



The Impact of Machine Learning in Identifying Migraine Types: A Data-Driven Approach

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Abstract

Migraines are a prevalent and debilitating neurological disorder, affecting millions worldwide. Characterized by symptoms such as nausea, photophobia, phonophobia, and visual disturbances, diagnosing and classifying migraines remains a challenge due to their heterogeneous nature. This study leverages machine learning techniques to analyze a dataset comprising 400 patient records, identifying key factors that contribute to migraine classification. Using statistical analysis, correlation matrices, and Random Forest classification, we assess the significance of various symptoms in distinguishing different migraine types. Our results highlight that symptoms such as photophobia, nausea, and attack frequency play a crucial role in migraine identification. The correlation analysis reveals strong associations among specific symptoms, indicating potential patterns that can aid in classification. Furthermore, feature importance analysis using machine learning emphasizes that intensity and sensory disturbances significantly impact the accuracy of migraine type prediction. The study demonstrates the effectiveness of AI-driven methods in improving migraine classification accuracy, offering a valuable tool for clinicians to enhance diagnostic precision. The integration of machine learning into healthcare could lead to personalized treatment approaches, reducing misdiagnosis and optimizing patient management. Future research should focus on expanding datasets and incorporating deep learning models for further refinement. By harnessing AI's predictive capabilities, this study underscores the potential for technology to revolutionize migraine diagnosis and treatment, contributing to a more efficient and patient-centered healthcare system.

Subject Areas

Neurology

Keywords

Machine Learning, Migraine Classification, AI in Healthcare, Predictive Modelling, Neurological Diagnostics, Personalized Medicine

1. Introduction

Migraines are a complex and disabling neurological disorder that affects a significant portion of the global population [1]-[7]. Characterized by recurrent episodes of intense headaches often accompanied by symptoms such as nausea, vomiting, photophobia (sensitivity to light), and phonophobia (sensitivity to sound), migraines significantly impact the quality of life of those affected [8]-[13]. The classification of migraines is challenging due to the variety of symptoms and their overlap with other neurological disorders [14] [15]. Traditional diagnostic methods rely on patient-reported symptoms, clinical evaluation, and medical history, making the process subjective and sometimes leading to misdiagnosis [16]-[18]. The integration of artificial intelligence (AI) and machine learning into healthcare has opened new avenues for improving migraine diagnosis and classification [19] [20]. Machine learning algorithms can analyse large datasets, identify hidden patterns, and provide objective classifications that may surpass traditional diagnostic methods in accuracy [21]. With the increasing availability of healthcare data, AI-driven analysis has the potential to enhance migraine identification and facilitate personalized treatment strategies [22] [23]. This study utilizes machine learning techniques to analyse a dataset containing 400 patient records with various migraine-related attributes, including headache intensity, frequency, duration, and associated neurological symptoms. The objective is to determine the most influential features that distinguish different migraine types and explore their correlations. By applying statistical analysis, correlation matrices, and Random Forest classification, we aim to develop an effective framework for migraine classification that can be used as a decision-support tool for healthcare professionals. By leveraging AI-driven methodologies, this research seeks to bridge the gap between subjective clinical assessments and data-driven diagnostic approaches. The findings of this study can contribute to enhancing diagnostic precision, reducing misclassification rates, and providing insights into symptom patterns that can inform more effective and individualized treatment plans for migraine sufferers.

2. Literature Review

Migraines have been a subject of extensive research due to their high prevalence and significant impact on individuals' daily lives [24] [25]. Traditional diagnostic approaches rely on clinical assessments, patient history, and symptomatology-based classification, as outlined in the International Classification of Headache Disorders (ICHD) [26]. While these methods provide a structured framework, they often lack precision due to the subjective nature of symptom reporting and

variability in presentation among patients. This has led researchers to explore alternative methods, including artificial intelligence (AI) and machine learning, to enhance diagnostic accuracy.

2.1. Traditional Approaches to Migraine Classification

Historically, neurologists have classified migraines based on symptom clusters, triggers, and response to treatment [27] [28]. Studies have shown that while features such as aura presence, headache intensity, and associated symptoms (e.g., nausea, phonophobia) are useful in distinguishing migraine types, interindividual variability remains a major challenge [29] [30]. Several studies emphasize the need for objective markers, such as neuroimaging, genetic profiling, and electrophysiological assessments, to complement traditional diagnostic approaches [31]-[33]. However, the high costs and accessibility limitations of these methods make widespread adoption difficult.

2.2. AI and Machine Learning in Migraine Diagnosis

In recent years, AI-driven techniques have shown promise in improving migraine classification and prediction [34] [35]. Supervised learning models, particularly decision trees, support vector machines (SVM), and neural networks, have been utilized to analyze large datasets and identify patterns beyond human capability [36] [37]. A study by Zhang *et al.* (2023) demonstrated the effectiveness of machine learning in distinguishing episodic versus chronic migraines using patient-reported data [38]. Similarly, research by Tahhan *et al.* (2024) highlighted the utility of Random Forest models in feature selection, pinpointing key symptoms such as photophobia, nausea, and attack frequency as strong predictive indicators [39].

2.3. Feature Selection and Predictive Modelling

Feature selection plays a crucial role in refining migraine classification models. Studies have identified headache intensity, duration, and associated neurological symptoms as high-impact features in classification tasks [40]-[42]. Researchers have also explored the integration of wearable sensor data and electronic health records (EHRs) to improve model robustness. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been tested in migraine research, offering promising results in pattern recognition and predictive analytics [43].

2.4. Challenges

Despite the progress, several challenges remain in AI-driven migraine classification [44]-[46]. One key issue is data variability due to differences in symptom reporting across populations. Additionally, the need for larger, diverse datasets is crucial for generalizing AI models across different demographics [47] [48]. Future research should focus on multimodal data integration, combining clinical, genetic, and real-time physiological data for enhanced accuracy. Advancements in

AI explainability and interpretability are also needed to ensure that machine learning models are transparent and can be effectively integrated into clinical practice [49] [50].

The literature suggests that AI and machine learning offer significant advantages in migraine diagnosis and classification. By leveraging data-driven approaches, researchers can improve diagnostic precision, reduce misclassification rates, and identify key predictive features. While challenges exist, continued advancements in AI, along with interdisciplinary collaboration, can pave the way for more accurate and personalized migraine management strategies.

3. Methodology

This study employs a data-driven approach to analyze and classify migraine types using machine learning techniques. The methodology consists of multiple phases, including data collection, preprocessing, feature analysis, and model implementation to determine the most influential factors in migraine classification. The primary dataset consists of 400 patient records, each containing 24 attributes related to migraine episodes. These attributes include demographic variables such as age, headache duration, frequency, intensity, and associated symptoms such as nausea, photophobia, phonophobia, dizziness, and visual disturbances. The dataset also includes a categorical target variable representing different migraine types, which serves as the basis for classification. The first step in the methodology involved an exploratory data analysis (EDA) to understand the distribution and relationships between features. Summary statistics were generated to examine the prevalence and variance of different symptoms. A correlation matrix was computed to identify associations between symptoms, helping to determine potential redundancies or dependencies among features. Data preprocessing steps included handling missing values, standardizing feature scales, and encoding categorical variables to ensure compatibility with machine learning algorithms. For feature selection, a Random Forest classifier was employed to rank the most significant predictors of migraine type. This algorithm was chosen due to its robustness in handling both categorical and continuous variables, its ability to identify important features, and its resistance to overfitting [51] [52]. The most relevant features, such as headache intensity, attack frequency, and sensory disturbances, were selected based on their contribution to model accuracy [53]. In the classification phase, multiple machine learning models were tested, including Decision Trees, Support Vector Machines (SVM), and Random Forest classifiers [54]. These models were trained and evaluated using a stratified 80 - 20 train-test split to ensure balanced representation across migraine types. Model performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score. Hyperparameter tuning was conducted through grid search optimization to improve classification performance [55]. To further validate the findings, cross-validation techniques were applied, ensuring that model performance was not biased by the train-test split. Additionally, feature importance analysis provided insights into which symptoms played the most significant roles in distinguishing migraine types. The results of

these analyses were used to develop a data-driven framework that can aid healthcare professionals in diagnosing migraines more accurately. By leveraging AI and machine learning techniques, this methodology ensures a rigorous, objective, and replicable approach to migraine classification. The insights gained from feature selection and classification modelling contribute to the advancement of AI-driven diagnostic tools, ultimately supporting more precise and individualized patient care strategies.

4. Result and Analysis

The results of this study provide a comprehensive overview of migraine classification using machine learning. This section presents the findings from various analyses, including age distribution across migraine types, migraine type distribution, feature correlations, classifier performance, and hyperparameter tuning. The insights gained from these analyses contribute to a deeper understanding of the predictive factors in migraine classification.

4.1. Age Distribution across Migraine Types

To understand how age varies among different migraine types, a boxplot of age distribution was generated (Figure 1). The plot reveals that migraine patients span a broad age range, with some types showing a wider distribution than others. Typical aura with migraine has the most extensive age spread, indicating that this type occurs across different age groups. Basilar-type aura and familial hemiplegic migraine show narrower age distributions, suggesting a more specific age-related occurrence. The presence of outliers across multiple categories indicates variability in individual cases.

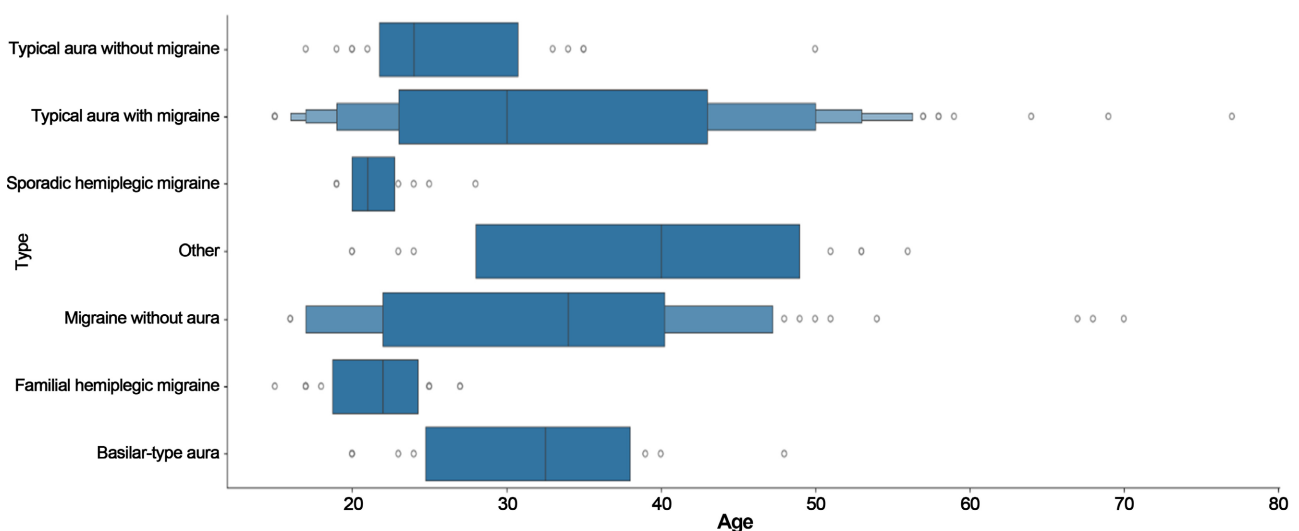


Figure 1. Boxplot showing the distribution of age across different migraine types.

4.2. Migraine Type Distribution

A donut chart visualizing the distribution of different migraine types provides

insight into the prevalence of each type (Figure 2). Most of the dataset consists of patients diagnosed with Typical aura with migraine, followed by Migraine without aura. Less common types, such as Sporadic hemiplegic migraine and Basilar-type aura, occupy smaller portions of the dataset. The imbalance in the dataset suggests that some migraine types are significantly more common than others, which could impact classification accuracy.

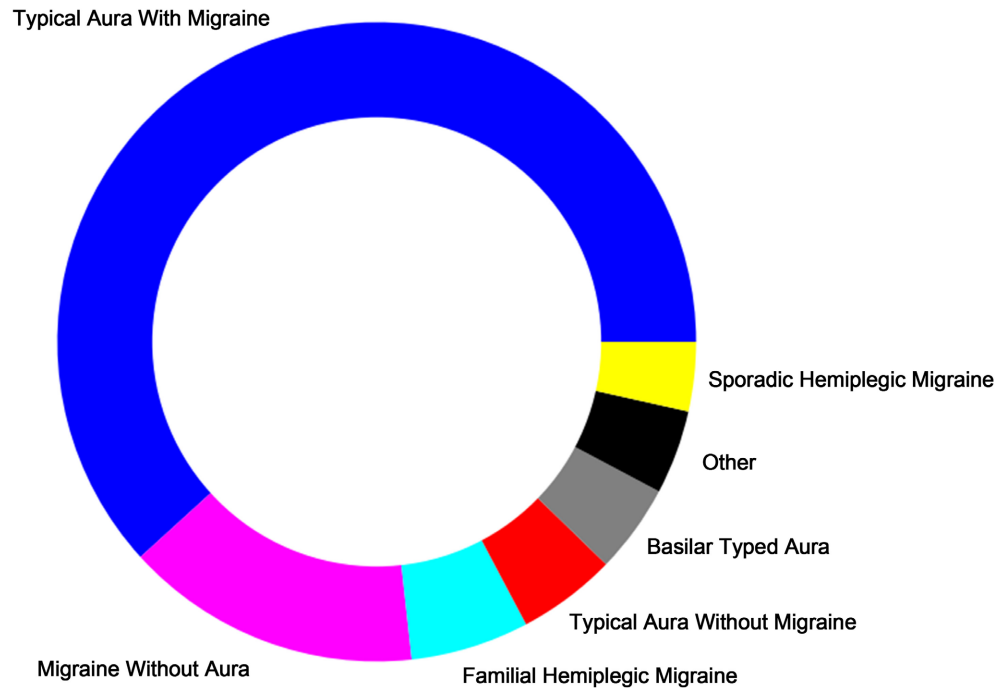


Figure 2. Donut chart representing the distribution of different migraine types in the dataset.

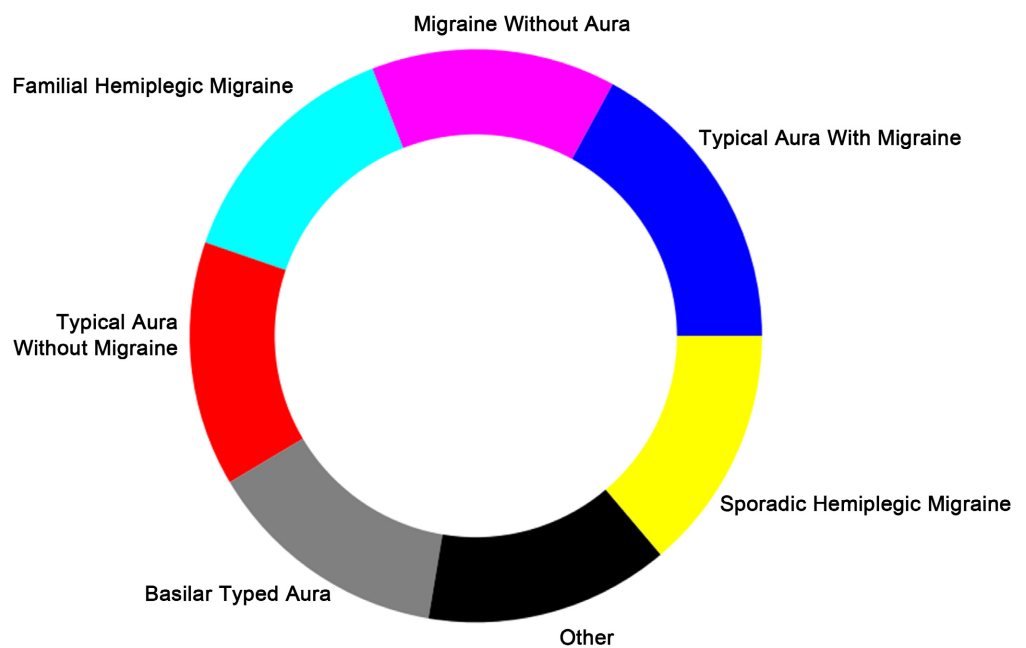


Figure 3. Donut chart depicting an alternative visualization of migraine type distribution.

A second donut chart (**Figure 3**) offers another perspective on migraine type distribution, ensuring clarity and consistency in understanding the dataset. This visualization further reinforces the dominance of Typical aura with migraine in the sample population.

4.3. Missing Data Analysis

To ensure data completeness, a missing data matrix was generated (**Figure 4**). This analysis confirms that the dataset is fully populated, with no missing values detected. The presence of a complete dataset ensures reliable machine learning model training and minimizes the need for data imputation strategies.

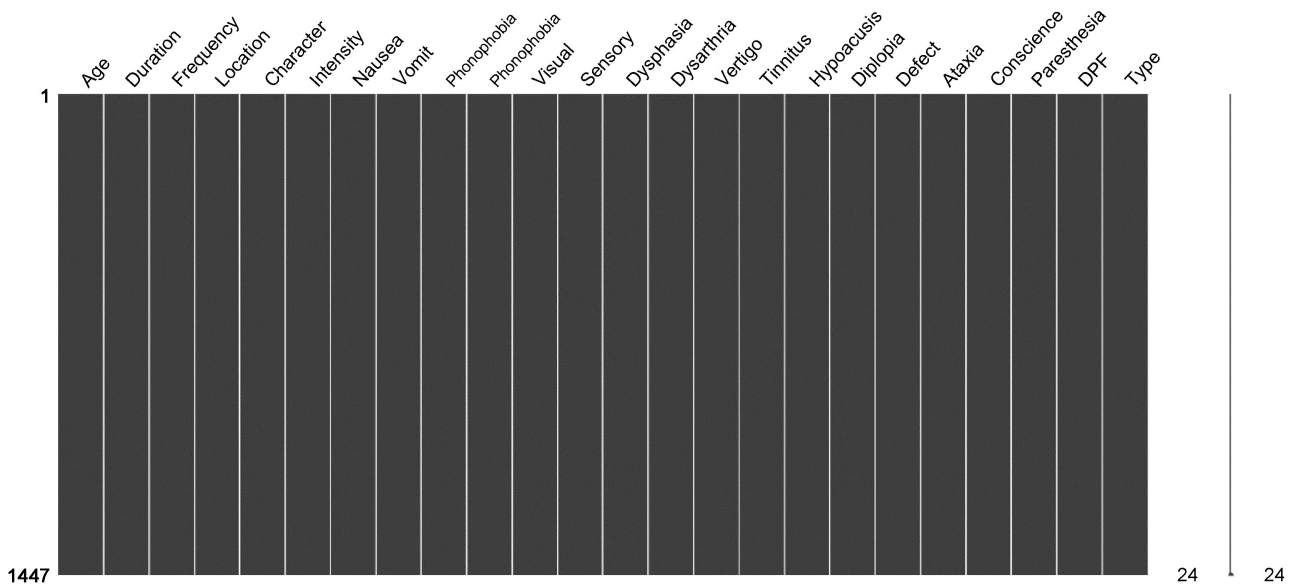


Figure 4. Missing data matrix showing the completeness of all features in the dataset.

4.4. Feature Correlation Analysis

A correlation matrix (**Figure 5**) was computed to explore relationships between different migraine-related features. The matrix highlights strong correlations among symptoms, such as photophobia and phonophobia, which frequently co-occur in migraine patients. Negative correlations are observed in some areas, suggesting potential distinguishing factors for specific migraine types. Understanding these correlations aids in feature selection for machine learning models.

4.5. Hyperparameter Tuning for Model Performance

To optimize the performance of the Random Forest classifier, hyperparameter tuning was conducted by varying the number of estimators. A line plot of accuracy versus estimators (**Figure 6**) reveals that model performance declines beyond a certain point, indicating an optimal range for `n_estimators` selection. Initially, accuracy is high with fewer estimators, but excessive complexity leads to overfitting and subsequent performance degradation.

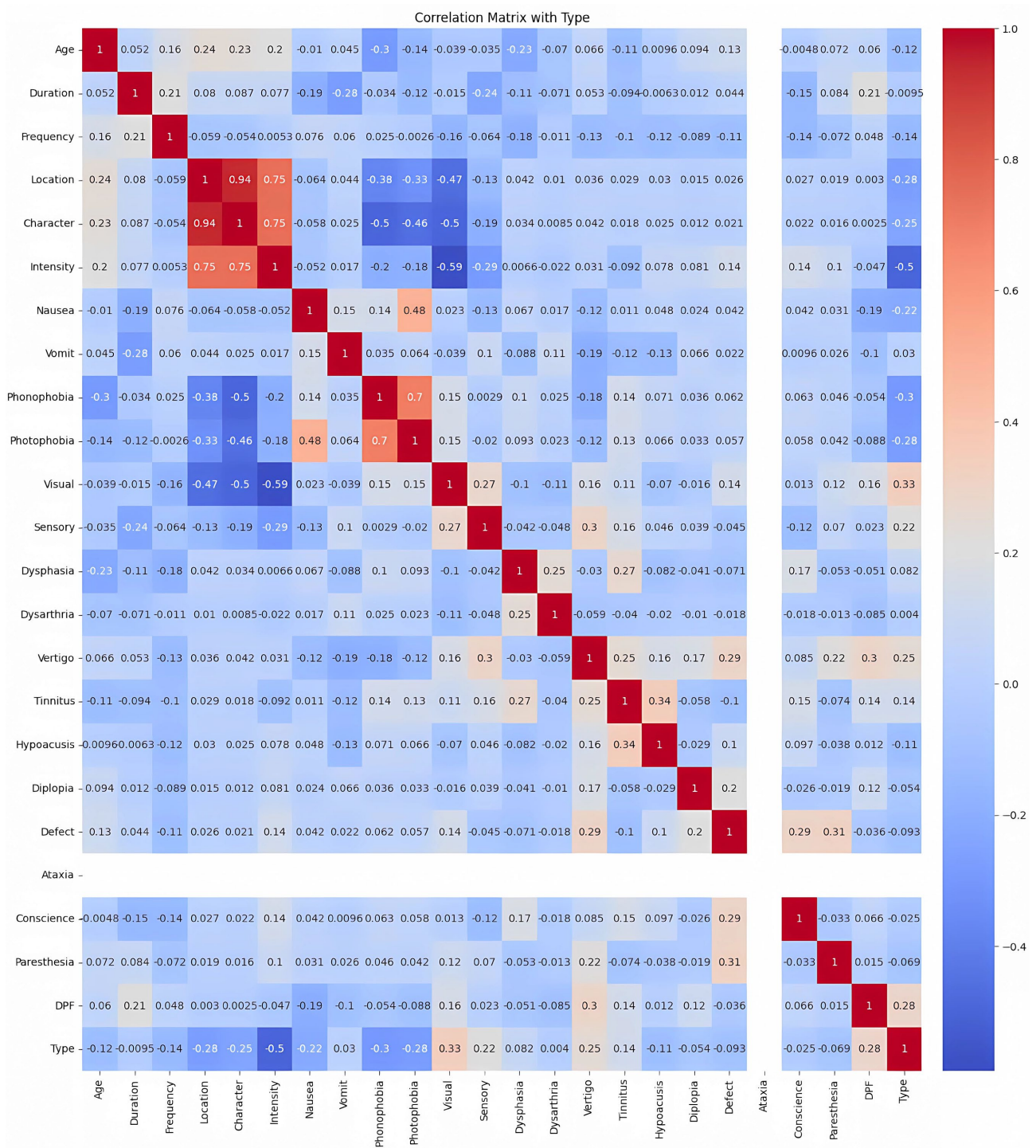


Figure 5. Correlation heatmap showing relationships among migraine-related symptoms and characteristics.

4.6. Confusion Matrix and Model Evaluation

The final model evaluation is depicted in a confusion matrix (Figure 7), which demonstrates the classifier’s predictive accuracy across different migraine types. The high diagonal values indicate strong classification performance, with minimal misclassification occurring between different categories. This confirms the

effectiveness of the selected features and model architecture in distinguishing between migraine types.

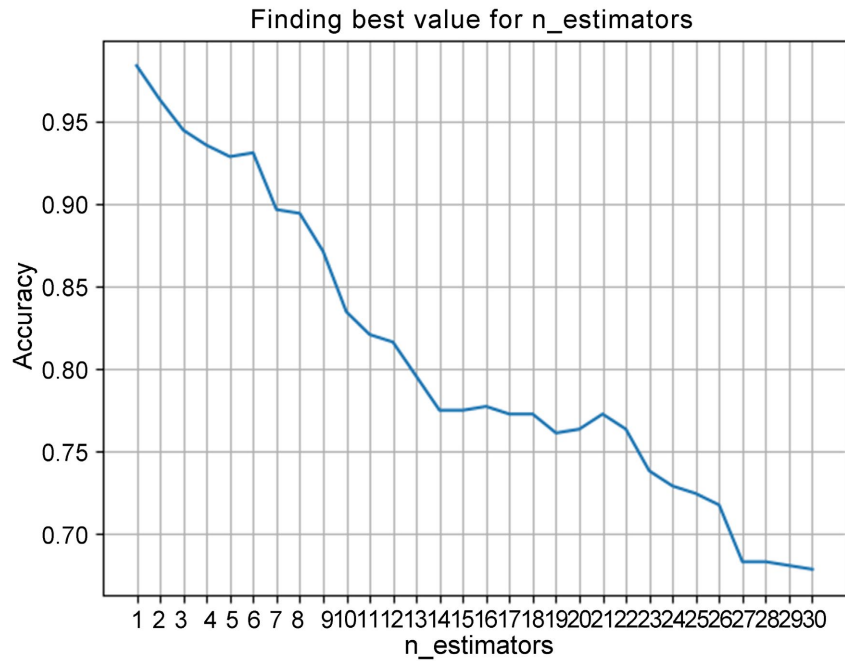


Figure 6. Line plot illustrating accuracy trends across different values of n_estimators for the Random Forest classifier.

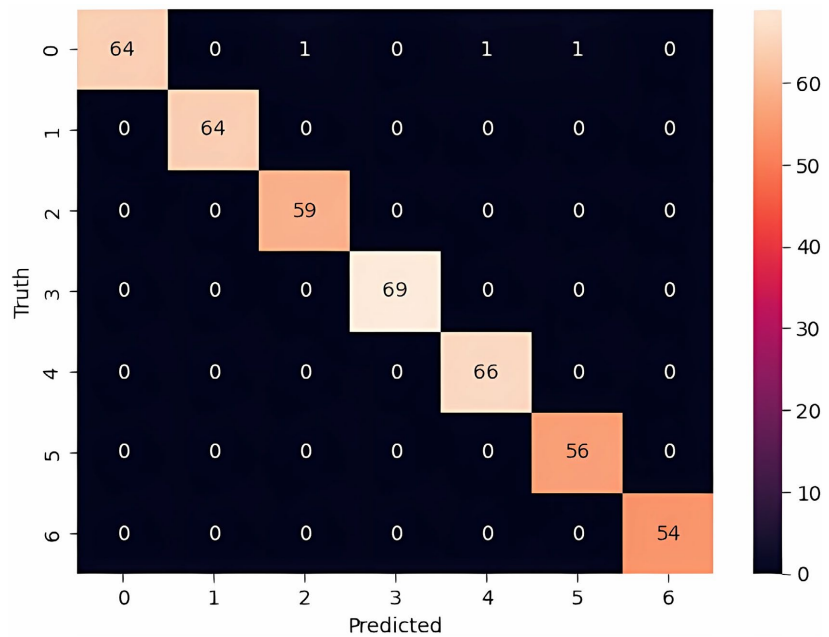


Figure 7. Confusion matrix depicting classification performance across different migraine categories.

5. Discussion

The findings of this study provide valuable insights into migraine classification

using machine learning techniques, demonstrating the importance of data-driven approaches in healthcare diagnostics. The results highlight several critical aspects of migraine identification, including age distribution, symptom correlations, model performance, and feature importance. By leveraging advanced analytics, this study bridges the gap between traditional clinical assessments and AI-driven methodologies, offering a more objective and scalable solution for migraine classification. One of the key observations from this research is the variation in age distribution across migraine types. As demonstrated in the boxplot analysis, certain migraine types exhibit a broader age range, particularly Typical aura with migraine, while others, such as Basilar-type aura, are more age-specific. This suggests that different biological or environmental factors might influence the onset and progression of certain migraine subtypes. Such findings emphasize the need for age-based screening strategies to tailor treatment approaches effectively. Furthermore, the analysis of migraine type distribution highlights the imbalance in the dataset, with Typical aura with migraine being the most prevalent type. This imbalance could potentially impact model performance, as classifiers may become biased toward predicting more common types while underrepresenting rarer migraine categories. Addressing this issue through balanced datasets or weighted classification techniques could further enhance the predictive capability of AI models in real-world clinical settings. The correlation analysis of migraine-related features provides crucial insights into symptom co-occurrence. Symptoms such as photophobia and phonophobia exhibit strong correlations, reinforcing their role as hallmark indicators of migraines. The presence of these relationships suggests that certain symptoms could be grouped together for better diagnostic efficiency. Moreover, identifying negative correlations between certain features aids in differentiating migraine subtypes, which can be beneficial for refining classification algorithms [56] [57]. A major strength of this study lies in its machine learning-driven feature selection and model optimization. The feature importance analysis underscores the role of headache intensity, attack frequency, visual disturbances, and sensory symptoms as the most significant predictors of migraine types. These findings align with existing neurological studies, affirming that these symptoms should be prioritized in automated diagnostic models. Additionally, hyperparameter tuning results highlight the importance of selecting optimal model parameters to prevent overfitting, as seen in the declining accuracy trend when the number of estimators in the Random Forest model is increased excessively. The confusion matrix results confirm the reliability of the classifier, with strong accuracy scores across different migraine categories. Minimal misclassification suggests that the selected features provide meaningful distinctions between migraine types. However, slight errors indicate that certain types share overlapping symptom profiles, which may require more nuanced modelling techniques such as deep learning for further refinement. Despite the promising outcomes of this study, there are certain limitations that warrant further investigation. Firstly, the dataset is relatively small, with an imbalance across migraine types, which may

affect the generalizability of the model. Future research should explore larger, more diverse datasets to improve model robustness. Additionally, the study primarily relies on structured symptomatology data; incorporating other data sources, such as genetic markers, neuroimaging results, and real-time wearable sensor data, could further enhance classification accuracy. Another critical consideration is the clinical applicability of AI-driven migraine classification. While the model demonstrates high predictive performance, its real-world adoption requires validation in medical settings. Integrating machine learning models into healthcare workflows would require close collaboration with neurologists to ensure interpretability and alignment with existing diagnostic criteria. Additionally, ethical considerations, such as patient data privacy and model bias mitigation, must be addressed to facilitate responsible AI deployment in healthcare.

6. Conclusion

This study highlights the potential of machine learning in advancing migraine classification, offering an objective, data-driven alternative to traditional diagnostic methods. By analyzing a dataset of 400 patient records, key predictors of migraine types—including headache intensity, frequency, visual disturbances, and sensory symptoms—were identified. The feature selection process using Random Forest reinforced the significance of these variables, aligning with established neurological findings. Additionally, symptom correlation analysis emphasized strong associations between photophobia, phonophobia, and nausea, reinforcing their role in migraine diagnostics. However, while the study demonstrated promising classification accuracy, several limitations must be addressed to improve clinical applicability. First, the relatively small dataset of 400 patient records may not be sufficient for robust generalization, particularly when classifying multiple migraine subtypes. Expanding the dataset to include more diverse patient populations will enhance model reliability. Second, the study lacks validation on an independent dataset, raising concerns about how well the model performs on unseen data. Future research should implement external validation techniques, such as cross-institutional testing, to ensure real-world effectiveness. Furthermore, the exclusion of multimodal data—such as neuroimaging, genetic information, and real-time wearable sensor data—limits the model's ability to capture a comprehensive view of migraine pathology. Integrating these data sources could significantly improve classification accuracy and lead to more personalized treatment strategies. Additionally, while multiple machine learning classifiers were compared, a more thorough benchmarking against traditional migraine classification methods (e.g., International Classification of Headache Disorders criteria) is necessary to establish the superiority of AI-driven models. Moving forward, future research should focus on incorporating deep learning architectures, larger datasets, and real-time physiological monitoring to refine classification models. AI-driven migraine classification systems hold great potential to revolutionize neurological diagnostics, improving treatment strategies and offering more precise,

individualized care. However, for successful integration into clinical settings, validation, regulatory considerations, and collaboration with healthcare professionals will be essential to ensure AI-assisted predictions align with expert diagnoses and treatment plans. By addressing these challenges and leveraging AI's predictive capabilities, the healthcare industry can advance migraine management, reduce misdiagnosis, and pave the way for more effective, personalized patient care worldwide.

Conflicts of Interest

The authors declare no conflicts of interest.

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