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CLASSIFICATION OF MIGRAINE TYPES BASED ON SYMPTOMS USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Migraine is a complex neurological disorder with heterogeneous clinical manifestations, making accurate subtype classification difficult using conventional diagnostic approaches. Diagnostic inaccuracies may result in inappropriate treatment and suboptimal patient outcomes. This study proposes an Artificial Neural Network (ANN) model to classify migraine subtypes based on patient-reported symptoms and clinical characteristics. A publicly available dataset containing 400 instances and 24 features—including demographic data, aura symptoms, neurological and autonomic indicators, genetic history, and disease burden—was utilized. Data preprocessing involved feature standardization, label encoding, and one-hot encoding, followed by an 80:20 split for training and testing. The ANN architecture comprised an input layer with 23 neurons, two hidden layers with 64 and 32 neurons using ReLU activation, and a seven-neuron output layer with softmax activation. The model was trained using the Adam optimizer and categorical cross-entropy loss for 50 epochs. Experimental results showed that the proposed model achieved a training accuracy of 91.56% and a testing accuracy of 93.00%, demonstrating strong generalization performance and effective learning of complex, non-linear symptom patterns. These results indicate that ANN-based classification has significant potential as a clinical decision-support tool for improving migraine subtype diagnosis and enabling more personalized treatment strategies.

Keywords: artificial neural networks, machine learning, medical decision support, migraine classification, symptom-based diagnosis

INTRODUCTION

Migraine, a complex neurological disorder characterized by recurrent severe headaches and a variety of associated symptoms, affects a significant portion of the global population, leading to substantial disability and diminished quality of life (Khan et al., 2024). Accurate diagnosis and classification of migraine subtypes are crucial for effective management and personalized treatment strategies (Li et al., 2023). Given the subjective nature of symptom reporting and the phenotypic overlap between migraine subtypes, traditional diagnostic methods often face challenges in achieving consistent and precise classification (Kwon et al., 2020). This challenge underscores the pressing need for advanced diagnostic tools that can leverage comprehensive symptom profiles to differentiate between various migraine presentations (Purnajaya and Jaya, 2025). Machine learning, particularly Artificial Neural Networks, offers a promising avenue for addressing this diagnostic complexity by identifying subtle, non-linear patterns within diverse symptom datasets (Purnajaya and Jaya, 2025). This study specifically aims to develop and validate an Artificial Neural Network model for classifying distinct migraine types based on a comprehensive set of patient-reported symptoms and characteristics (Purnajaya and Jaya, 2025). This approach leverages computational efficiency and diverse mathematical learning to identify the most effective classification algorithm (Shahid et al., 2024). The developed Artificial Neural Network utilized a Kaggle dataset comprising 400 instances and 24 features, including demographic information, aura-related symptoms, associated neurological and autonomic symptoms, genetic markers, and disease burden indicators, to classify seven distinct migraine types (Purnajaya and Jaya, 2025). The subsequent data preprocessing steps, including label encoding, one-hot encoding for the target variable, and standardization of input features, were critical to optimizing the model's performance and ensuring robust classification (Gryglas-Dworak et al., 2024). This systematic preparation ensures that the neural network can effectively learn intricate relationships between symptoms and migraine subtypes, thereby improving diagnostic

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accuracy and supporting tailored therapeutic interventions (Khan et al., 2024). This methodology facilitates the identification of nuanced symptomatic patterns that distinguish various migraine classifications, thereby refining prognostic assessments (Khan et al., 2024). By employing advanced machine learning techniques, this research contributes to the growing body of knowledge on AI applications in headache medicine, offering a potential tool for improved clinical decision-making (Espinoza-Vinces et al., 2025).

LITERATURE REVIEW

Migraine is a multifaceted neurological disorder characterized by recurrent attacks of moderate-to-severe headache, often unilateral and pulsating in nature, lasting 4-72 hours if untreated, and aggravated by routine physical activity (Khan et al., 2024; Purnajaya and Jaya, 2025). Accompanying symptoms frequently include nausea, vomiting, photophobia, phonophobia, and osmophobia, while approximately one-third of patients experience aura manifesting as transient visual, sensory, or aphasic disturbances preceding the headache phase (Kwon et al., 2020; Khan et al., 2024). Subtypes such as migraine without aura, migraine with aura, familial/sporadic hemiplegic migraine, and basilar-type migraine are differentiated by specific symptom clusters, including motor weakness, brainstem aura symptoms (e.g., vertigo, dysarthria, tinnitus), and non-headache features like cutaneous allodynia or vestibular-cochlear dysfunction (Li et al., 2023; Purnajaya and Jaya, 2025). Prodromal and postdromal phases may involve fatigue, mood changes, yawning, or cognitive fog, underscoring the syndrome's temporal and symptomatic heterogeneity that challenges precise subtyping (Li et al., 2023; Yella et al., 2025).

The integration of machine learning and deep learning models has significantly advanced the field of migraine classification, moving beyond traditional statistical methods to uncover complex symptomatic patterns (Khan et al., 2024). Early applications often focused on conventional machine learning algorithms to distinguish between migraine and other headache types or to classify broad migraine categories (Khan et al., 2024). However, more recent investigations have begun to explore the utility of deep learning, specifically Artificial Neural Networks, for their capacity to model intricate, non-linear relationships within high-dimensional clinical symptom data (Gitto et al., 2020; Kwon et al., 2020). For instance, studies have successfully employed Support Vector Machines with notable accuracy in classifying multiple migraine subtypes from clinical questionnaire data, demonstrating the potential for established machine learning algorithms as decision-support tools (Purnajaya & Jaya, 2025). However, these models sometimes struggle with the high dimensionality and inherent noise of self-reported symptom data, often necessitating extensive feature engineering (Kwon et al., 2020; Purnajaya & Jaya, 2025).

The emergence of deep learning, particularly with architectures like ANNs, offers a solution to this limitation by automatically extracting hierarchical features from raw data, thereby reducing the reliance on manual feature engineering and enhancing classification robustness (Espinoza-Vinces et al., 2025). Such models have demonstrated superior performance in various medical diagnostic tasks, including the classification of headache disorders, by analyzing self-reported symptoms from large patient cohorts (Kwon et al., 2020). This advancement is particularly relevant for migraine, where the heterogeneous nature of symptoms, including non-headache manifestations, presents a significant challenge for accurate subtyping (Li et al., 2023). This complexity further emphasizes the need for sophisticated AI-driven approaches capable of discerning subtle diagnostic indicators within diverse symptom presentations (Yella et al., 2025).

METHOD

In this study, we developed an Artificial Neural Network (ANN) to classify migraine types based on a symptom dataset obtained from Kaggle (Migraine Symptom Dataset for Classification). The dataset consisted of 400 instances and 24 features, where 23 input features represented clinical symptoms and patient characteristics, including (The sample data is shown in Image 1):

- Demographic and temporal factors: Age, Duration (attack length), Frequency (attack recurrence).
- Aura-related symptoms: Visual disturbances, Sensory changes, Motor dysfunction, Aphasia, Dysarthria, Scotoma, Paresthesia, Diplopia, Ataxia, Dysphasia, Hemiparesis.
- Associated neurological and autonomic symptoms: Amnesia, Nausea, Vomiting, Photophobia, Phonophobia.
- Genetic and historical markers: Family History.
- Aura-specific metrics: Aura Duration, Aura Frequency.
- Disease burden indicator: Migraine Frequency.

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Age	Duration	Frequency	Location	Character	Intensity	Nausea	Vomit	Phonopho	Photophol	Visual	Sensory	Dysphasia	Dysarthria	Vertigo	Tinnitus	Hypoacusi	Diplopia	Defect	Ataxia	Conscienc	Paresthesi	DPF	Type
30	1	5	1	1	2	1	0	1	1	1	2	0	0	0	0	0	0	0	0	0	0	0	Typical aura with migraine
50	3	5	1	1	3	1	1	1	1	2	1	0	0	1	0	0	0	0	0	0	0	0	Typical aura with migraine
53	2	1	1	1	2	1	1	1	1	2	0	0	0	0	0	0	0	0	0	0	0	0	Typical aura with migraine
45	3	5	1	1	3	1	0	1	1	2	2	0	0	1	0	0	0	0	0	0	0	0	Typical aura with migraine
53	1	1	1	1	2	1	0	1	1	4	0	0	0	0	0	0	0	0	0	0	0	1	Typical aura with migraine
49	1	1	1	1	3	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	Migraine without aura
27	1	5	1	1	3	1	0	1	1	2	0	0	0	1	1	0	0	0	0	0	0	0	Basilar-type aura

Image 1: Sample Data

The target feature indicated the migraine type, encompassing seven distinct categories: Basilar-type aura, Familial hemiplegic migraine, Migraine without aura, Other, Sporadic hemiplegic migraine, and Typical aura with migraine. Accurate classification of these subtypes is clinically critical, as it informs tailored therapeutic interventions and prognostic assessments. The flowchart of this research is shown in Image 2.

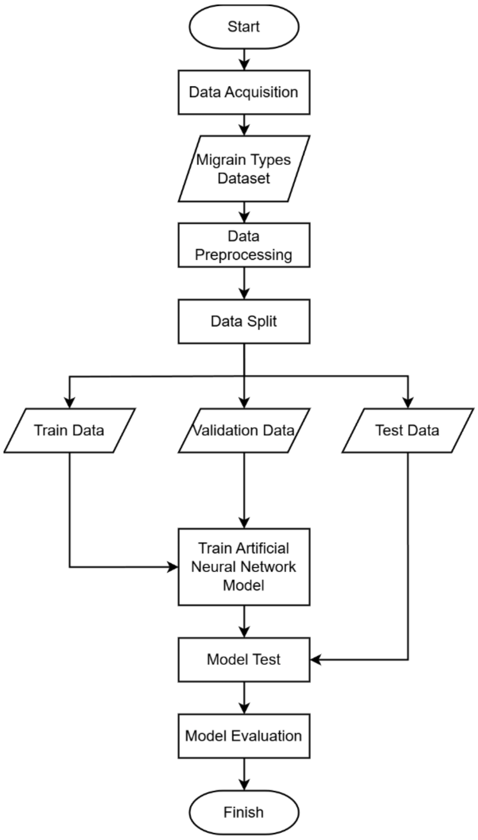

Image 2: Research flowchart

Data preprocessing was conducted to ensure optimal model performance. First, the categorical target variable (Type) was transformed into numeric classes using label encoding, followed by one-hot encoding to facilitate multi-class classification. Additionally, the input features were standardized using standard scaler to normalize the data distribution, which enhances model convergence during training by reducing feature scale disparities.

The dataset was partitioned into training (80%) and testing (20%) sets to evaluate model generalization. The ANN architecture was designed with:

- An input layer containing 23 neurons, corresponding to the 23 input features,
- Two hidden layers with 64 and 32 neurons, respectively, utilizing the Rectified Linear Unit (ReLU) activation function to introduce non-linearity and improve feature learning,
- An output layer with 7 neurons and a softmax activation function, enabling probabilistic multi-class classification.

The model was compiled using the Adam optimizer, known for its adaptive learning rate efficiency, and categorical cross-entropy loss, suitable for multi-class problems. Training was conducted over 50 epochs with a batch size of 16, and a 20% validation split from the training set was used to monitor overfitting. This approach ensured robust learning while maintaining computational efficiency.

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RESULTS AND DISCUSSION

The performance of the Artificial Neural Network (ANN) was rigorously evaluated using standard classification metrics on both the training and testing datasets. The model achieved a training accuracy of 91.56% with a corresponding training loss of 0.2254, demonstrating strong learning capability on the labeled data. Notably, the test accuracy reached 93.00%, slightly surpassing the training accuracy—an observation that suggests effective generalization without overfitting. This outcome is particularly encouraging, as it indicates that the model maintains robust predictive performance on unseen data, a critical requirement for clinical applicability.

The training dynamics further validated the model's stability, with the loss function steadily decreasing and accuracy consistently increasing across epochs. The absence of significant divergence or oscillation in these metrics suggests that the Adam optimizer efficiently navigated the loss landscape, achieving stable convergence. The model's ability to distinguish between all seven migraine subtypes with high accuracy underscores its potential utility in clinical decision support systems, where precise classification can guide personalized treatment strategies. This section presents the results with clear descriptions. Results can be supplemented with tables, graphs (pictures), and/or charts. The discussion section describes the results of processing data or information, interpreting the findings logically, linking them to relevant reference sources, and the implications of the findings. [Times New Roman, 12, normal].

Findings

The performance of the Artificial Neural Network (ANN) was rigorously evaluated using standard classification metrics on both the training and testing datasets. The model achieved a training accuracy of 91.56% with a corresponding training loss of 0.2254, demonstrating strong learning capability on the labeled data. Notably, the test accuracy reached 93.00%, slightly surpassing the training accuracy—an observation that suggests effective generalization without overfitting. This outcome is particularly encouraging, as it indicates that the model maintains robust predictive performance on unseen data, a critical requirement for clinical applicability. The training dynamics further validated the model's stability, with the loss function steadily decreasing and accuracy consistently increasing across epochs. The absence of significant divergence or oscillation in these metrics suggests that the Adam optimizer efficiently navigated the loss landscape, achieving stable convergence. The model's ability to distinguish between all seven migraine subtypes with high accuracy underscores its potential utility in clinical decision support systems, where precise classification can guide personalized treatment strategies.

Discussion

The high classification performance of our ANN model (93.00% test accuracy) demonstrates its efficacy in deciphering complex relationships between heterogeneous migraine symptoms and their corresponding subtypes. The model's success stems from its ability to process a comprehensive feature set. This multimodal feature space enabled the model to identify discriminative patterns among subtypes. For example, hemiplegic migraines were likely characterized by co-occurring motor weakness (Hemiparesis) and speech impairments (Aphasia/Dysphasia), whereas migraines without aura may have been distinguished by the absence of such neurological signs.

The model's robustness can be attributed to three key design choices:

- Strategic preprocessing: Feature standardization mitigated scale disparities, while one-hot encoding preserved categorical distinctions.
- Optimized architecture: Two hidden layers (64/32 neurons) with ReLU activation provided sufficient non-linearity to capture symptom interactions without over-parameterization.
- Balanced training protocol: An 80:20 data split with 20% validation ensured representative learning across all classes.

While the ANN model demonstrated strong classification performance, several limitations must be acknowledged. The current analysis may be constrained by potential class imbalance, particularly for less prevalent migraine subtypes such as the "Other" category, which could lead to biased performance across classes. Additionally, the inherent "black-box" nature of neural networks poses challenges for clinical interpretability, as the model's decision-making process remains opaque to end-users. Future work should prioritize addressing these limitations through several avenues. First, techniques such as stratified sampling or synthetic minority oversampling (SMOTE) could be employed to mitigate class imbalance effects. Second, explainable AI methods like SHAP values or LIME analysis should be incorporated to enhance model transparency and provide clinicians with meaningful insights into feature contributions. From an architectural perspective, the model could benefit from further refinement through the addition of regularization techniques like dropout layers or batch normalization, coupled with systematic hyperparameter optimization. These advancements will be crucial for transitioning from proof-of-concept models to clinically actionable decision-support tools that can operate effectively within existing healthcare workflows while maintaining rigorous standards of patient care and ethical implementation.

CONCLUSION

This study successfully developed and evaluated an Artificial Neural Network (ANN) for the classification of seven migraine subtypes based on a comprehensive set of clinical and demographic features. The model demonstrated robust performance, achieving 93.00% test accuracy while maintaining strong generalization capabilities, as evidenced by its higher test accuracy compared to training accuracy (91.56%). The ANN effectively captured complex relationships between diverse symptom profiles—including aura-related, neurological, autonomic, and genetic markers—enabling precise discrimination between migraine subtypes. Key methodological strengths, such as strategic data preprocessing, optimized network architecture, and balanced training protocols, contributed to the model's high predictive performance. Despite these promising results, certain limitations must be addressed to enhance clinical applicability. Potential class imbalance, particularly for rare subtypes, and the inherent opacity of ANN decision-making processes present challenges for real-world deployment. Future research should focus on improving model interpretability through explainable AI techniques (e.g., SHAP, LIME) and expanding dataset diversity to ensure generalizability across populations. Additionally, architectural refinements, such as dropout regularization and hyperparameter optimization, could further improve performance.

The findings underscore the potential of machine learning in supporting clinical decision-making for migraine diagnosis, offering a foundation for future development of AI-assisted diagnostic tools. By integrating multimodal data—including biomarkers and comorbidities—and validating findings in clinical settings, such models could evolve into valuable aids for neurologists, ultimately contributing to personalized treatment strategies and improved patient outcomes. Further research should prioritize ethical implementation and human-AI collaboration to ensure these technologies enhance, rather than replace, clinician expertise. This study highlights the feasibility of ANN-based migraine classification and sets the stage for future advancements in computational neurology, bridging the gap between machine learning innovation and clinical practice.

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