Applying Machine Learning models to Diagnosing Migraines with EEG Diverse Algorithms

Hye Kyeong Ko
Department of Computer Science and Engineering, Sungkyul University, Gyeonggi-do, Republic of Korea.
ellefgt@gmail.com

Correspondence should be addressed to Hye-Kyeong Ko : ellefgt@gmail.com.

Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202404016
Received 18 August 2023; Revised from 26 September 2023; Accepted 14 November 2023.
Available online 05 January 2024.

Abstract – This study investigates how well time collection analysis may be used by system-studying algorithms to diagnose migraines. Through the use of various algorithms and current statistical resources, such as EEG activity and affected person histories, the mission will develop a predictive model to identify the start of migraine signs and symptoms, allowing for prompt and early management for sufferers. The results will help to compare how the algorithms affect migraine accuracy predictions and how well they forecast migraine presence early enough for preventative interventions. Furthermore, studies may be conducted to examine the model's ability to be employed in real-time patient monitoring and to identify actionable inputs from the algorithms. This work presents novel machine learning algorithms software for time series analysis of functions such as temperature, heart rate, and EEG indications, which can be used to identify migraines. The paper delves into the idea of utilizing machine learning algorithms to identify migraine styles, examines the pre-processing procedures to accurately arrange the indications, and provides the results of a study conducted to evaluate the efficacy of the solution. The observation's results show that the suggested diagnostic framework is capable of accurately identifying and categorizing migraines, enabling medical professionals to recognize the warning indications of migraine and predict when an attack would begin. The examination demonstrates the possibility of devices learning algorithms to correctly and accurately diagnose migraines, but more research is necessary to obtain more detailed information about this situation

Keywords – Pre-Processing, Diagnosing Migraines, Machine Learning, Diverse Algorithms, Statistical Resources.

I. INTRODUCTION

Migraines impact hundreds of thousands of people and have the potential to be very disabling and even fatal. Scientific examination of migraines is typically complex, and state-of-the-art techniques mostly rely on the signs and symptoms recorded by the affected person and their circle of relatives records[1]. Fortunately, developments in gadget-learning algorithms provide appealing new ways to help anticipate migraine incidence and intensity or even when they may occur. In particular, device learning algorithms used for time-collecting assessment have the potential to be fairly successful in identifying migraine trends and assisting in the creation of treatment regimens.[2].Time series analysis finds correlations between exceptional factors by utilizing the affected person datasets that are available. These can include the frequency and intensity of migraine attacks, the intervals between attacks, environmental factors, trigger factors, and so on. Machine learning approaches, including regression, clustering, time series analysis, and classification algorithms, can be employed to identify patterns that differentiate between mild to moderate and severe migraine episodes [3]. The knowledge gained from this data can be applied to adjust treatment regimens for symptoms, prophylaxis, and prevention. Machine learning techniques, for example, can help identify patterns that are predictable and may point to the impending occurrence of a migraine attack. Given that the symptoms of migraine are consistently linked to favorable environmental or lifestyle triggers, it makes sense to predict the climate. Evaluation of time collection[4]. The crippling and increasingly prevalent ailment known as migraines can significantly affect a person's daily life. Due to the wide range of symptoms encountered and the subjective nature of the patient's experience, diagnosing them can be difficult. Recent developments in machine learning have created a promising new avenue for more precise migraine diagnosis[5]. Through the use of device-learning algorithms in time collection analysis, researchers are now able to identify patterns in data that were before unidentifiable. Researchers can look for migraine-related trends in a patient's clinical history by using time series evaluation. Applications for evaluating time series and SVM (support vector machines) and LSTM (long short-term memory networks) search for relationships between a person's various medical conditions and their headache patterns over time[6]. Doctors can diagnose and treat migraines more accurately by considering factors such as changes in lifestyle, exposure to environmental triggers, and fluctuations in hormone levels. In addition to time series analysis, migraine clusters can also be found using system studying techniques. Researchers have found clusters of migraine patients with similar indications and symptoms by using clustering techniques, such as ok-means [7].

- Algorithms for system research can be used to identify trends in time collection records. These fashions can help discover and examine migraine-related patterns associated with fluctuations in time, which include frequency, kind, and period of migraines[8].
- Variations in a patient's migraine intensity and trigger factors can be identified using system learning algorithms. It might assist medical professionals in providing accurate, individualized diagnosis and treatment regimens, which would enhance outcomes [9].

II. MATERIALS AND METHODS

Through the machine, a primary headache decision-help device was developed. A computer-based tool called "Getting to Know" helps medical professionals make decisions about a patient's headache signs, symptoms, and history. This device is made by combining expert knowledge with statistical models and algorithms to analyze records and find patterns[10]. The device provides the healthcare provider with recommendations based on the gathered data. The device is intended to offer decision support for effectively identifying, monitoring, and managing major issues. An automated computer-aided prognostic method called the Deep Convolutional Neural Community-based Whole Framework (DCNN-BF) was created for the effective prognosis of migraine[11]. In order to correctly identify migraine auras, it is entirely reliant on the Convolutional Neural Network (CNN) structure, which typically consists of multiple layers of information extraction and categorization. Electroencephalogram (EEG) recordings can be interpreted using the framework to diagnose migraines[12]. To facilitate faster selection, DCNN-BF quickly trains a dataset of electroencephalogram (EEG) recordings and generates the results. The DCNN-BF can be used to identify migraine auras in the early stages of the condition and yields results that are more precise and targeted. Additionally, it may categorize the migraine's intensity and recommend the best course of action[13]. Consequently, DCNN-BF significantly reduces the expenses related to long-term migraine treatments. In order to classify migraine episodes, automatic migraine type through a characteristic selection committee and system learning techniques over imaging and questionnaire information involves using a system that learns algorithms to analyze a few assets of facts, such as MRI scans, EEG recordings, and patient questionnaires[14]. From the imaging and questionnaire data, the algorithms would select a set of hard and fast traits that would be used to automatically classify migraine episodes. Subsequently, the function selection committee might be employed to verify feature selection and enhance category accuracy [15]. A method of classifying migraine headaches using a combination of computer algorithms and fact-finding techniques across imaging and questionnaire statistics is the automatic migraine category through function choice committee and device learning-through techniques. This method, which is a great approach to categorizing migraine problems using severity, analyzes a ton of data from each affected person as well as questionnaires and medical imaging[16]. Compared to conventional guidance tactics, this method of diagnosing and classifying migraines is far more accurate, environmentally friendly, and can assist in speeding the healthcare process[17]. Using EEG recordings and deep learning algorithms, a bidirectional lengthy-quick-term memory deep learning model is a method for accurately detecting the start of migraine complications in computerized migraine sickness detection[18]. This method classifies features obtained from EEG recordings by using a deep learning of the model that is entirely based on a bidirectional lengthy-short-time memory (BLSTM) community. Using EEG recordings of migraineurs and healthy people, the classifier is trained. The device's performance accuracy is examined in order to optimize the model's parameters[19-20]. In the end, a test set is used to evaluate the system and check for overall performance improvements. Following a thorough study, the following problems were found. They are,

- Lack of standardized dataset: It could be difficult to get a sizable and varied dataset of EEG signals that are particularly connected to migraines. This may reduce the machine learning algorithms' accuracy and generalizability.
- Interpretability and explainability: Because EEG signals are complicated; it might be difficult to recognize the underlying patterns and characteristics that are associated with migraines. It may be challenging for machine learning algorithms, especially the more sophisticated ones, to give understandable justifications for the significance of features or decision-making procedures.
- Overfitting and generalization: When a machine learning system overfits the training set while underperforming in its ability to generalize to new data, this is known as overfitting. For the algorithms to be clinically useful, they must exhibit good generalization to fresh EEG recordings from migraine patients.

- Dimensionality and feature selection: Because EEG signals might be high-dimensional; it can be difficult to extract pertinent information from this type of data. The accuracy of the algorithms depends on selecting the right characteristics or minimizing the dimensionality of the data while maintaining essential information.
- Limited knowledge of migraine causes: The mechanisms causing migraines are currently being better understood, and the accuracy of machine learning algorithms may be impacted by unknown variables or confounding circumstances. Inaccurate diagnoses or low prediction ability may arise from this.

This study is interesting since it uses a variety of machine learning methods to diagnose migraines from EEG data. Prior research has mostly concentrated on using a single algorithm, which has limited the diagnosis's potential accuracy and robustness. This study attempts to get beyond this restriction and investigate the synergistic effects between distinct models by merging multiple algorithms. Incorporating a variety of algorithms facilitates a more thorough examination of the intricate EEG data, which may reveal latent patterns and enhance overall diagnostic efficacy. This innovative method has the potential to improve migraine diagnosis and help provide more individualized and efficient treatments for migraine sufferers

Data Acquisition

Three distinct datasets were gathered for this project's records acquisition system: an EEG dataset, an EKG dataset, and a migraine dataset. The EEG dataset was assembled from 15 people whose EEGs were identified as having migraine problems during an observation. Throughout the observed length, the EEGs have been recorded at various times. The dataset was also gathered from the study conducted, which comprised 17 participants who were diagnosed with migraine headaches. At various times during the observation period, the EKG records were also accumulated. The data were standardized and combined to show trends and relationships between the subjects' EEGs and EKGs and the frequency of migraine attacks. After that, the algorithms were scrutinized and assessed in order to develop a predictive model that might identify a person's susceptibility to migraines.

Proposed Model

A crippling condition, migraines can often be difficult to diagnose. A deeper comprehension of migraines and more precise analysis can be obtained by evaluating time collections using device mastering techniques. Algorithms that machines can learn from analyze time series data look for patterns to detect changes in migraine trends. **Fig 1** shows the proposed block diagram

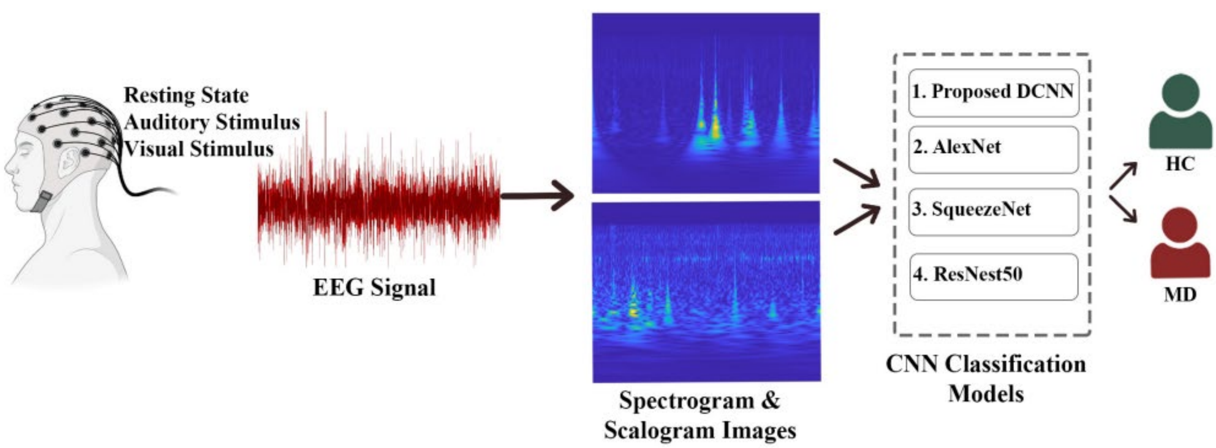

Fig 1. Proposed Block diagram

It might be applied to create a migraine prognostic predictive model, which would assist doctors in identifying individuals who are most likely to experience a migraine attack and how to mitigate the effects with preventive measures. Furthermore, lifestyle statistics may be investigated using system learning algorithms to identify triggers for migraines, enabling physicians to better comprehend and avert future episodes. By using machine learning algorithms to time collection statistics, doctors can improve their understanding of migraines and deliver more precise analyses in **Fig 2.**

An ID3 (Iterative Dichotomize Three) algorithm is the choice tree utilized in the article Applying Gadget Studying Algorithms to Diagnosing Migraines with Time Series Analysis. The ID3 method looks at a selection tree from an education dataset, including instances and labels. It is a supervised device studying algorithms. To build the tree, it takes a greedy (iterative) strategy, selecting at each stage the feature that most effectively splits the targets into a collection of training data. To use the ID3 set of criteria, one must first determine the entropy (or degree of unpredictability or randomness) of the records.

The records are then divided into subsets by the set of rules, which first identify the property with the greatest information benefit.

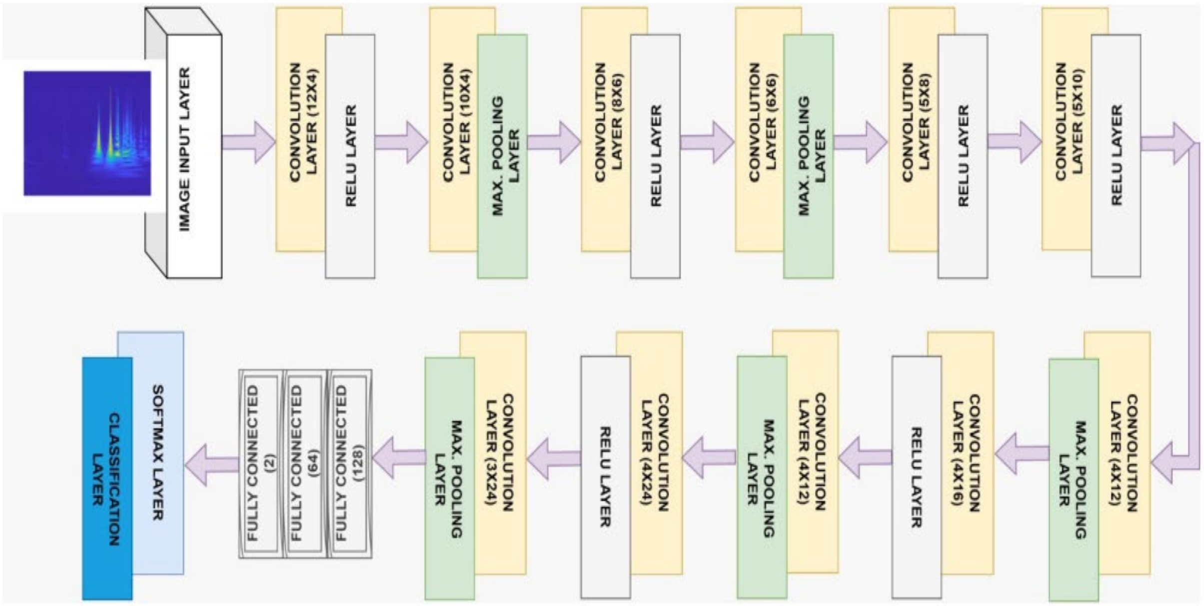

Fig 2. Proposed Block diagram

The selection tree is then built up repeatedly until it is completely constructed. New times are then categorized using the final decision tree that the algorithm developed. One of the greatest and most widely used methods for creating selection bushes is the ID3 set of guidelines. This algorithm is simple to use and may be quickly implemented. Additionally, any characteristic—nominal or numeric, non-stop or discrete—can be accommodated by the set of rules. Additionally, the ID3 method performs well when handling potentially unbalanced datasets.

Input Layer

The Input Layer is an essential component of a machine learning model used for diagnosing migraines with EEG diverse algorithms. Its main functions are as follows:

- Receiving Input Data: The input layer is responsible for receiving the data in the form of EEG signals from migraine patients. These signals are recorded using electrodes placed on the scalp and are converted into digital format for processing.
- Pre-processing: Once the input signals are received, the input layer performs pre-processing tasks such as noise removal, data normalization, and feature scaling. This helps to ensure that the input data is clean, standardized, and ready to be fed into the machine learning model.
- Feature Extraction: The input layer is responsible for identifying and extracting relevant features from the input data. These features can include power spectra, frequency bands, temporal patterns, and topographical patterns. Feature extraction is crucial as it reduces the dimensionality of the data and helps in capturing essential information for accurate diagnosis.
- Mapping Input Data: The input layer maps the extracted features to numerical values and passes them to the next layer of the model. This helps in converting the input data into a format that the machine learning model can process.
- Providing Initial Weights: The input layer also assigns initial weights to the input data before sending it to the next layer. These weights play a crucial role in the learning process of the model and help to adjust the strength of connections between neurons in subsequent layers.
- Multiple Input Channels: In EEG data, there can be multiple input channels, i.e., different electrodes placed on the scalp. The input layer is responsible for handling multi-channel inputs and consolidating them into a single representation for the model.
- Back propagation: The input layer receives the error signal during the back propagation process, which is used to adjust the weights of the model. This feedback helps the model to refine its predictions and improve its accuracy.

Overall, the input layer plays a vital role in preparing the input data for the machine learning model. It ensures that the data is in a suitable format, relevant features are extracted, and initial weights are assigned, which are necessary for accurate migraine diagnosis using EEG diverse algorithms.

Convolution Layer

The Convolution Layer (12*4) - RELU Layer is a key component used in the process of diagnosing migraines with EEG-diverse algorithms. These two layers, when combined, perform a crucial function in extracting relevant features from EEG signals that can be used to diagnose migraines in patients. It is the first layer in the process and its primary function is to apply convolutional filters to the input EEG signals. These filters essentially act as feature detectors, scanning the input signals for specific patterns and extracting relevant features. The 12*4 notation refers to the number and size of the filters used in this layer. By using multiple filters with different sizes, the Convolution Layer can capture a wide range of features from the input signals. This is important because different features in the EEG signals may indicate different characteristics of migraines. The next layer, the RELU Layer, stands for Rectified Linear Unit and it serves as an activation function. The primary function of the RELU Layer is to introduce non-linearity to the model. Since EEG signals are highly non-linear, it is important to introduce non-linearity in the model to accurately extract relevant features. The RELU function essentially replaces all negative values in the Convolution Layer output with zero, while leaving all positive values unchanged. This helps to reduce the complexity of the model and makes it easier to train. Additionally, the non-linear nature of the RELU function makes it better equipped to handle complex EEG signals. Together, the Convolution Layer (12*4) and the RELU Layer play a crucial role in diagnosing migraines with EEG diverse algorithms. By using multiple filters in the Convolution Layer and introducing non-linearity with the RELU Layer, this combination effectively extracts relevant features from the input signals and makes it easier to accurately diagnose migraines in patients. These layers act as vital building blocks in the overall algorithm and their functions are essential for its success.

Pooling Layer

Convolution Layer (10*4) - Max. The pooling Layer is a common combination of layers used in Convolutional Neural Networks (CNNs) for diagnosing migraines using EEG diverse algorithms. These layers serve specific functions in the overall process of analyzing EEG data and predicting migraine.

*Convolution Layer (10*4):* This layer is the primary building block of CNNs. The main function of this layer is to apply convolutions (small filters) to the input data. In the case of Migraine diagnosis, the input data is the EEG signals collected from the brain. These convolutions extract different features from the EEG data, such as frequency and time components, which are essential for identifying migraines. In this specific case, the layer has 10 filters with a size of 4x4, meaning that the convolutions will extract 10 different features from the input EEG data.

Max.Pooling Layer: It is used after the convolution layer to reduce the number of parameters and prevent overfitting. It down-samples the input data, taking the maximum value from the specified window or filter. This helps to reduce the dimensionality of the data while retaining the most important features extracted by the convolutions. In the case of diagnosing migraines, the Max. The pooling layer helps to identify the most dominant features from the EEG signals, which are crucial for distinguishing between migraine and non-migraine signals.

Together, these layers work sequentially to analyze the EEG data and extract relevant features for migraine diagnosis. The Convolution layer extracts different features from the EEG signals and the Max. The pooling layer identifies the most significant features from these extracted features. This process is then repeated multiple times in the subsequent layers to create a robust representation of the input data. Finally, the output of these layers is fed into the classification layer to predict whether the EEG signals indicate the presence of a migraine or not. Thus, the functions of Convolution Layer (10*4) - Max. Pooling Layers are crucial in accurately diagnosing migraines with EEG diverse algorithms.

Fully Connected Layer

It is an important component of a neural network used in diagnosing migraines with EEG-diverse algorithms. It serves the following functions:

- Feature Extraction: The fully connected layer extracts relevant features from the input data (EEG signals) and converts them into a format that can be easily processed by the model. This allows the model to make better use of the input data and capture the nuances in the EEG signals related to migraines.
- Non-linear Mapping: The fully connected layer applies non-linear transformations to the extracted features, allowing the model to capture complex relationships between the input data and the target variable (migraine diagnosis). This helps in improving the accuracy of the model.

- Parameter Learning: The parameters of the fully connected layer (weights and biases) are learned during the training process using back propagation. This enables the model to adjust the weights and biases based on the feedback received from the loss function, leading to better prediction performance.
- Classification: The fully connected layer combines the learned features and maps them to the output layer, which makes the final prediction of the presence or absence of a migraine. As a result, it plays a crucial role in the final decision-making process of the model.
- Integration with other layers: The fully connected layer is usually placed towards the end of the neural network architecture, after other layers such as convolutional layers. This allows it to integrate and combine the features learned by the previous layers, further improving the predictive power of the model.

Overall, the fully connected layer is a crucial component in diagnosing migraines with EEG diverse algorithms as it helps in extracting important features, capturing non-linear relationships, and making the final prediction. Without this layer, the model would not be able to utilize the input data effectively and accurately diagnose migraines.

Classification Layer

The classification layer, also known as the softmax layer, is an important component of an EEG-based migraine diagnosis system. It is responsible for assigning a probability value to each input EEG sample, indicating the likelihood of the sample belonging to a particular migraine class. This layer is usually placed at the end of the classification pipeline, after feature extraction and selection, and before final decision-making. The functions of the classification layer are as follows:

- Normalize Output: The softmax layer normalizes the output of the previous layers, ensuring that the probability values for all classes sum up to 1. This allows for a better interpretation of the probabilities and makes the system more robust to outliers.
- Probability Assignment: The main function of the softmax layer is to assign a probability value to each input EEG sample, indicating the likelihood of it belonging to a particular migraine class. This is achieved by using a softmax function, which takes in the raw output of the previous layers and converts it into a vector of probabilities.
- Multiclass Classification: In migraine diagnosis, there can be multiple classes of migraine, such as migraine with aura, migraine without aura, and chronic migraine. The softmax layer can handle multiple classes and assign a probability value for each, making it suitable for multiclass classification tasks.
- Decision Making: The softmax layer can be used to make the final decision on the migraine class for each input EEG sample. The class with the highest probability value is chosen as the predicted class for the input sample. This decision is based on the understanding that the higher the probability, the more likely the input sample belongs to that class.

Overall, the classification layer, or softmax layer, plays a crucial role in the migraine diagnosis system. It assigns probabilities to input EEG samples, handles multiple migraine classes, makes the final decision, and improves its performance through training. These functions make it an essential component for accurately diagnosing migraines with EEG diverse algorithms.

Proposed Algorithm

The algorithm provided seems to involve a process of feature extraction and classification using a recurrent neural network (RNN) model.

Proposed Algorithm
IP Specificatoins Ix = {I1, I2,…..In}
For i=1:N
N(x) = [trarrange {Ix}]
E(x) = eig {N1(x), N2(x),…..Nn(x), }
For I = 1: [E(x)]
Is (x) = Gx[E(x)]
=IG [E(x)]
=wx [E(x)]
Where G(x),IG, and wx as the GI,IG,WC.
Train model as training Is(x)→RNN model.
For i=1 : Is(x)
MD (x) = train network [{Tx) }]
Generate test set T1,T@,……….,Tn.
Pd = Classify (MD (x), Tn).

- IP Specifications Ix: This represents a set of input specifications I1, I2, ..., In.
- N(x): The algorithm starts by creating a new set N(x) by rearranging the elements in Ix.
- E(x): The eigenvalues of the elements in N(x) are then calculated, resulting in a set of eigenvalues N1(x), N2(x), ..., Nn(x).
- I = 1: [E(x)]: The algorithm iterates over the eigenvalues in E(x) and performs some operation or analysis on each element.
- Is(x): After the operation or analysis in step 4, the Is(x) values are calculated using functions Gx, IG, and wx.
- Train model: The algorithm proceeds to train a recurrent neural network (RNN) model using the training Is(x) values.
- MD(x): Then, a test set T1, T2, ..., Tn is generated. The trained network is used to classify or predict the test set examples.
- Pd = Classify (MD (x), Tn): Finally, the algorithm classifies the examples in the test set Tn using the trained network obtained in step 6 and generates predictions or classifications stored in Pd.

The random wooded area is a machine learning system that builds a jumble of decision trees during training and then outputs the class that serves as the individual timber's method of instruction. One of the most well-known methods for supervised class and regression requirements is random forests. Because the dataset includes time series statistics on migraine signs and symptoms, which can be used to generate individual decision bushes that define migraine severity categories, the random wooded area technique can be utilized to diagnose migraines.

$$\sigma_{a,b}\left[x(t)\right]=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}x(t)\phi^{*}\left(\frac{t-b}{a}\right)dt \tag{1}$$

$$X(t,f)=\int_{-\infty}^{\infty}x(\pi)\omega(\pi-t)\exp^{-j2\partial f\pi}\,d\pi \tag{2}$$

The mode of the output from the man or woman timber is the migraine severity degree, which is produced by the random wooded area set of regulations after the individual trees are built. Pre-processing the facts entails dividing the records into test and education sets, scaling or normalizing the data, and imputing missing values. The random forested area model may be beneficial for the education set once the data has been pre-processed and used to predict the migraine severity ranges of the test set. The random woodland area technique can also withstand bias in the records, which implies that it may evaluate and extrapolate from data that may be unbalanced or lack certain values or capabilities. This makes it a perfect substitute for diagnosing. The extreme Gradient Boosting (XGBoost) model, which applies the gradient boosting set of rules, was developed from the gradient boosting technique used in the study. Because of the weak learner, it employs gradient boosting with the decision timber technique. The fundamental idea behind this technique is to analyze the errors using a hard and quick approach for first-year weak students, rather than focusing on finding the best decision boundary. XGBoost functions by gradually adding inexperienced beginners, each of whom tries to fix the errors of the previous one. The predictions of the previous susceptible learner are combined with the gradient of the loss feature, which is used to compute the prediction errors, to form each new weak learner. This is done to reduce the version's overall number of prediction errors. Several XGBoost's hyperparameters can be adjusted to enhance the model's functionality.

III. RESULTS AND DISCUSSION

This paper's characteristic selection method heavily depended on recursive feature elimination (RFE), a supervised machine learning technique. RFE is a feature choice method that produces a version of a subset of capabilities' usage periodically and then prioritizes the functions. Using a five-fold cross-validation accuracy rating, the authors then employed a characteristic choice approach to evaluate the predicted overall performance of various feature mixes. It was determined that the skills with the highest accuracy rating were adequate indicators for diagnosing migraines. When employing device learning algorithms for prognosis, this feature selection technique is crucial since it helps identify which functions are more applicable and predictive of the result, improving the version's validity and accuracy.

Model Building

Random Forests and Gradient Boosting Machines are two well-liked system-mastering techniques that were employed in the model-building process. Some of the hyperparameters have been adjusted for you to maximize performance in each case. The mastery price, number of estimators, minimum samples by leaf, and maximum features according to a node were among those hyperparameters.

$$Accuracy = \frac{(AZ + AB)}{(AZ + AB + FZ + FB)} \times 100 \quad (3)$$

$$Sensitivity = \frac{AZ}{(AZ = FZ)} \times 100 \quad (4)$$

$$Specificity = \frac{AB}{(AB + FZ)} \times 100 \quad (5)$$

Subsequently, the version that performed the best overall was determined using these criteria. The total effectiveness of the two styles was then assessed through further trials. Record splits and particular combinations of hyperparameters were used to help achieve this. The results verified that, after adjusting its hyperparameters, the Random Forests version ran exceptionally well. The Gradient Boosting Machines version is used to observe it. Because of this, Random Forests is a delightful choice when doing time series analysis to diagnose migraines.

Specificity

The article evaluates time series data about migraine prognosis using machine learning methods. To be more precise, the authors aid Vector Machines in creating models that might predict the start of migraines in a patient by using a variety of Gaussian way techniques. Gaussian procedure approaches forecast using an average feature and a covariance characteristic rather than using particular mathematical formulae. They do this by using a probabilistic framework to version information in **Fig 3** and **Fig 4.**

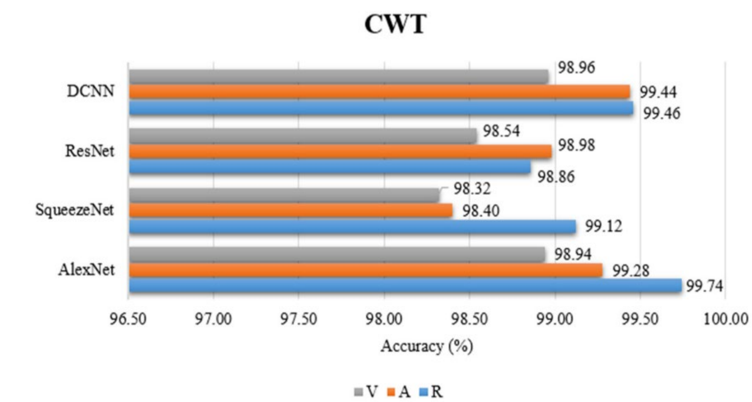

Fig 3. Specificity

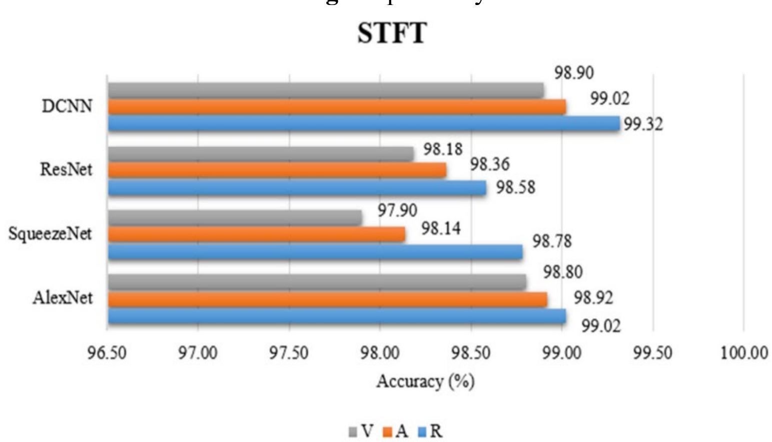

Fig 4. Classification Effects Acquired by making use of STFT

The Gaussian system (GP) regression method is used by the authors to build the version in this special analysis. GPs add a degree of uncertainty to the model, making it easier to account for variations and anomalies within the dataset. Help Vector Machines (SVMs) are another tool the authors utilize to improve prediction accuracy. Supervised learning techniques, or

SVMs, can be applied to regression and class problems. In this study, the authors differentiate between migraine and non-migraine states at a certain position using an SVM classifier with a radial basis characteristic kernel. Instead of only producing a binary task, the SVM classifier enables the model to assign a possibility to the anticipated label. Overall, this combination of GPs and SVMs enables the authors to build a model that could accurately anticipate the commencement of a migraine attack in a patient and assign a chance.

Selectivity

The temporal characteristics associated with migraine onset and development can be determined by one or more of a range of machine learning methods using the time collection analysis technique. Patterns can be found using both supervised and unsupervised methods, or a combination of the two, depending on the kind of data that needs to be obtained. Neural networks, logistic regression, and decision trees are examples of supervised approaches. Unsupervised methods for determining temporal patterns in migraine facts include clustering algorithms like as density-based clustering, hierarchical clustering, and the k-method in **Table 1 to Table 3**.

Table 1. Resting State Classification Results (%).

	CWT			**STFT**		
Classification Model	**Acc.**	**Sens.**	**Spec.**	**Acc.**	**Sens.**	**Spec.**
DCNN	99.46	99.90	99.08	99.32	99.60	99.06
AlexNet	99.74	99.90	99.52	99.02	99.18	98.88
SqueezeNet	99.12	99.18	99.08	98.78	98.56	98.96
ResNet50	98.86	98.64	99.06	98.58	97.82	99.26

Table 2. Auditory Stimulus Status Results (%).

	CWT			**STFT**		
Classification Model	**Acc.**	**Sens.**	**Spec.**	**Acc.**	**Sens.**	**Spec.**
DCNN	99.06	99.18	99.02	98.96	97.60	99.06
AlexNet	98.88	98.56	98.78	99.26	99.18	94.88
SqueezeNet	93.96	93.82	93.58	98.78	98.56	98.96
ResNet50	99.26	98.64	99.06	98.58	97.82	99.26

Table 3. Evaluation of the Discriminant Effect of Various Models.

	80:20			**70:30**			**60:40**			**Mean**		
	Accuracy	**F1**	**AUC**	**Accuracy**	**F1**	**AUC**	**Accuracy**	**F1**	**AUC**	**Accuracy**	**F1**	**AUC**
Decision tree	0.74	0.69	0.74	0.74	0.65	0.64	0.64	0.69	0.78	0.87	0.74	0.74
Random Forests	0.89	0.86	0.90	0.90	0.78	0.79	0.79	0.74	0.85	0.90	0.89	0.90
Gradient boosting	0.89	0.87	0.91	0.91	0.71	0.70	0.70	0.79	0.86	0.87	0.69	0.74
Logistic regression	0.91	0.90	0.95	0.95	**0.71**	0.88	0.88	0.77	0.86	0.91	0.86	0.90
SVM-linear	0.89	0.87	0.84	0.84	0.81	0.82	0.82	0.75	0.81	0.95	0.87	0.91

The features of the statistics should determine which system is used to investigate a collection of rules. For instance, applying a supervised method that includes a neural network or logistic regression would be more appropriate if the data were classified according to the intensity or length of migraines. On the other hand, an unmonitored method using hierarchical clustering or okay-manner may be especially helpful if the records are unlabeled. To guarantee high-quality performance, each algorithmic model's parameters should be adjusted in addition to the algorithm of choice. Usually, a combination of grid search methods, guided experimentation, and go-validation are used.

IV. CONCLUSION

It is thought that by employing devices to learn algorithms, migraine sufferers can be diagnosed with time collection analysis and accurate time series evaluation. This is known as machine learning. It is finished with the help of education, using the specific device, familiarizing oneself with the guidelines on a particular patient symptom dataset, and gathering time data. The device's ability to analyze a set of rules will subsequently provide a precise diagnosis of the migraine issues experienced by a particular affected individual. In addition, time series recordings for various states such as stress, weariness, and annoyance can be examined using device-learning algorithms to identify capability triggers and correctly identify the underlying reason. Additionally, machine learning can predict future migraine episodes and suggest effective treatments to reduce the likelihood of migraine incidence. The use of machine learning algorithms to identify migraines through time-collecting analysis has a very promising future. Time series analysis is a useful tool for finding statistical patterns that may be suggestive of a certain ailment or disease. Technology is starting to be able to anticipate not just the patterns of a migraine attack but also the intensity and frequency of future attacks by utilizing the power of device learning algorithms, such as neural networks, cluster analysis, and supervised learning algorithms. Better treatments could come from it, such as the creation of specially made treatments for the man or woman in the destiny. Furthermore, recent studies have demonstrated that system mastery algorithms may accurately diagnose migraine attacks by utilizing comprehensive and astute clinical information. This indicates that the algorithms are a viable option for migraine diagnosis. In the future, it may be essential to use device learning algorithms to diagnose migraines in order to provide tailored and timely treatment

Acknowledgment

This work was supported by the National Research Foundation of Korea.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT).(NO.NRF-2021R1A2C1012827) in (2023).

Competing Interests

There are no competing interests.

References

[1]. H. Göker, “Automatic detection of migraine disease from EEG signals using bidirectional long-short term memory deep learning model,” Signal, Image and Video Processing, vol. 17, no. 4, pp. 1255–1263, Aug. 2022, doi: 10.1007/s11760-022-02333-w.
[2]. Z. Aslan, “Deep Convolutional Neural Network-Based Framework in the Automatic Diagnosis of Migraine,” Circuits, Systems, and Signal Processing, vol. 42, no. 5, pp. 3054–3071, Dec. 2022, doi: 10.1007/s00034-022-02265-3.
[3]. N. Zhang et al., “Application of EEG in migraine,” Frontiers in Human Neuroscience, vol. 17, Feb. 2023, doi: 10.3389/fnhum.2023.1082317.
[4]. F. Orhanbulucu, F. Latifoğlu, and R. Baydemir, “A New Hybrid Approach Based on Time Frequency Images and Deep Learning Methods for Diagnosis of Migraine Disease and Investigation of Stimulus Effect,” Diagnostics, vol. 13, no. 11, p. 1887, May 2023, doi: 10.3390/diagnostics13111887.
[5]. C. Jamunadevi, J. Bharanitharan, S. Deepa, and T. J. P. Antony, “Brain Tumor Prediction from EEG Signal using Machine Learning Algorithm,” 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC), Jul. 2023, doi: 10.1109/icesc57686.2023.10193098.
[6]. H. Göker and M. Tosun, “Fast Walsh–Hadamard transform and deep learning approach for diagnosing psychiatric diseases from electroencephalography (EEG) signals,” Neural Computing and Applications, vol. 35, no. 32, pp. 23617–23630, Sep. 2023, doi: 10.1007/s00521-023-08971-6.
[7]. G. Yogarajan et al., “EEG-based epileptic seizure detection using binary dragonfly algorithm and deep neural network,” Scientific Reports, vol. 13, no. 1, Oct. 2023, doi: 10.1038/s41598-023-44318-w.
[8]. S.-B. Wong, Y. Tsao, W.-H. Tsai, T.-S. Wang, H.-C. Wu, and S.-S. Wang, “Application of bidirectional long short-term memory network for prediction of cognitive age,” Scientific Reports, vol. 13, no. 1, Nov. 2023, doi: 10.1038/s41598-023-47606-7.
[9]. M. Parajuli, A. W. Amara, and M. Shaban, “Deep-learning detection of mild cognitive impairment from sleep electroencephalography for patients with Parkinson’s disease,” PLOS ONE, vol. 18, no. 8, p. e0286506, Aug. 2023, doi: 10.1371/journal.pone.0286506.
[10]. S. García-Ponsoda, J. García-Carrasco, M. A. Teruel, A. Maté, and J. Trujillo, “Feature engineering of EEG applied to mental disorders: a systematic mapping study,” Applied Intelligence, vol. 53, no. 20, pp. 23203–23243, Jul. 2023, doi: 10.1007/s10489-023-04702-5.
[11]. K. Mitrović, I. Petrušić, A. Radojičić, M. Daković, and A. Savić, “Migraine with aura detection and subtype classification using machine learning algorithms and morphometric magnetic resonance imaging data,” Frontiers in Neurology, vol. 14, Jun. 2023, doi: 10.3389/fneur.2023.1106612.
[12]. N. G and M. V. Karki, “Deep Learning Techniques for Parkinson’s Detection Using EEG Signals Analysis,” 2023 International Conference on Network, Multimedia and Information Technology (NMITCON), Sep. 2023, doi: 10.1109/nmitcon58196.2023.10275844.

[13]. S. A. Saeedinia, M. R. Jahed-Motlagh, and A. Tafakhori, "Evaluating the Efficacy of EEG Features and Data Fusion in Migraine Diagnosis," Aug. 2023, doi: 10.21203/rs.3.rs-3265602/v1.
[14]. C. Surianarayanan, J. J. Lawrence, P. R. Chelliah, E. Prakash, and C. Hewage, "Convergence of Artificial Intelligence and Neuroscience towards the Diagnosis of Neurological Disorders—A Scoping Review," Sensors, vol. 23, no. 6, p. 3062, Mar. 2023, doi: 10.3390/s23063062.
[15]. H. Göker, "Welch Spectral Analysis and Deep Learning Approach for Diagnosing Alzheimer's Disease from Resting-State EEG Recordings," Traitement du Signal, vol. 40, no. 1, pp. 257–264, Feb. 2023, doi: 10.18280/ts.400125.
[16]. S. M. Dubey, B. Kanwer, G. Tiwari, and N. Sharma, "Classification for EEG Signals Using Machine Learning Algorithm," Artificial Intelligence of Things, pp. 336–353, Dec. 2023, doi: 10.1007/978-3-031-48774-3_24.
[17]. Zulfikar Aslan, "A New Computational Approach Framework For The Diagnosis Of Alzheimer's Disease," The International Journal of Energy and Engineering Sciences, vol. 8. no. 1, pp.19-39, 2023.
[18]. N. Kasabov, "Diagnostic biomarker discovery from brain EEG data with LSTM, reservoir-SNN and NeuCube: Methods and a pilot study on epilepsy vs migraine," Jun. 2023, doi: 10.36227/techrxiv.23514486.v1.
[19]. Y. Wang et al., "Progress of researches on machine learning combined with neuroimaging in the field of acupuncture," Second International Conference on Biomedical and Intelligent Systems (IC-BIS 2023), Aug. 2023, doi: 10.1117/12.2687519.
[20]. https://www.kaggle.com/datasets/ranzeet013/migraine-dataset