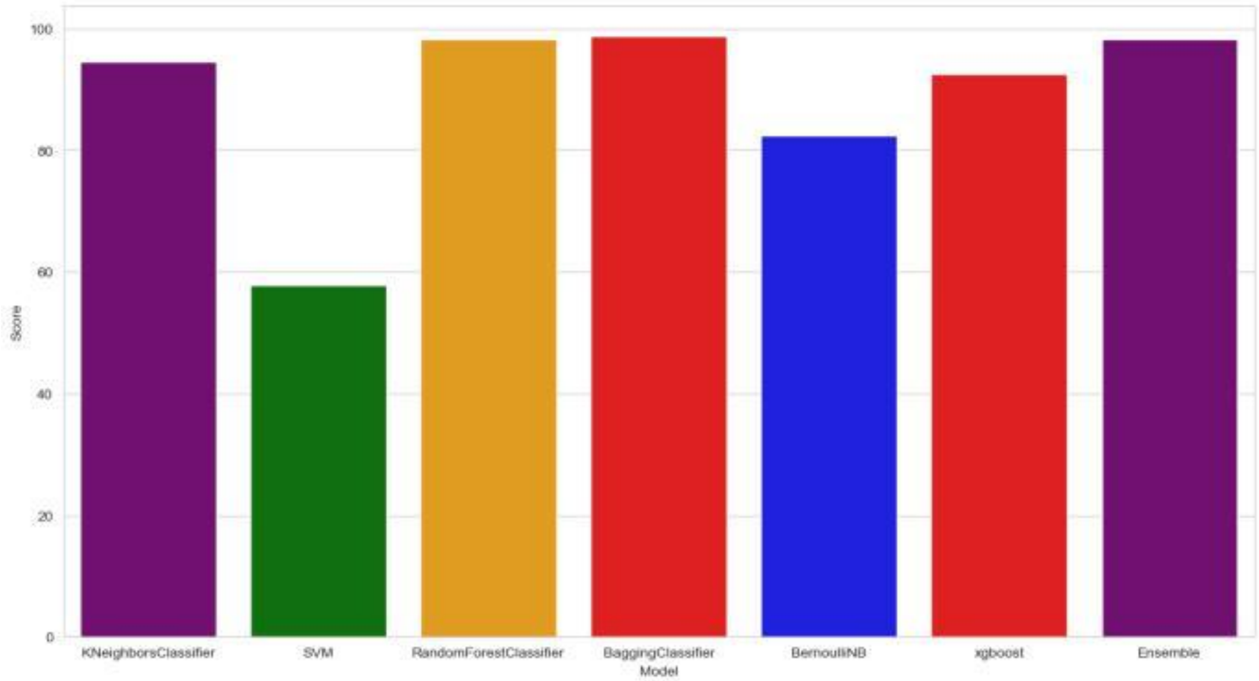

Figure 7. *Flow chart of the methodology.*

5. Conclusions

The In conclusion, our research represents a significant break-through in migraine classification through the use of advanced machine learning techniques. By successfully developing an ensemble model that combines Random Forest, XGBoost, and Extra Trees classifiers, we achieved an accuracy rate of 99.42%, demonstrating the model's superior capability in predicting migraine types. This study not only contributes to the field of neurology by offering a more precise and effective method for migraine diagnosis but also sets a prece-dent for the application of similar techniques in other areas of medical research. The implications of this work are far-reaching, suggesting a future where data-driven methodologies can significantly enhance patient care and treatment outcomes in various medical disciplines.

Abbreviations

BMI	Body Mass Index
DPF	Acute Treatments for Episodic Migraine

Author Contributions

Firoz Hasan: Conceptualization, Methodology, Formal Analysis, Investigation

Rubina Khatun: Data curation, Resources, Formal Analysis

Engr. Mohammad Salman: Writing – original draft

Dewan Mamun Raza: Writing – review & editing

Tarek Mahmud: Writing – review & editing

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Data Availability Statement

The data is available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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