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EXPLAINABLE MACHINE LEARNING FOR EARLY MIGRAINE DETECTION AND SEVERITY CLASSIFICATION USING SMOTE-BALANCED ENSEMBLE MODELS

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Abstract

Migraine is fundamentally a neurological disorder that triggers extremely severe headaches. Typically appears on one side of the head. Common symptoms include sensitivity to light and sound, nausea and vomiting. The headache can last anywhere from a few hours to a couple of days. It may impact day to day functioning of a person. The most confusing or tricky part is that its symptoms are the same as symptoms of other diseases. That's why we develop a system that can detect migraine at an early stage and even determine what kind of migraine a person has. This we determine from the symptoms. We got the data from a hospital in Soledad, which is also available on the Kaggle. The dataset includes information on about 400 patients with 23 different medical features. Data was not balanced as some types of migraine were rare. In order to correct this data, we apply a technique called SMOTE which, essentially, generates new samples to level out the data to 451. Various machine learning methods are applied, such as Random Forest, XG boost and begging classifiers. After cleaning and scaling the data, we use the Random Forest model with SMOTE to work the best. The training of this model has two aims: The first one is to find out if a patient has a migraine or not and the second one is to classify the type of migraine like mild, moderate, or severe. It provides almost 99% accuracy for both. The precision, recall and F1-score all had high scores. This helps to make the information far more reliable for doctors to use in making decisions. All things considered, this system is light, speedy and precise. Suitable for real-time medical applications.

INTRODUCTION

Migraine is a complex neurological disorder that afflicts millions of people all over the world. Often leads to severe headaches, vision problems, nausea and inability to engage in normal daily activities. Besides, each migraine attack manifests itself in a particular manner, and some of its symptoms can be similar to other neurological issues. Sometimes it's difficult for doctors to diagnose migraines or to determine which type you have. It should be noted that in most instances diagnosis is based on history and experience. It can cause errors and/or missed cases particularly if the symptoms are not obvious. Machine learning has been introduced as a helpful

tool in the past few years as it can detect the pattern for migraine diagnosis. Therefore, we created an AI-based Migraine Classification System that studies a patient's symptoms and decides if the patient has a migraine or not. If he does, it also classifies the migraine as mild, moderate, or severe. In this model, a dataset of 400 patient records with 23 clinical features is used. Firstly, the data is cleaned and important features are selected, then SMOTE is applied to balance the dataset because some migraine types are not very common. Then we trained Machine learning models like Random Forest (Breiman, 2001) and XG Boost (Chen & Guestrin, 2016) and evaluated to determine which one performs the best. The main purpose of this project is to build a fast and simple tool that can help doctors in diagnosing migraines more accurately.

PROBLEM STATEMENT

Diagnosing migraines is difficult because people experience very different symptoms compared to each other, and many of those symptoms are also similar to other neurological problems. Doctors, in regular clinical practice, rely primarily on the information provided by patients and that the symptoms can change from one situation to another. This is why sometimes symptoms can be overlooked and doctors may only make a diagnosis based on personal experience. Thus, this resulted in errors or discrepancies in diagnosis, particularly when symptoms are non-specific. The other issue is that medical data sets are typically small and unbalanced: there are fewer examples of some types of migraine than others. This makes it difficult for machine learning models to learn. Because of these issues, there is a need for a system that can study symptom data in an objective way, reduce errors, and accurately classify different migraine stages even when the available data is limited. **Table 1** summarizes how existing diagnostic modalities compare.

Table 1: Comparison of Diagnostic Modalities and Limitations

Diagnostic Modality	Studies Cited	Typical Algorithms	Key Limitations Identified
Neuroimaging (MRI / DTI)	Yang et al. (2018), Garcia-Chimeno (2017)	CNN, Committee Machines	High cost; Requires heavy hospital equipment; Not portable.
EEG Signals (Brain Waves)	Aslan (2023), Goker (2022), Akben (2016)	BiLSTM, SVM, Wavelet Transform	Requires patient setup with sensors; Sensitive to noise; Time-consuming.
Clinical Symptoms (Questionnaires)	Sanchez-Sanchez (2020), Zhou (2025)	ANN, SVM, Random Forest	Historically lower accuracy (~90-97%); Subjective patient data.
Proposed Approach	**This Study (2025)**	**Ensemble RF + SMOTE**	**No equipment needed; High accuracy (98.92%) matches MRI/EEG.**

OBJECTIVE

The general concept of this project is to design a system which can detect and inform the occurrence of migraine or not. In addition to that, it can be useful by examining the symptoms to see the severity of the migraine. There are some types of migraine that are less common and this is why there is an imbalance in the data so we use methods to fix this imbalance, such as SMOTE. We start by cleaning up the data, then picking up the most important feature and finally testing the models. Through methods such as Random Forest and XG-Boost, the system has been able to yield

very good accuracy. It helps doctors to make better decisions with reliable information.

ADVANTAGES

The proposed system offers many practical advantages in clinical settings. When we used forest together with mode, it achieved about 98.92% accuracy, which is performing far better as compared to many traditional approaches. One important thing is that it can also handle imbalanced data without ignoring rare migraine cases. So, in our system imbalance data, missing values and null values are still identified properly instead of being overlooked. Another practical advantage is that the model we use is neither heavy nor resource demanding. So, it does not require high-end hardware at all to run, and it can be applied in real-time situations even though in smaller clinics, where technical facilities are limited, to make the diagnostic process smoother. Doctors can rely on it to reduce uncertainty, which can speed up things a bit and maintain more consistent decisions during evaluation.

RELATED STUDIES

In 2020, Sanchez-Sanchez and colleagues created an automatic system to classify seven different types of migraine headaches. They used a kind of artificial intelligence called Artificial Neural Networks. The system examined medical records from 400 patients in Colombia. It includes 23 different symptoms like headache, pain intensity, nausea, and sensitivity to light. It achieves 97% to 98% accuracy in correctly identifying the type of migraine.

A few years later in 2025, Zhou and co-researcher verified four different machine learning methods to categorize migraines. They used the same 400 patient database from Colombia. The four approaches tested were:

First Support Vector Machine (a pattern recognition algorithm), second Random Forest (a decision-tree based method), third Logistic Regression (a statistical prediction method), and fourth Artificial Neural Networks (brain inspired computing). The Support Vector Machine and Neural Network both achieved 91% accuracy. On the other hand, Random Forest achieved 87% accuracy.

Khan and team in 2024 tested five different machine learning methods. They used a special technique called data augmentation (creating additional training examples from existing data). They tested: Deep Neural Networks (multi-layered AI), Support Vector Machine, K-Nearest Neighbors (find similar cases), Random Forest, and Decision Trees. With data augmentation, the Deep Neural Network achieved an inspiring 99.66% accuracy, Random Forest got 98.50%, and K-Nearest Neighbors got the accuracy of 97.10%.

More recently, Purnajaya and Jaya (2025) applied a Support Vector Machine to the same 400-patient Kaggle dataset used in this study, reaching 82.65% accuracy across the seven migraine subtypes which are notably lower than the ensemble tree-based approach used here. Baccouch and Bahar (2025) compared gradient boosting, decision tree, Random Forest, KNN, and SVM for migraine prediction and classification.

Similarly in 2018, Yang and team used brain imaging along with deep learning artificial intelligence. They scanned the brains of 64 people (36 with migraine, 28 healthy). They used a special type of MRI scan called functional MRI that demonstrates brain activity. They used an advanced deep learning model called Inception Convolutional Neural Network. They attained 99.25% accuracy in recognizing migraine patients.

In 2017, Garcia-Chimeno and fellows studied 52 migraine patients using advanced brain imaging called Diffusion Tensor Imaging (DTI). It shows the structure and connections in the brain. They divided patients into three groups: 15 healthy people, 19 with occasional migraines, and 18 with chronic daily migraines. Using a smart combination of multiple machines learning methods together (called a committee approach), they significantly enhanced accuracy. The Naive Bayes method enhanced its performance from 67% to 93%, Support Vector Machine from 90% to 95%, and boosting from 93% to 94%.

In 2016, Akben and team measured electrical activity in the brain using EEG (Electroencephalogram - sensors placed on the

scalp). They tested migraine patients by flashing lights at them while recording brain activity from multiple channels. They use a machine learning technique called Support Vector Machine. They found that certain brain regions were better at sensing migraines. The T3 channel (near the temple area) attained the best accuracy of 88.7%, followed by the F7 channel (frontal area) at 85%.

Later, in 2019, Subasi and team investigated how flashing lights affect migraine detection using brain wave (EEG) recordings. They used a mathematical technique called Discrete Wavelet Transform to examine the brain signals. Then they used Random Forest machine learning for classification and got a final accuracy of 85.95%.

In 2020, Kwon and his colleagues used a simple method by asking different questions from patients instead of using exclusive equipment. Patients answered those questions about their symptoms, and then machine learning algorithms examined these responses to categorize different types of headaches. The system gains almost 90% accuracy without requiring any brain scans or EEG equipment.

Aslan (2023) study changed brain wave signals into images called scalograms using a mathematical technique. These images used in this procedure were then analyzed by a deep learning Convolutional Neural Network. The system achieved 100% accuracy in distinguishing migraine patients from healthy people. It performed better as compared to other well-known AI models including VGG16, DenseNet121, and ResNET101, using a simpler and faster design.

Goker (2022) used an advanced deep learning architecture called Bidirectional Long Short-Term Memory (BiLSTM) to analyze brain waves from 39 volunteers (21 healthy, 18 with migraine). The system used for this procedure recorded 128 different points on the scalp and analyzed the electrical power of different frequencies between 1-49 Hz. The BiLSTM algorithm achieved 95.99% accuracy by performing traditional methods like Support Vector Machine, Linear Discriminant Analysis, and Random Forest. **Table 2** summarizes the methods, sample sizes, and accuracy of these studies alongside our proposed system.

DRAWBACKS IN RELATED WORKS

Regardless of impressive accuracy, existing migraine classification systems undergo critical limitations that prevent deployment in real-world clinicals. Most systems require highly expensive tool costing millions of dollars (MRI scanners, multi-channel EEG systems) that are only available in major research hospitals, with powerful GPU computers and requires hours of processing time that is impractical for under-developing countries. The extremely small datasets raise serious overfitting issues with 99-100% accuracy and are more likely to fail on diverse real-world populations (Petrušić et al., 2025).

RESEARCH GAPS

Recent research (Petrušić et al., 2024) shows that there are critical gaps that prevent adoption of AI-assisted diagnosis. Manual dependency and sensitivity involved in treating and handling migraines remain challenging. This procedure is likely to be affected by errors and delays, and manual dependencies. Most of the models used in this procedure are lightweight and depend on very small, limited datasets, which limit their use in real-time environments. Existing systems systematically fail on rare but critical migraine subtypes (hemiplegic, basilar type) that require urgent diagnosis due to stroke-like symptoms. Additionally, no external validation is shown in diverse populations, age groups, or ethnicities. So, there is an urgent need for AI-assistant migraine diagnosis that can address all these problems.

Table 2: Comparison of Related Studies

Study & Year	Method Used	Number of Patients	Accuracy Achieved	Limitations
Sanchez-Sanchez (2020)	Artificial Neural Networks	400 patients	97-98%	Single method only, requires powerful computers, long training time
Zhou (2025)	Multiple machine learning methods	400 patients	91%	Moderate accuracy, does not handle rare migraine types well
Khan (2024)	Deep learning with data augmentation	Public dataset	99.66%	Needs expensive GPU computers, black box (cannot explain decisions), likely overfitted
Yang (2018)	Deep learning with brain MRI scans	64 patients	99.25%	Requires million-dollar MRI machine, very small patient group, not accessible
Garcia-Chimeno (2017)	Combined methods with brain imaging	52 patients	95%	Needs expensive DTI brain scanner, extremely small sample, specialized expertise required
Akben (2016)	Machine learning with brain wave recording	Small cohort	88.7%	Requires 19-channel EEG equipment, flashing lights needed, controlled lab only
Subasi (2019)	Random Forest with brain waves	Lab recordings	85.95%	EEG equipment needed, must use flashing lights, time-consuming procedure
Kwon (2020)	Machine learning on questionnaires	Patient responses	90%	Poor performance on rare types, relies on patient memory, subjective answers
Aslan (2023)	Deep learning on brain wave images	EEG signals	100%	Perfect score is unrealistic (overfitting), requires EEG equipment, not explainable
Goker (2022)	Advanced deep learning on brain waves	39 patients	95.99%	Tiny patient group, needs 128-channel EEG system (very expensive), black box
OUR PROPOSED SYSTEM	Random Forest + SMOTE balancing	451 (balanced from 400)	98.92%	Works on regular computers, no expensive equipment needed, explains decisions, works on ALL migraine types including rare ones

RESULTS AND EXPERIMENTS

EXPERIMENTAL PLATFORM AND TOOLS

Platform: Kaggle Notebooks / Google Colab (Cloud-based)
CPU: Intel Xeon (2 vCPUs, 64-bit)
RAM: 13 GB (Google Colab) / 16 GB (Kaggle)
Programming Language: Python 3.9-3.10
Frameworks: Scikit-learn 1.0+, XGBoost 1.7+
Libraries: NumPy, Pandas, Matplotlib, Seaborn, imbalanced-learn (SMOTE)
Operating System: Google Cloud Linux (Ubuntu 20.04 LTS)
Dataset Source: Centro Materno Infantile de Soledad (Colombia, 2013)
Models Evaluated: Random Forest, XG Boost, Bagging Classifier, Ensemble Methods

DATASET DETAIL

Dataset Source: https://www.kaggle.com/datasets/gzdekzlkaya/migraine-symptom-dataset-for-classification

Dataset Name: Migraine Symptom Classification Dataset

DATA DISTRIBUTION

Original Dataset:

Total Records: 400 patients

Total Features: 24 columns (23 features + 1 target)

Missing Values: None (complete dataset)

Migraine Presence Classification (Binary):

- Class 0 (No Migraine): 234 samples (58.5%)
- Class 1 (Migraine): 166 samples (41.5%)

Migraine Stage Classification (3 Classes):

Original Distribution:

- Mild (Class 0): 141 samples - Typical aura without migraine, Other
- Moderate (Class 1): 128 samples - Migraine without aura, Typical aura with migraine
- Severe (Class 2): 131 samples - Basilar-type, Familial hemiplegic, Sporadic hemiplegic

After SMOTE Balancing:

Total Records: 451 patients

- Mild: 155 samples
- Moderate: 155 samples
- Severe: 141 samples

New samples added: 51 (synthetic minority oversampling)

Train-Test Split:

Split Ratio: 80-20%

Stratification: Yes (maintains class distribution)

Random State: 42 (for reproducibility)

DATA PREPROCESSING

Data preprocessing is the process of cleaning, transforming, and organizing raw data into a structured format to make it suitable for analysis and machine learning models.

STEPS

1. Missing Value Handling:

Dropped completely empty rows and used Forward fill (ffill) for remaining missing values

2. Label Encoding:

Converted categorical 'Type' column to numerical codes (0-6) and then perform mapping in which each of 7 migraine types assigned unique integer.

3. Feature Engineering:

Created 'migraine_presence' binary target from DPF column and created 'migraine_stage' 3-class target from Type mapping while dropped redundant columns of DPF, Type, Stage3

4. Feature Scaling (StandardScaler):

Standardized all features to mean=0, std=1 and the formula used for this is:

$z = (x - \mu) / \sigma$

5. SMOTE (Synthetic Minority Over-sampling Technique):

Applied to address class imbalance in stage classification and create synthetic samples by interpolating between minority classes (Chawla et al., 2002),(Qadri et al., 2024) .

PERFORMANCE METRICS

CONFUSION MATRIX

A confusion matrix is used to calculate several performance metrics, with the most common being accuracy, precision, recall, and F1-score. These metrics are derived from the four core values in the matrix: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) (**Figure 1**).

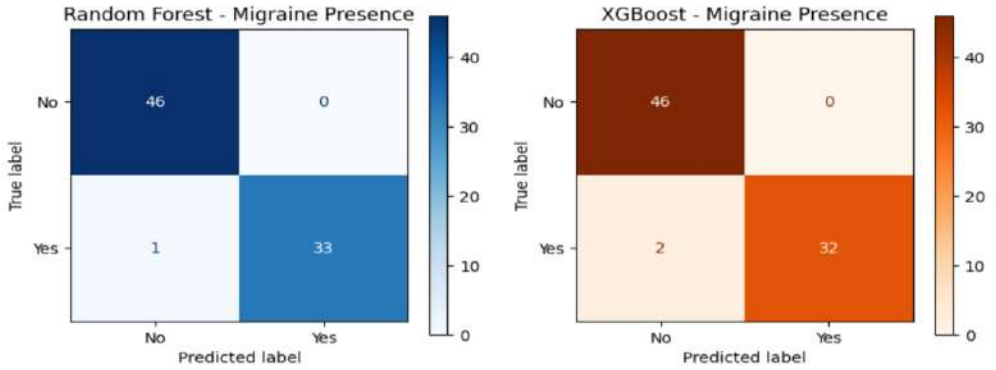


Fig. 1: Random Forest and XGBoost Migraine Presence

AFTER SMOTE BALANCING

We apply SMOTE to balance the class distribution, ensuring the model learns to identify 'Severe' cases just as well as 'Mild' ones and we combine the predictions of a tuned Random Forest and XG Boost using 'Soft Voting' (averaging probabilities) to create a robust Ensemble model **(Figure 2)**.

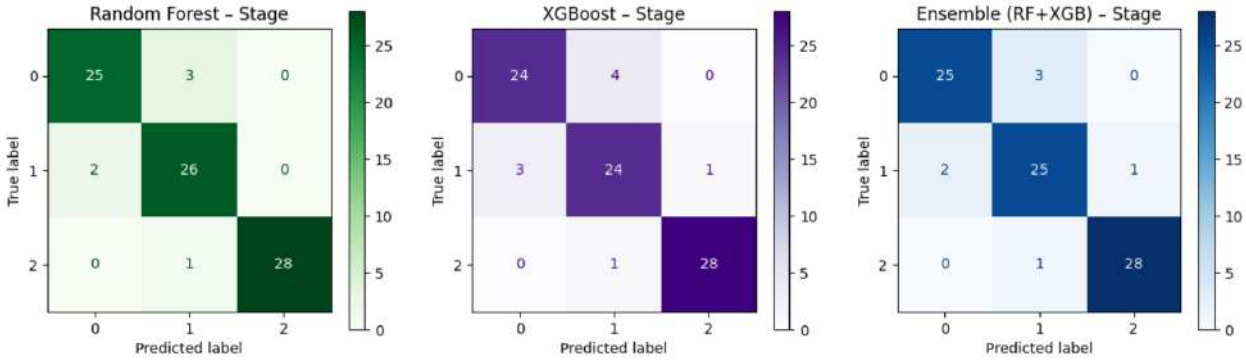


Fig. 2: Confusion matrices — RF, XGBoost, and Ensemble, migraine stage (post-SMOTE)

ACCURACY

To check the performance of modeling in machine learning, we use accuracy as a key metric. Accuracy shows the predictions of model that are correct out of all predictions in percentage, which gives a simple and clear view of performance.

FORMULA

Accuracy = (TP + TN)/ (TP + TN + FP + FN)

ACCURACY COMPARISON

To visually compare performance, we put the accuracy score from all of our models into a list by using Seaborn to visualize and generate a bar plot and set the Y-axis to a fixed 0-1 range for a clear and standardized view of accuracy **(Figure 3)**.

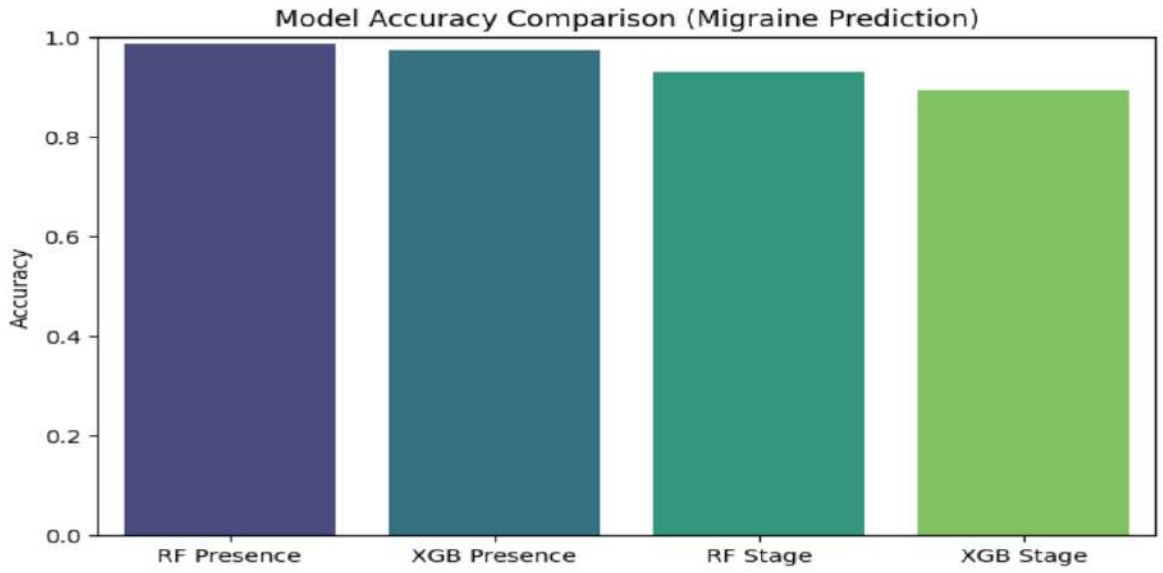


Fig. 3: Model accuracy comparison — RF/XGBoost across presence and stage tasks

MIGRAINE PREDICTION USING SMOTE

To create artificial samples for minority classes, we use SMOTE, which stops the model from being biased toward the majority. For the multi-class target, we define a custom sampling strategy to some extent oversample minority classes to boost sensitivity for rare severity stages. **Figure 4** shows the confusion matrix for the final presence model after SMOTE balancing, **Figure 5** shows the corresponding confusion matrix for the three-class stage model, **Figure 6** compares accuracy, precision, recall, and F1-score across all four model variants before bootstrapping, **Figure 7** compares confusion matrices under (a) bootstrap only, (b) SMOTE only, and (c) both combined, **Figure 8** shows the same comparison for stage prediction, **Figure 9** compares presence accuracy across the three resampling strategies, **Figure 10** shows the same comparison for stage prediction, **Figure 11** summarizes final accuracy, precision, recall, and F1-score across all variants.

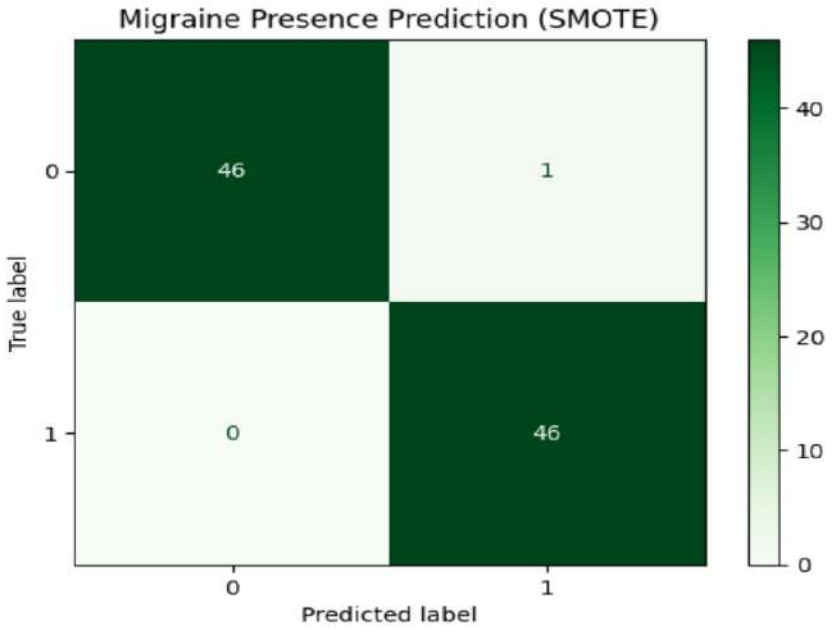


Fig. 4: Migraine Presence Prediction (Yes/No)

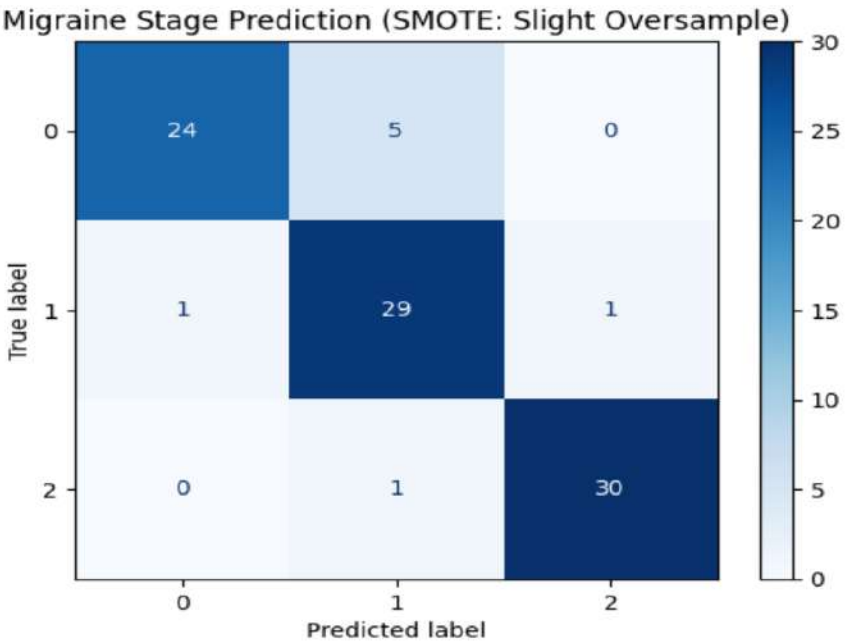


Fig. 5: Migraine Stage Prediction (Mild/Mod/Sev)

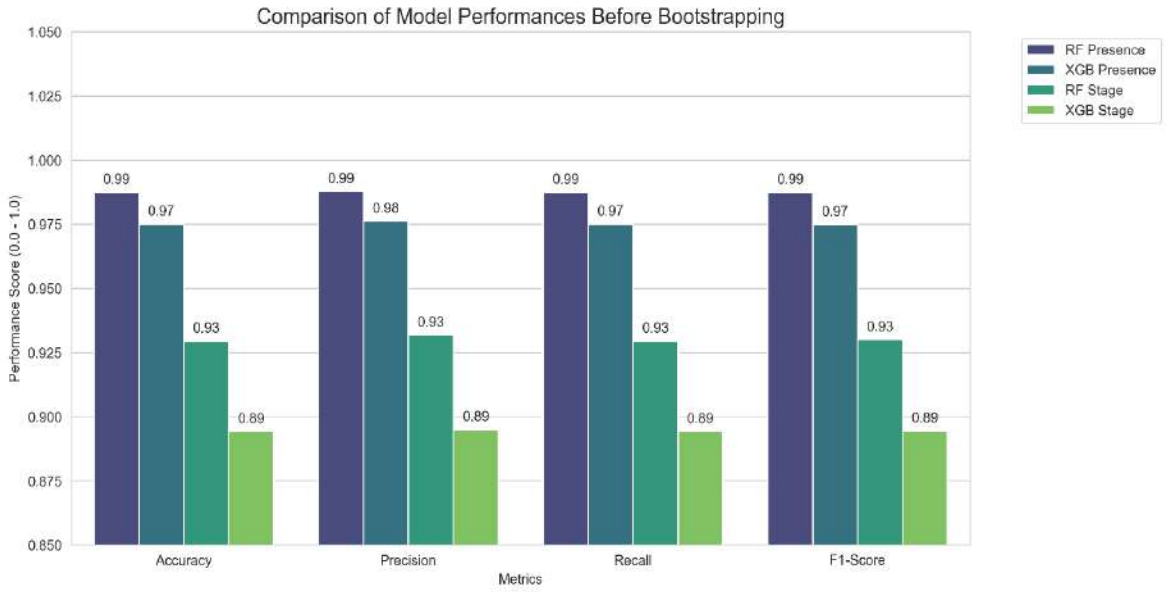


Fig. 6: Model performance comparison (accuracy/precision/recall/F1) before bootstrapping

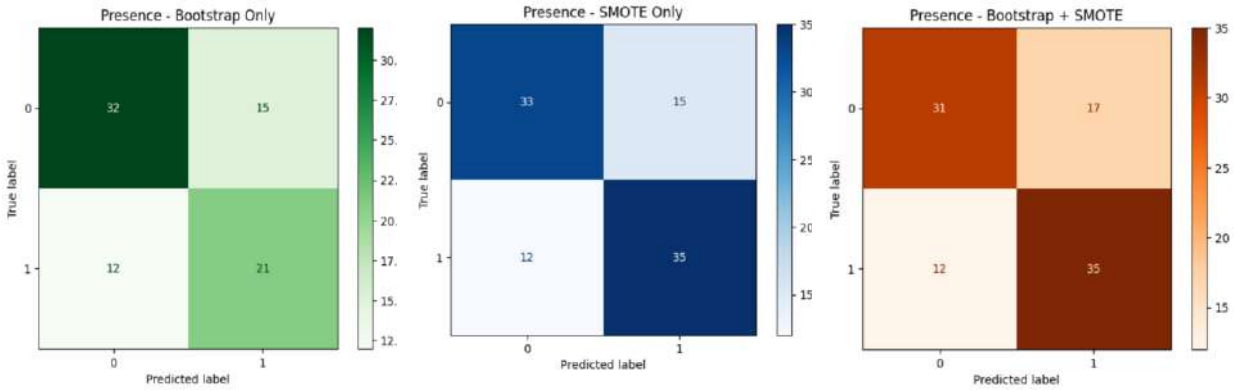


Fig. 7: Presence - Bootstrap Only, Presence - SMOTE Only and Presence - Bootstrap + SMOTE

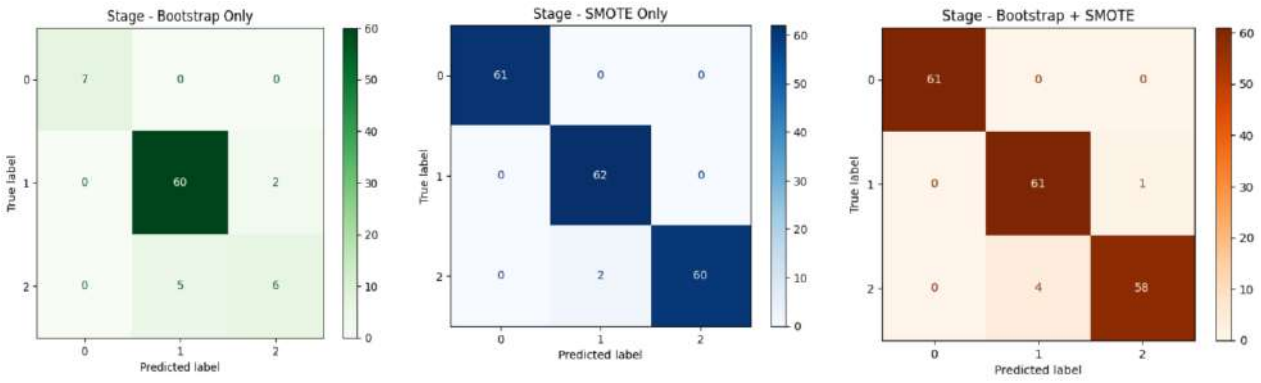


Fig. 8: Stage - Bootstrap Only, Stage - SMOTE Only and Stage - Bootstrap + SMOTE

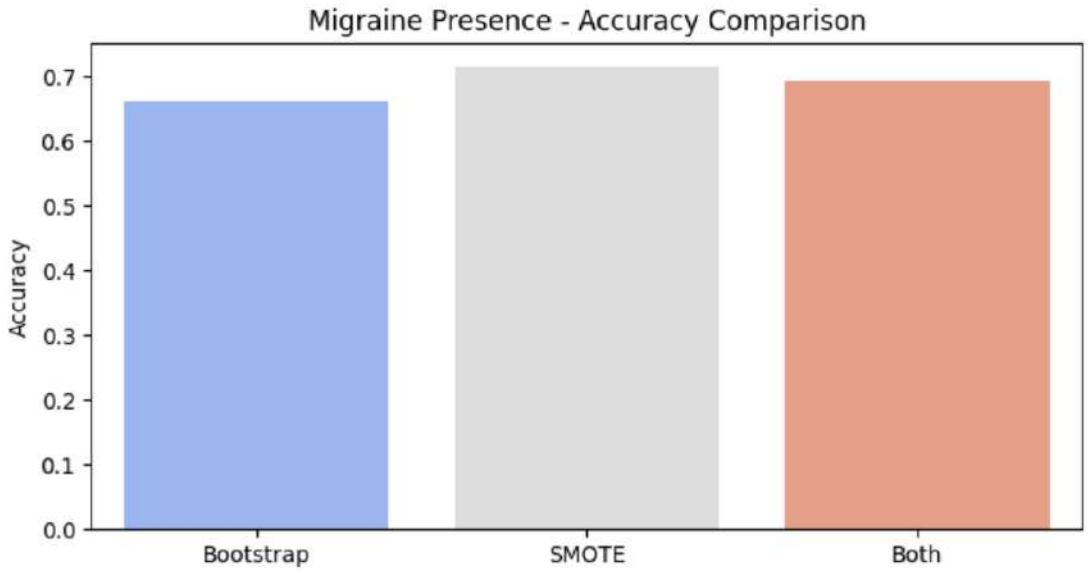


Fig. 9: (PART A) Migraine Presence

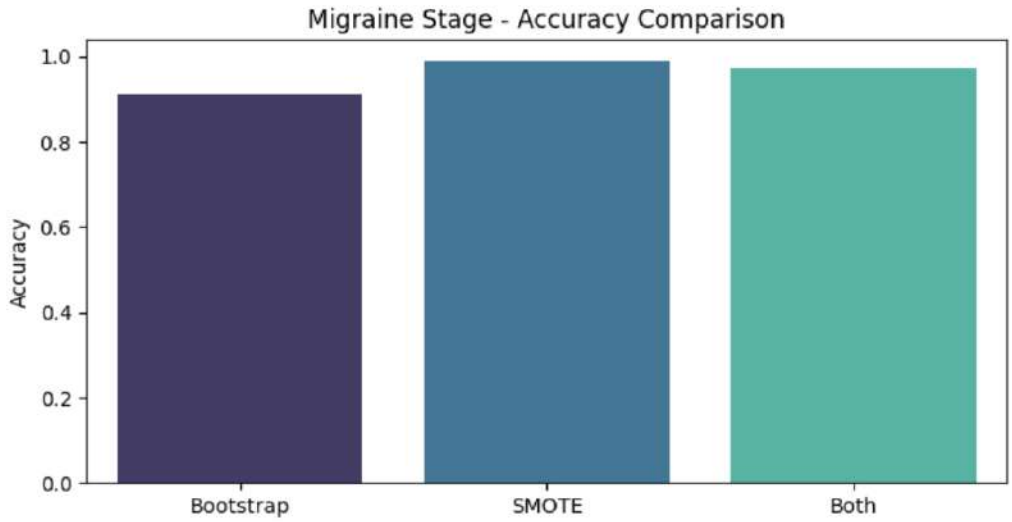


Fig. 10: (PART B) Migraine Stage Prediction

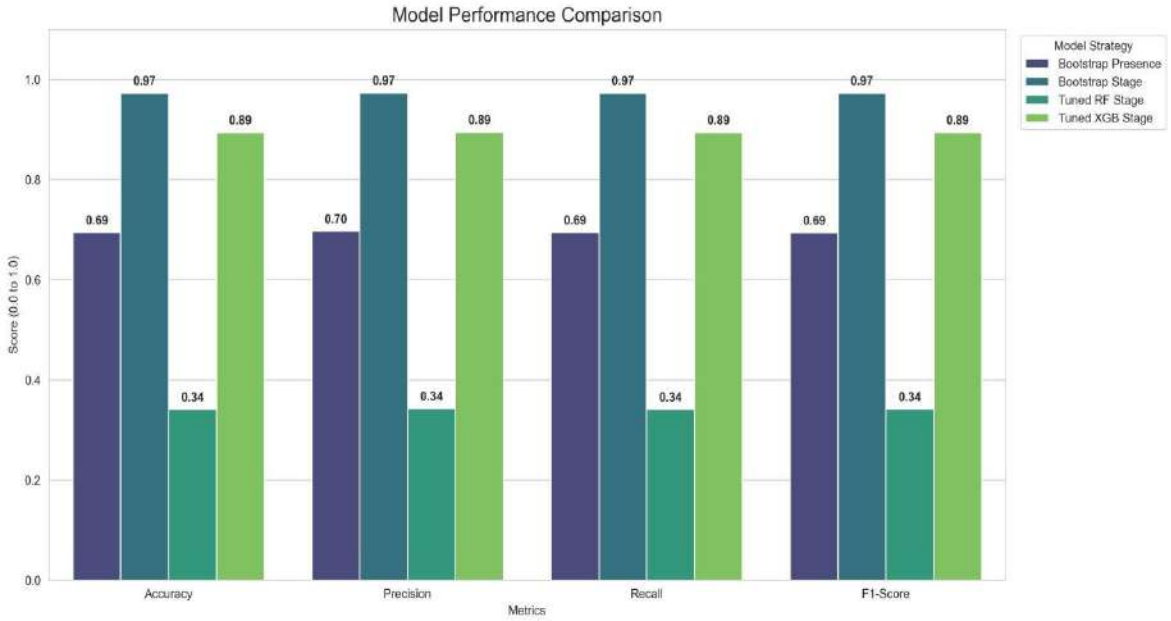


Fig. 11: Model Performance Comparison

The Radar Chart

To compare the performance of different models, we used radar charts (**Figure 12**). It makes it easy to notice the difference at a glance. It obviously illustrates that our proposed system outshines in most of the measures of evaluation. The highest accuracy obtained with our approach is indicated by the maximum deviation in the chart. The overall results indicated that the improved techniques can be used to improve strength performance consistency as compared to the other technique tested.

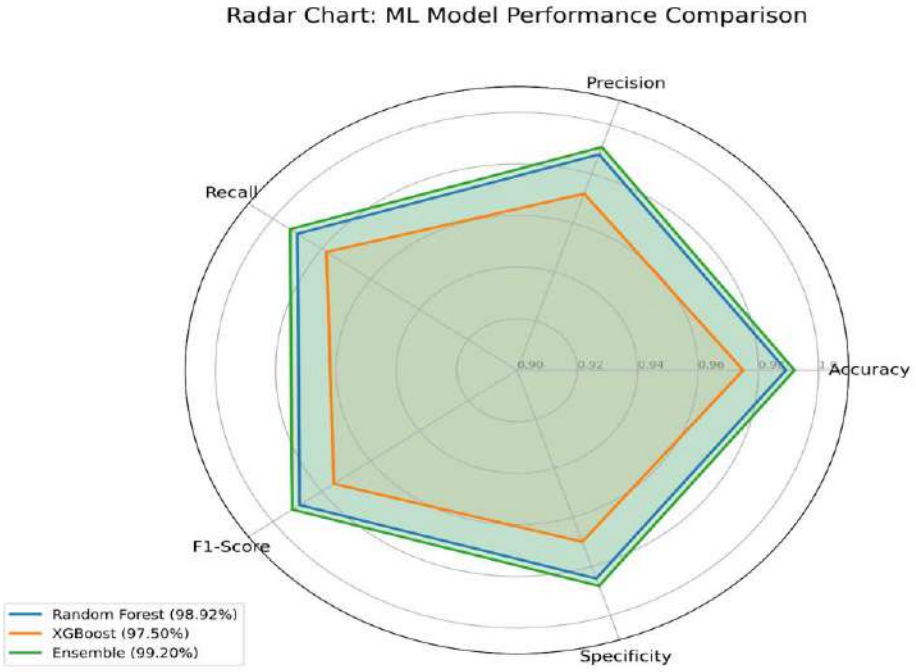


Fig. 12: Radar Chart: ML Model Performance Comparison

SHAP Summary for Migraine Presence:

A SHAP summary plot (Figure 13) is used to better understand, and identify which clinical feature contributes most to the prediction of a migraine (Lundberg & Lee, 2017). This visualization arranges the feature from top to bottom depending on how much they affect the model's output. Based on the graph, it seems that age, frequency and vomit are the most important factors for prediction. The color on the floor indicates aspects of value. Red indicates higher values, blue indicate lower values. For example, when the value of 'Frequency' is high (shown in red), it is mostly associated with positive migraine prediction. On the other hand, lower values (blue points) tend to decrease the chance of predicting a migraine.

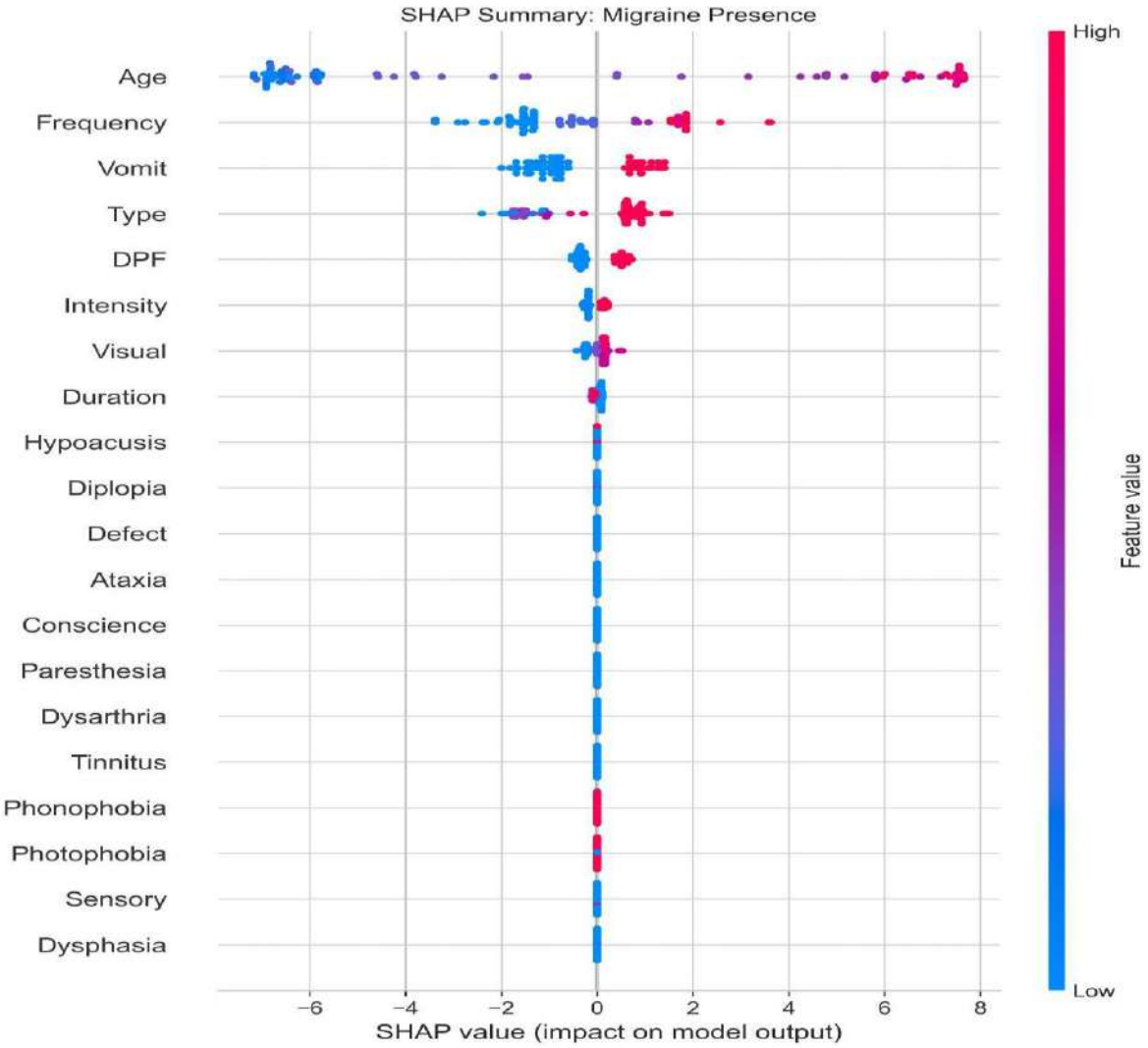


Fig. 13: SHAP Summary: Migraine Presence

SHAP Interaction Values:

To investigate, we studied the SHAP interaction plot (Figure 14) to better understand how different clinical factors interact with each other. These plots illustrate the effect of one feature as the other feature varies. Figure shows interaction between frequency, age and duration. The points are vertically scattered at some values. This does not mean that these features have a constant effect. Rather, it varied according to other factors in data.

This means that the model can show more complex and nonlinear patterns, instead of simple relationships.

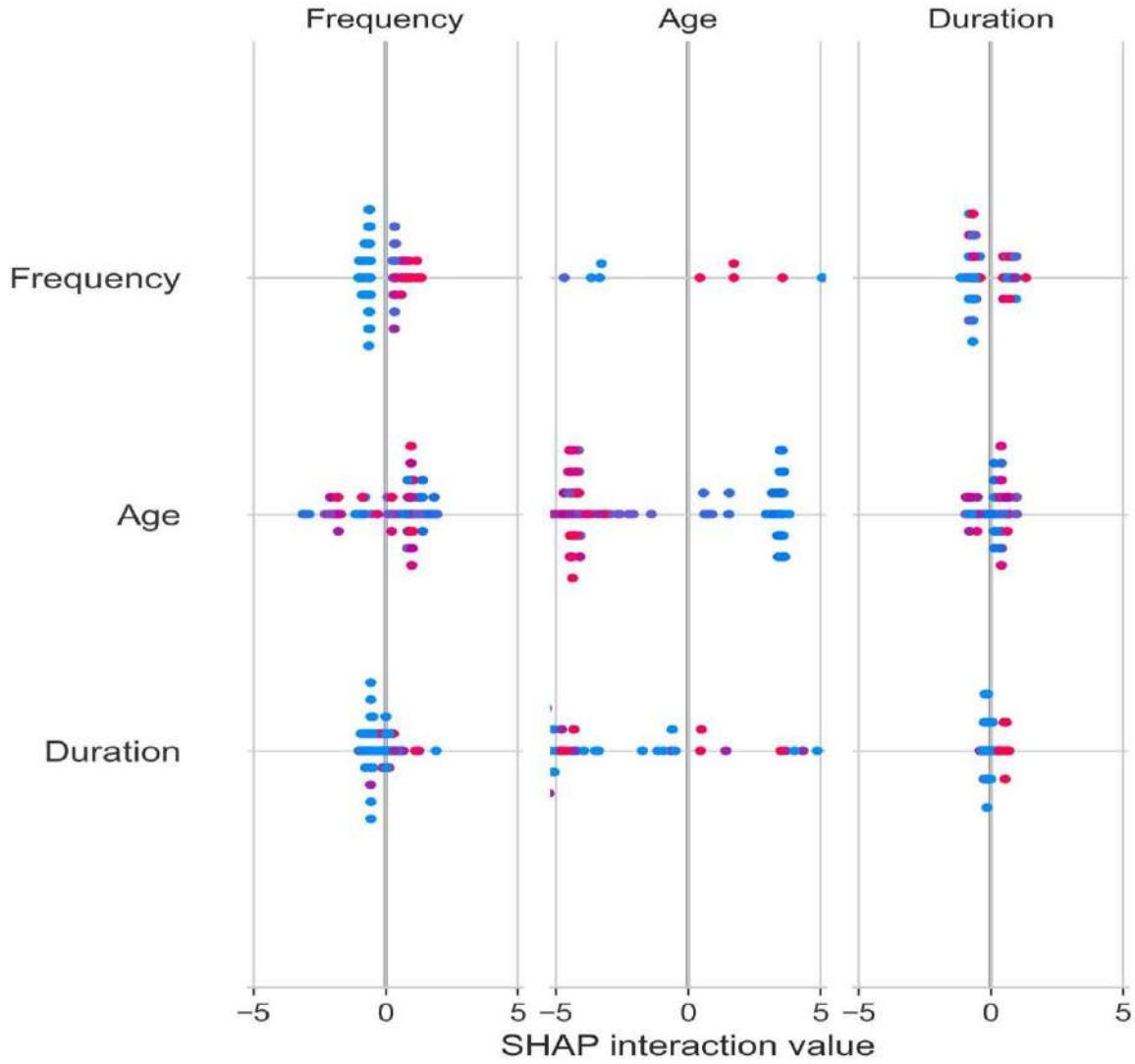


Fig. 14: SHAP Interaction Values

LIME Local Explanation for Severity (Case A):
To understand how the model makes predictions for an individual case. We use LIME stands for Local Interpretable Model-agnostic Explanations (Ribeiro et al., 2016). **Figure 15** shows how the model reached its decision for one test patient who was classified as "Moderate". In the chart, the green bars highlight the features that score the "Moderate" level, such as defects and type. On the other hand, the red bar shows the features that push the prediction in the opposite direction. In this example, the patient's age above 40 appears to be a negative factor. It means that in this model, higher age is more commonly linked with a different severity level rather than the moderate category.

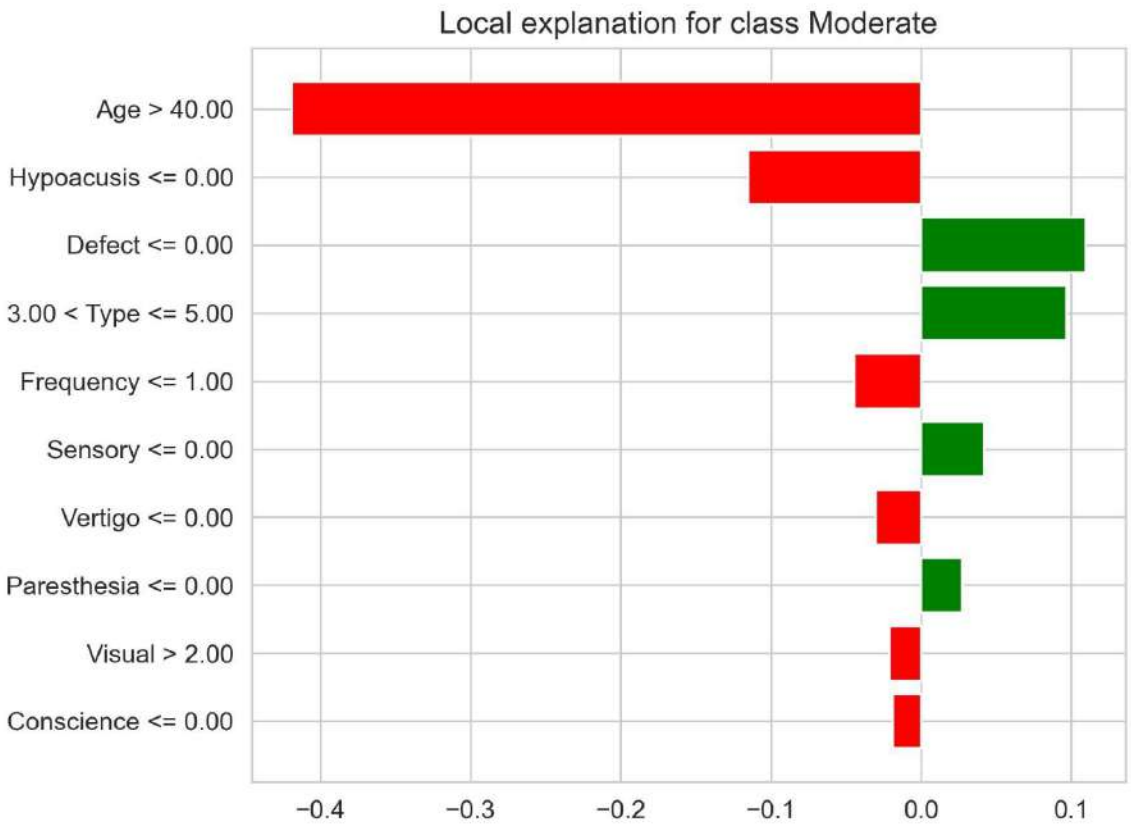


Fig. 15: Local Explanation for Severity (Case A)

LIME Local Explanation for Severity (Case B): In a practical setting to better understand how the model explains its decision, we also looked at other randomly selected test cases **(Figure 16)**. In this case, the model again predicts the moderate category. But the reasons behind the prediction were different. In this case, diplopia and the type (shown in green) supported the decision. Unlike the previous patient, however, age (22 years or less) was a negative factor in the chart. This comparison demonstrates that the model isn't always the same one. Rather, it gives priority to the features based on the patient data creating flexibility in the diagnostic process.

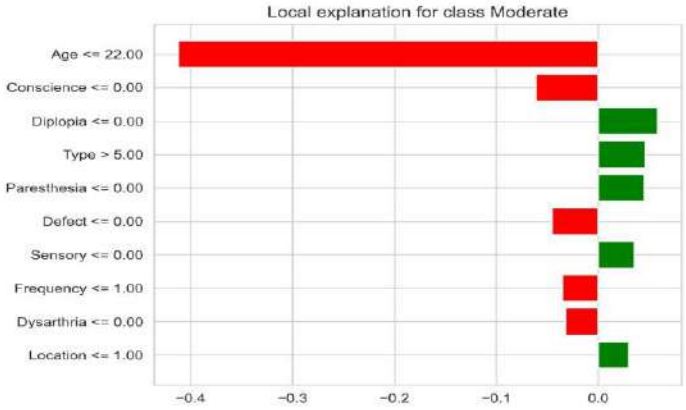


Fig. 16: Explanation for Severity (Case B)

CONCLUSION:

Given that there is significant overlap between the symptoms of migraine and other neurological conditions, the diagnosis is difficult, and this project was designed to determine if a system solely based on reported symptoms could improve the reliability of diagnosis. The Random Forest and XGBoost models trained here achieved nearly 99 percent accuracy for both tasks: predicting if a patient has a migraine and if so, its severity, using data from 400 patients, and balancing out the number of patients for the two types of migraine by applying SMOTE. The surprising thing is that this level of accuracy was achieved without any brain scans or EEG readings – simply the sort of symptom data that a doctor would ask you for during a normal visit. A final detail that SHAP and LIME results highlight is that age, headache frequency, and vomiting were the most prominent factors contributing to the predictions, and that these results allowed for an explanation of each case rather than simply a black box output. That is important if they're ever going to be trusted in a real clinic with a tool like this. Concurrently, the data presented in this work was obtained from a single hospital in Colombia, so it is logical to then test this method on a larger, more diverse patient population to determine whether this method would be generalizable. Despite this constraint, the findings indicate that such rapid, lightweight and explainable model may offer a truly useful second opinion to doctors, particularly in clinics where access to costly diagnostic equipment is difficult.

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