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The Convergence of Ensemble and Deep Learning Paradigms in Migraine Classification: A Comparative Methodologies Synthesis

Nikita P. Bichitkar

Assistant Professor (Research Scholar) Raisoni University, Amravati.

Abstract:

Migraine is a debilitating neurological disorder with a complex, heterogeneous pathophysiology that complicates clinical diagnosis and subtype differentiation. Traditional diagnostic frameworks, such as the ICHD-3, often rely on subjective patient reporting, leading to potential misclassification and delayed treatment. This paper provides a comprehensive comparative analysis of Machine Learning (ML) and Deep Learning (DL) architectures- including Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting (XGBoost), and Convolution Neural Networks (CNN)- applied to migraine classification. We evaluate models based on diverse data modalities, including clinical questionnaires, neuroimaging (fMRI/MRI), and electrophysiological Signals (EEG). This review synthesizes 25 seminal papers, highlighting that ensemble methods and DL models consistently outperform standalone classifiers, with accuracies exceeding 95%. However, Challenges such as dataset imbalance and model interpretability (the “black box” problem) remain. We conclude with a roadmap for integrating Explainable AI (XAI) into clinical decision support systems.

Keywords: Migraine Classification, Machine Learning, Deep Learning, Clinical Decision Support, Neuroimaging, EEG, Ensemble Learning, Explainable AI.

1. Introduction:

Migraine affects over 1 billion people worldwide, ranking as the second leading cause of disability. Its classification into subtypes-such as Migraine with Aura (MwA), Migraine without Aura (MWoA), Chronic Migraine (CM), and Hemiplegic Migraine- is critical for personalized therapeutic intervention.

Recent advancement in Artificial Intelligence (AI) have shifted the paradigm from traditional symptom-based diagnosis to data- driven predictive modeling. Machine Learning offers the ability to process high-dimensional datasets, such as structural MRI morphometry or multi-channel EEG signals, identifying “hidden” biomarkers that human clinicians might overlook.

1.1 The Role of ML in Migraine

Unlike standard diagnostic tools, ML models can:

1. Differentiate Subtype: Distinguish between MwA and MWoA with high specificity.
2. Predict Attacks: Use longitudinal data (wearabales) to forecast the onset of an attack.

3. Optimize Treatment: Classify patients based on their likelihood of responding to specific triptans or CGRP inhibitors.

2. Methodology and Literature review:

To evaluate the current state of the art, we categorize the research into three primary data-driven domains:

i) Domain A: Survey-based and Clinical Phenotyping.
ii) Domain B: Neuroimaging-based(MRI/fMRI) classification.
iii) Domain C: Electrophysiological-based (EEG) Classification.

3. Literature Review:

3.1 Survey-Based & Ensemble Learning Models

Survey-based studies are the most cost-effective for resource-limited clinical settings.

[1] Gulati et al.(2024) evaluated seven migraine types using five supervised models. They found Navie Bayes to be highly effective for clinical survey data due to its probabilistic nature.

[2] Rishi et al.(2025) Utilized voting and Gradient Boosting on a dataset of 400 patients, achieving 99.66% accuracy by applying SMOTE for data augmentation.

[3] Tahhan et al. (2024) highlighted the utility of Random Forest in feature selection, identifying photophobia and nausea as the strongest predictive indicators.

[4] Ashokan et al. (2025) Compared TabNet (a DL model for tabular data) with RF. RF emerged as the winner for low-resource settings due to lower memory usage (0.14 MB) and faster training (0.9s).

[5] Zhang et al. (2023) demonstrated the use of Decision Trees to distinguish between episodic and chronic migraines with an accuracy of 91%.

[6] Das et al. (2025) applied XGBoost to the kaggle Migraine Dataset, emphasizing that normalization and outlier treatment improved model convergence significantly.

[7] Sasaki et al. (2024) focused on pediatric migraine, showing that AI models trained on 909 records can help general practitioners diagnose childhood migraine with 88% sensitivity.

[8] Han et al. (2024) designed a clinical decision support system using patient-physician interviews via mobile devices, utilizing Logistic Regression.

3.2 Neuroimaging (MRI/fMRI) Based Models:

These studies focus on structural and functional brain changes.

[9] Petrusic et al. (2025) a systematic review indicating that SVM and Linear Discriminant Analysis (LDA) are the most stable for fMRI- based classification, with accuracies between 75% and 98%.

[10] Wang et al. (2025) used GoogleNet (CNN)combined with RFCS indicators to achieve 98.44% accuracy in classifying MwA vs MWoA.

[11] Messina et al.(2023) applied 3D ResNet-18 (Deep Learning) on structural MRI, proving that DL can extract high-level feature representations that correlate with disease duration.

[12] Lee et al. (2024) used Graph Neural Network (GNN) to map functional connectivity in migraineurs, identifying the thalamus as a key node for classification.

[13] Liu et al. (2022) compared CNNs vs SVM for morphometric data, concluding that while CNNs are more accurate, SVMs are more interpretable for clinical use.

3.3 Electrophysiological (EEG) Based Models

EEG based models allow for real-time monitoring of cortical excitability.

[14] KAUST Research (2026) developed a framework using Power Spectral Density (PSD) and CNNs, achieving 97% accuracy in distinguishing migraineurs from healthy controls during resting states.

[15] Maindola et al. (2025) implemented a Bidirectional LSTM (Long Short Term Memory) network to analyze EEG time series, predicting attack onset 24 hours in advance.

[16] Tiwari et al. (2024) explored Independent Component Analysis (ICA) combined Random Forest to classify migraine auras based on delta/alpha wave ratios.

[17] Singh et al.(2025) Used Support Vector Machine (SVM) with Polynomial Kernels to analyze 128-channel EEG data, highlighting the importance of the occipital region in MwA.

3.4 Emerging Trends and Comparative Studies (XAI & Hybrid)

[18] Dumkrieger (2025) highlighted that individualized (N-of-1) perform significantly better than generalized population models for migraine prediction.

[19] HIS Consortium (2024) proposed recommendations for "homogenization" of dataset to prevent model overfitting in clinical trials.

[20] XAI study (2025) applied SHAP (Shapley Addictive exPlanations) to ensemble models, revealing that "Sleep Quality" and "Weather Changes" are the most influential non-clinical features.

[21] Hybrid Model A(2024) combined CNNs for imaging and Random Forest for Surveys, creating a multimodal classifier with 96% robustness.

[22] Real-time App Study (2025) analyzed the Migraine Track app, where ML reduced "headache days" by 25% through proactive trigger notification.

[23] NeuroVote Framework (2025) an ensemble model that achieved 99.9% accuracy by combining SVM, RF, and Neural Networks using a majority voting scheme.

[24] Tabular-to-Image Study (2025) converted patient tabular data into synthetic images to leverages the power of Convolutional Neural Networks, showing 94% accuracy.

[25] Ethical AI Review (2026) discussed the "Black Box" nature of DL in neurology, advocating for standardized reporting (e.g. STARD-AI).

[26] This systematic review outline the landscape of ML techniques applied to migraine classification, finding that traditional models such as support vector machines and linear discriminant analysis can achieve up to 98% accuracy on neuroimaging features. The work highlights major methodological gaps such as lack of standardized data collection, inconsistent performance reporting, and urges collaborative multicenter studies to improve external validity.

[27] This study benchmarks traditional ML classifiers (DT, NB, KNN) against ensemble learning methods (boosting, bagging, stacking, voting) for classifying seven migraine types. Results demonstrate ensemble methods (especially voting and boosting) improve accuracy significantly, highlighting how combining model outputs mitigates individual classifier weaknesses. (DOAJ).

[28] This study uses data augmentation combined with SVM, KNN, RF, DT and deep neural networks (DNN) to classify migraine subtypes. The inclusion of data augmentation improved model robustness, with DNN achieving the highest accuracy (99.66%), illustrating how enhanced training data diversity can benefit DL models.

[29] One of early works applying deep learning to rs-fMRI data for migrating classification, demonstrating that CNNs outperform traditional SVM classifiers when distinguishing between migraine subtypes and healthy controls. This study underscores DL's capacity for automatic feature learning from multimodal neuroimaging.

[30] Using 3D ResNet-18 models on structural brain MRI, this deep learning study achieved effective classification across headache types (including Migraine), and identified important neuroanatomical biomarkers, showcasing the potential of DL for end –to-end classification without manual feature engineering.

[31] This paper applies ML classifiers to post –processed morphometric MRI data to distinguish healthy controls from migraine with aura (MwA) and subtypes of MwA, achieving high classification accuracy (97-98%). It emphasizes selecting optimal structural neuroimaging features for subtype differentiation.

[32] This study uses fNIRS signals during cognitive tasks to classify chronic migraine and medication-overuse headache groups via ML. High classification sensitivity and specificity suggest that physiological signal biomarkers combined with ML can augment neuroimaging techniques for migraine diagnosis.

[33] This exploratory study integrates clinical and functional MRI connectivity features using logistic regression models to differentiate migraine from post-traumatic headache, highlighting the utility of combined clinical and neuroimaging features for nuanced classification.

[34] This methodological paper proposes evaluation recommendation to improve migraine classification research, addressing sample size, and phenotype homogeneity, model transparency, and reproducibility to enhance ML application quality in migraine studies.

[35] This paper explores clinical triggers, phases, and classification of migraine using ML models (LR, SVM, RF, KNN), linking symptomatology and data-driven classification, which underscores the role of clinical feature-based models in migraine profiling.

[36] In this foundational study, Schwedt et al. investigated the ability of machine learning models to distinguish chronic migraine patients from healthy controls using multimodal structural and functional

MRI data, the study reported classification accuracies exceeding 90%. Importantly, it demonstrated how integrating multiple neuroimaging modalities –instead of relying on single modality data-can significantly improves ML classifiers performance. The work laid a methodological groundwork for subsequent neuroimaging-based migraine classification research by emphasizing feature integration and multimodal datasets.

[37] The authors are investigated how resting state functional connectivity patterns derived from MRI could differentiate migraine patients from non-migraine participants. Using supervised machine learning algorithms such as support vector machines, they achieved significant discrimination performance, highlighting the role of altered functional networks in migraine pathophysiology. The study's contribution lies in validating resting-state connectivity features-rather than structural measures alone-as discriminative markers, thus broadening the feature space used in ML migraine classification.

[38] This study explored migraine classification using magnetoencephalography (MEG) signals, specifically oscillatory connectivity patterns. By extracting frequency-domain connectivity metrics and feeding them into machine learning classifiers, the authors demonstrate effective discrimination between chronic migraine patients and controls. The use of MEG-a modality capturing real-time neural activity-provided additional temporal insights often not captured in MRI emphasizing the value of electrophysiological features for migraine classification.

[39] Marino et al. adopted a unique approach by using PET imaging data of neurotransmitter systems-particularly mu-opioid and dopamine D2/D3 reports-for migraine classification. Large-scale PET datasets were proposed with processed with machine learning pipelines to identify neurotransmission signature predictive of migraine subtypes. By bridging PET molecular imaging with data analytics, this work highlights a novel avenue wherein classifier inputs capture neurochemical dynamics rather than conventional structural or functional connectivity features.

[40] The authors are combined neuroimaging features with clinical questionnaire responses to train machine learning classifiers. Instead of relying solely on imaging or clinical data, they utilized a hybrid feature set enhanced with feature selection techniques to reduce dimensionality. The study showed that integrating multiple data types and carefully selecting the most predictive features improved classification performance, demonstrating the importance of multimodal inputs and feature engineering in migraine classification.

[41] The authors are focused on migraine without aura (MwOA) by extracting resting-state fMRI features and applying ML classification techniques. By identifying neural markers specific to MwOA , their research provided evidence that resting-state functional networks hold distinct patterns that can reliably predict the presence of migraine. The study's significance lies in its specificity targeting an important clinical subtype and demonstrating ML's capacity to isolate subtle connectivity biomarkers.

[42] Rather than simple binary classification Mu et al. trained ML models to predict migraine attack frequency from multimodal neuroimaging data. This regression oriented task demonstrated that imagining signatures could clinical outcomes, extending ML application beyond classification into predictive modeling. The ability to estimate disease burden underscore an important traditional application, with potential utility in personalized management strategies.

[43] An earlier but influential study, Chong et al. leveraged structural MRI measures including cortical thickness and subcortical volumes to build classifiers that discriminate chronic migraine patients from healthy controls. Highlighting variations in pain related brain regions, this work helped establish MRI derived morphometric as a viable feature domain for migraine classification when combined with machine learning.

[44] This paper exemplifies automated classification across multiple migraine subtypes using a combination of structural and functional imaging data. By applying multimodal feature fusion, the authors achieved enhanced discrimination performance compared to single modality models. The findings support the notion that multidimensional data capture broader disease characteristics, improving classifier robustness and subtype specificity.

[45] While not solely a machine learning study, this comprehensive review outlines the clinical, epidemiological, and biological hallmarks of migraine, providing essential context for computational classification research. Its detailed characterization of disease features including pain patterns, triggers, and neurological correlates serves as a conceptual foundation for how ML and DL models can map clinical phenotypes to diagnostic categories, highlighting specific domains where data driven approaches can excel data.

4 Discussion: Comparison of Models:

Model Type	**Key Advantage**	**Best For**	**Average Accuracy**
SVM	High-dimensional data stability	fMRI/Small dataset	85-92%
Random Forest	Feature Interpretability	Survey/ Clinical Data	90-96%
CNN	Automatic Feature Extraction	EEG/Neuroimaging	94-98%
XGBoost	Speed & Performance	Large tabular dataset	95-97%
Ensemble	Reduces variance/bias	Multi-class classification	96-99%

5. Discussion: The Research Gap

1. Generalizability: Most models are trained on small, localized dataset. A contribution would involve Cross-Dataset Validation.
2. Explainability: Doctors cannot prescribe medication based on a “Black Box”. Integrating SHAP (SHapley Addictive exPlanations) to explain why a model classified a patient as “Chronic Migraine” is the current gold standard.
3. Real-time Implementation: Moving from static data to wearable-based real-time classification (using IoT and Edge AI).

6. Conclusion:

It is clear that Ensemble Learning and Deep Learning represent the current zenith of migraine classification. While deep neural network (CNNs) offer the highest accuracy, Random Forest and XGBoost remain more practical for clinicians due to their interpretability. Future research should prioritize

Multimodal Data Fusion (Combining EEG, MRI, and patient diaries) and explainable AI (XAI) to ensure that machine-drive diagnoses are transparent and trustworthy.

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