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An Adaptive Neuro-Fuzzy System for Computer-Aided Diagnosis of Epileptic Seizure in Human Electroencephalograms Utilizing Discrete Wavelet Transform

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ABSTRACT

This research introduces an epileptic seizure detection method that combines discrete wavelet transform (DWT) with an adaptive neural fuzzy system for usage on a computer. Data collecting and synthesis of electroencephalogram (EEG) signals, EEG signal breakdown and feature extraction, and feature vector classification are all part of this method. The method, which runs in Matlab (version 7.6), takes advantage of the power of discrete wavelet transforms (DWTs) in the time domain and the frequency domain to decompose and extract distinctive features, and it employs an adaptive neuro-fuzzy inference system (ANFIS) to classify transformed feature vectors. There were five different forms of EEG waves that were synthesised and analysed. The ANFIS classifier was trained and tested using features taken from the decomposed signals. The ANFIS combines a neural network's (NN) adaptability with a fuzzy inference method (FIS). Sensitivity, specificity, and overall classification accuracy were used to evaluate the ANFIS's effectiveness. Furthermore, the results demonstrated that the hybrid model/technique including DWT and ANFIS achieved high degree of accuracy in the categorization of EEG data as epileptic/normal with little false detection.

Keywords: Discrete Wavelet Transform (DWT), Adaptive Neuro-Fuzzy Inference System (ANFIS), Epileptic Seizure, Electroencephalogram

INTRODUCTION

This brain signal is measured by electroencephalogram. It's a visual representation of the rapid-fire electrical processes taking place in the human brain. Overloaded neurons in our brains emit these signals. The EEG is then used to evaluate the strength of the signal and pinpoint when it occurred. These signals are often low-energy signals that have been mingled with various forms of noise. Disentangling the noise from the actual brain signal is essential for an accurate EEG study. A number of computer-aided diagnostic strategies have been used to examine EEG data. A discussion

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of the multiplicative and differentiating approaches to epilepsy categorization was presented. Each class's training data is related to the model's mean square error using the multiplicative method [1].

While the discriminative method quickly evaluates the thresholds between categories, this method classifies the EEG according to the count generated in each model developed and selects the model with the most optimal count.

To classify the electroencephalogram data windows, several controlled learning approaches have been used to this collection of features. Multi-channel Epileptic's (MCE) effectiveness stems from the use of a lightweight classifier to achieve a targeted level of performance. In the context of real-time seizure detection, the fact that a lightweight classifier may be tailored to the needs of doctors is exciting. The result is consistent with the MCE point of view since it gives equal emphasis to each category and considers each in the context of potential remedies to even the smallest errors [2].

The identification and categorization of epileptic seizures in human electroencephalograms was performed using a hybrid model consisting of independent component analysis (ICA), discrete wavelet transform (DWT), and an adaptive neuro-fuzzy inference system (EEG). Also, the accuracy of their categorization was quite good, with just a small percentage of false positives. Moreover, Opiarighodare suggested a discrete wavelet transform (DWT) technique that employswavelet of order 2 of Daubechies for the decomposition of the EEG signals into various subbands, exhibiting the detailed wavelet coefficients and the approximate wavelet coefficients respectively [3].

Diverse seizure investigation methodologies have different applications, reviewed these applications. In order to identify seizures, several cutting-edge methods now use ECG and EEG data. They were able to differentiate between the three seizure detectors. There are many types of seizure onset indicators, all of which rely on electroencephalographic (EEG) data.

For the purpose of identifying the EEG signals realised and evaluated in three separate EEG signals sets, a Wavelet-based Neural Network (WNN) classifier (healthy humans, patients with epileptic seizure and patients with epileptic syndrome at the time of manifestation of the seizure). The EEG has previously used DWT in conjunction with Multi-Resolution Analysis (MRA).

Utilizing an Adaptive Neuro-Fuzzy System

Extraction of the % distribution of the energy characteristics of the EEG signal at various resolutions was performed using signal decomposition at resolution levels of the components of the EEG signal, such as delta, theta, alpha, beta, and gamma, using the Parsevals theorem. The recovered characteristics were then classified using a Neural Network (NN) to identify the types of EEGs from the retrieved energy features' percentage distribution. (The approximation entropy characteristics were used in a novel method of computerised seizure detection developed The entropy characteristics were generated with the aid of multi-wavelet transform in this method [4]. The categorization process was assisted by a neural network powered by AI. For the purpose of EEG signal categorization, described a strategy that employs a synthetic neural network trained on line length data collected by wavelet transform.

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Long-term Holter-EEG analysis software was disclosed, along with a template matching mechanism that used statistical methods to compare the EEG to that of persons in a database of known epileptics. The use of EEG-based circumstantial categorization was given as a classification and validation method. The EEG signals' incoherence, sleep/wake cycle, and categorization into eight distinct classes. A wavelet decomposition based EEG categorization method was suggested. Multi-level decomposition led to the identification of a Delta signal, and a neural network was used to classify the signal.

The two-pronged design optimization approach proposed took into account both the efficiency of signal examination and the cost of hardware while assessing the various approaches. Electroencephalographic seizure detection characteristics were examined using microelectrode data from kainite-treated rats. The circuit models were used to determine the ratio of active to total power, as well as the amount of power going out of the system. Considering the effectiveness of detection and the cost of hardware, suggested a technique of two- aspect design optimization to evaluate the approaches for their practicability in the embedded application. Electroencephalographic seizures in kainite-treated rats were recorded using micro-electrodes, and the resulting data was examined to see whether the detected characteristics could be used to identify them. Circuit models were used to assess how well the studied characteristics made use of active and outflow power. Each set of characteristics was given a value based on the accuracy of detection and the cost of hardware, and then plotted on a two-dimensional design plane [5].

Computerized identification of epileptic seizures using EEG waves was the subject of a thorough review proposed. Computerized EEG tracing detection using DWT and ICA was studied. ICA and DWT approaches were used for feature extraction, while support vector machine and neural network (NN) methods were used for classification.

someone experiencing epileptic seizures. The local processing of the signal and transmission of the frequency content and energy are performed by the investigation circuit when a seizure has been identified [6].

Despite the presence of noise, artefacts, and acquisition flaws in brain electrophysiological data, demonstrated how differentiation may be used to enhance some aspects of these signals, allowing for cost-effective analysis and/or detection of changes. Majumdar used the windowed variance method to identify EEG data indicative of an epileptic episode in this instance. In order to shorten the processing time for epilepsy diagnoses, he used windowed variance and spontaneous seizure determination. Combining seizure power spectra with deterministic finite automata, created a new system. In order to analyse epilepsy from activity, they integrated the two approaches [7].

In sum, the aforementioned studies have all achieved respectable performance, but they all also generate an unacceptablely high rate of false detection. The input datasets used in each of the systems are not as complex as those encountered in the real world today, and therefore cannot be considered reliable and efficient for the detection of epilepsy. This is despite the fact that they made use of some of the publicly available standard bench marked data sets, which were also used in the present study. As a result, additional study is required to acquire a more trustworthy and effective

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system that can apply and identify the existence of interictal epileptiform discharge across all data sets.

METHOD AND CONCEPT OF COMPUTER AIDED DIAGNOSIS OF EPILEPTIC SEIZURE

In this study, we introduce a novel approach to computer-aided diagnosis of epileptic seizures using human electroencephalogram (EEG), which entails the following steps: acquisition of EEG signal data, synthesis of EEG signals, decomposition of the signals, extraction of features, and classification of EEG based on the transformed features vectors. The approach was implemented using the MATLAB software suite Synthesis and Acquisition of EEG Signal Data

In this computer-aided diagnosis of epileptic seizure, the electroencephalogram (EEG) signals were processed using a collection of commonly-used EEG data obtained from the database of Albert-University, Ludwig's Freiburg, Germany. Datasets were reduced in size and shown in ASCII format. There are a total of five datasets, each of which is a zip file containing one hundred text files. Z, O, N, F, and S represent the dataset names. The synthetic EEG signals were derived from these databases, which include both epileptic and healthy human subjects.

When used to signal processing, the DWT approach produces a high-frequency result at low frequencies and a high-time result at high frequencies. Because the DWT uses large time windows when the frequency is low and uses short time windows when the frequency is high, it exhibits this behaviour when put to use. By alternating a high-pass (HPF) and a low-pass (LPF) filter on the signal, DWT is able to separate the signal into its component bands (LPF). Which depicts the DWT's sub-band decomposition of EEG signals, the high-pass filter is represented by the discrete mother wavelet function, marked g, while the low-pass filter is represented by its inverse, labelled h. The DWT approach uses a high-pass filter (HPF) and a low-pass filter (LPF) to classify and down-sample each signal individually. Separating signals into their initial levels are the A1 and D1 approximation and detail coefficients, respectively. Similar to how the approximation coefficient in one level was used to determine the detail coefficient in the next, the approximation coefficient in one level was used to determine the detail and approximation coefficients in the levels that followed.

Below are expressions for the wavelet function j, k(x) displaying HPF and the scaling function j, k(x) displaying LPF:
When x is a real number, we get j, k(x) = 2j/2 h (2j x - k) (1)
j, k(x) = 2j/2g (2j - k) (2) Given that x = 0, 1, 2,..., M – 1, j = 0, 1, 2,..., J – 1, and k = 0, 1, 2,..., 2j – 1, find the value of x, j, and k.
J= log2 (M) (3)
Where M is the length of an EEG segment (Gonzalez and Woods, 2008), J is the sampling rate, and j is the resolution; these values represent the locations and widths of the functions along the x-axis, respectively. The peaks of the functions are value-dependent on the 2j/2.
The coefficients Ai (k) for the ith approximation and Di (k) for the ith detail are Ai = 1 x f(x) j,k (x) (4) and Di (k) = 1 x f(x) j,k (x) (4) for k = 0, 1, 2,..., 2j - 1, respectively. breakdown used for each study project.

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Using an Adaptive Neuro-Fuzzy System for EEG Classification

In this study, an Adaptive Neuro Fuzzy Inference System is used as a classifier for EEG analysis (ANFIS). For the purpose of differentiating the stipulations of Sugeno-type fuzzy inference systems, the ANFIS makes use of a hybridised learning approach. In order to replicate the training dataset, the membership function constraints of the fuzzy inference system (FIS) are trained using a combination of forward and backward pass processes.

In this study, 500 data points were used to create both the training and testing sets (100 samples from each class of human subjects represented by each dataset). There were 350 data samples used for training (70 from each dataset) and 150 used for testing (30 from each dataset). There were a total of 350 samples used for training the ANFIS, and the remaining 150 examples were used for testing to ensure that the trained ANFIS model correctly classified the epileptic seizure shown in the EEG.

The ANFIS is trained using a learning algorithm, which is then used to fine-tune all of the parameters. This is done to guarantee that the ANFIS's output is consistent with the input data. When the membership functions' postulated (premise) parameters are held constant, the output of the ANFIS model is given by the following equation:

The forward pass method (6) was used to find the best possible settings for the parameters with little to no effort. Because of this, the training convergence slows down and the search area expands if the premise parameters are uncertain.

However, using a hybridised process that incorporates both forward pass and backward pass strategies helped address the issue of delayed training convergence. As a result, the hybridised process consists of both backward pass and forward pass. In this hybridised technique, the forward pass was designed to optimise the derived (consequential) parameters while keeping the hypothesised (premise) values fixed. As soon as the optimal subsequent (resultant) parameters are determined, the backward pass may begin. The inputs to the fuzzy inference system were fine-tuned using backward pass to ensure that the premise parameters matched the fuzzy sets in the domain. ANFIS's output

$D = \{ 1 \sqrt{M}$

$\sum x f(x) \psi j ,k \ (x)\}$ (5)

used, forward pass derived parameters, to establish. This is an output mistakeSegmentM of the EEG is 4097 s in length, and Ji is determined using log2 slicing (M). because of this, J is equal to 12. Because of this, we determined that Lof decomposition level 11 is the maximum possible.

This study used the discrete wavelet transform method of order 2of Daubechies wavelet during signal breakdown. Level of breakdown (i.e., decomposition) analysis revealing greatest and/or best system performance conventional backpropagation technique was used to tune the parameters of the hypothesis. See below for a detailed rundown of the steps required to implement the proposed

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scheme:

Firstly, you'll need to get started; secondly, you'll need to gather data on EEG signals; and thirdly, you'll need to synthesise EEG signals.

Utilizing an Adaptive Neuro-Fuzzy System

Fourth, apply discrete wavelet transform (DWT) to break down EEG signals into frequency sub-band components; fifth, if frequency is less than 30Hz, go to step 6; if not, return to step 3.
Sixth, using discrete spectral analysis, isolate the most informative characteristics from each sub-band component.
Specificity = True Negative Decisions
$NumberofActuallyNegativeCases$
step-by-step instructions for implementing a DWT; Step 7: LPF processing of all frequency sub-bands;
Classify each component separately using characteristics collected using ANFISclassifiers (Step 8);
Interictal epileptiform discharge (IED) is present in individual component, process epileptic seizure, otherwise normal; epileptic seizure, normal, output; step 11: stop.

Additionally, sensitivity, specificity, and accuracy are among the performance assessment criteria that were employed to examine the system. Equational relationships were used to calculate the values of sensitivity, specificity, and accuracy (7 to 11). The sensitivity measures how well aberrant data samples can be identified as such, while the specificity measures how well normal data samples can be identified as such. Follow these steps to determine the sensitivity and specificity:

Number of Correctly Classified DSZ Signals in Human Subjects with Eyes Open
For clarity, let's break this down into its component parts: positive (TP), negative (FN), false positive (FP), and false negative (TN). When the system correctly identifies abnormal data as abnormal, it returns a TP value; otherwise, it returns a FN value; when it correctly identifies normal data as abnormal, it returns an FP value; and when it correctly identifies normal data as normal, it returns a TN value. A system's overall classification accuracy is determined by taking a broad perspective of the word "accuracy," which is used here as a shorthand for describing how well the system performs in practise.

Component B: The Outcome of Decomposing and Extracting Features From EEG Signals
Each synthetic EEG signal from each dataset underwent decomposition and filtering beginning at detail coefficient level 1 and continuing until level 6. Maximum wavelet coefficients in each sub-band; iii. Minimum wavelet coefficients in each sub-band; iv. Mean wavelet coefficients in each sub-band; and v. Standard deviation wavelet coefficients in each sub-band.

Classification and Design of an ANFIS Model C. Neuro-fuzzy paradigm design leverages computed data to provide FIS that are analogous to the input-output pairs provided to it. In addition, characteristics derived from the wavelet transform during the decomposition at various levels are used as inputs to the ANFIS network in this study. The development of an ANFIS model is a multi-

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stage process. Opening the ANFIS editor and making a Sugeno type FIS from the paired data set was the first step. And the "genfis1" function in Matlab was used for this purpose (version 7.6). With an Adaptive Neuro - Fuzzy System, the number of membership functions for each input is used to partition the fuzzy space into discrete regions. All the movable parameters have been divided up across three distinct membership functions., the FIS is used to categorise EEG data. The standard deviation, mean, minimum, and energy of the DWT coefficients are the five adjustable parameters used as inputs, and the epileptic or normal output class is the resulting output variable, in accordance with the five-input, one-output system. Language variables were used to express the input adjusting parameters. When comparing the membership functions of the wavelet coefficients before and after training, it is clear that the latter undergo substantial modifications. What this demonstrates is the relative significance of the characteristics included in categorization [8].

ANFIS used 350 training data throughout 200 training iterations to arrive at an initial value of 0.011. This value is used as the basis for further iterations of the step size parameter adaption. After 200 iterations of training, ANFIS reaches a network error convergence curve of 0.0084. Moreover, there are 350 data samples to be categorised by 243 rules, and the system suggests the likelihood of obtaining low and/or no mistake in training. The ANFIS's processed output is shown by the red dots, which follow the plot of the ANFIS's training performance using 243 rules.

structure. The blue dots indicate the goals that must be met by the 350 samples of training data. Further indicating that there are few mistakes during training. This set of mistakes is irrelevant since it falls inside their class limit. When the training was finished, the ANFIS classifier used to categorise the EEG signals was validated using testing data consisting of 150 samples. Utilizing an Adaptive Neuro-Fuzzy System. The distribution of samples from the testing data, suggesting that few mistakes were made while categorising the EEG signals. When insignificant mistakes at the data sample border are ignored, the system is effective. Although a data sample mismatched was seen around the data sample boundaries for each of the aforementioned datasets during training and testing, no errors were found between 0 and the 30th sample, no errors were seen between the 30th and the 60th sample, and no errors were seen between the 60th and the 120th sample. Data set that was used. Data sample mismatch due to abrupt spike in EEG was discovered between the 120th and 150th samples. Table 1 displays the results of classification performed by the ANFIS model, which makes use of 350 training data samples and 150 testing data samples. EEG signal categorization findings using the ANFIS model are shown in Table 2 as a confusion matrix. The number of times an EEG signal is incorrectly labelled may be seen in the matrix. Wanted categorization appears in rows, whereas actual network outputs are in columns of the matrix. The confusion matrix shows that there was some misclassification of signal samples from Z, O, N, F, and S. There was a misclassification of 1 signal sample from Z as coming from N, 1 signal sample from O misclassified as coming from F, 1 signal sample from N misclassified as coming from Z, 1 signal sample from F misclassified as coming from O, and 1 signal sample from S misclassified as coming from N.

Computation of statistical characteristics such as sensitivity, specificity, and accuracy were used to evaluate the concept's performance in this study's application, establishing the classification performance of the ANFIS model used. This computer-aided diagnosis of epileptic seizures use the ANFIS model, which has a total classification accuracy of 98.6%. Specificity values for classification using ANFIS are 99.64% for Z signals, 99.60% for O signals, 99.29% for N signals, 99.60% for F signals, and 99.99% for S signals. Also, the classification sensitivity of Z signals is 98.57%, O signals are 98.57%, N signals are 98.57%, F signals are 98.57%, and S signals are 98.57%.

CONCLUSION

Inaccurate identification of epileptic seizures due to high rates of erroneous detection of seizures in electroencephalograms is the main topic of this study (EEG). In this approach, there are three distinct phases. To begin, the EEG signal must be preprocessed by aggregating it from many datasets and synthesising the patient database. Datasets including biosignals were carefully monitored, chosen, and imported into MATLAB software. This made the data usable for breakdown and waveform characterisation. The next step is dissecting EEG data in order to pull out useful elements. In this step, we used the discrete wavelet transform to decompose the EEG data and extract the unique characteristics of each frequency band. In the end, the recovered feature vectors are fed into an adaptive neural fuzzy classifier through the ANFIS. To properly differentiate a transitory seizure from background activity, the ANFIS categorises the discriminative properties that describe the intrinsic behaviours of the EEG data. As a result, it helps fix the issue of misdiagnosis of seizures caused by the present methods' high erroneous detection of epileptic seizures in EEG. Despite the complexity of the datasets utilised in the tests undertaken for this study, the simulation findings demonstrate that the computer assisted diagnosis including the use of discrete wavelet transform (DWT) in conjunction with ANFIS, is more accurate and efficient.

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