Identification and Monitoring the Details of COMA Patient using Resilient Propagation Basis Function Neural Network Classifier Algorithm for Monitoring Brain Signals through Wireless Sensor Network

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Abstract

Coma is an unconscious state wherein the patient is unable to respond. Therefore, the IoT sensor can be used to monitor the patient's coma brain solution where a wave of effective signal data is considered. The processing of brain waves based on the coma patient monitoring may be a very difficult analysis of the previous system's signal. The method proposed in the investigation, through the IoT sensors, is based on the positive signal changes found in the brain waves in the coma patients and is analyzed based on machine learning. In this article, a brainwave monitoring system developed in three steps using a Wireless Sensor Network (WSN), is continuously monitored for a patient's physical parameters in coma. The proposed Resilient Propagation Basis Function Neural Network (RPBFNN) classification algorithm identifies the coma patient's state and alerts the patient. The system has followed three stages: Preprocessing, feature selection and classification. The first stage is Ensemble Filter-based preprocessing to remove the noise from the sensor data. Gaussian random frequency domain wavelet distribution (GRFDW) based feature selection is the second stage to collect the features (sub-band EEG signals, Standard deviation, variance Skewness). Then the final stage is the implementation of Resilient Propagation Basis Function Neural Network to identify the coma patient state level and alert the patient or system.

Keywords:
Resilient Propagation Basis Function Neural Network (RPBFNN), Gaussian random frequency domain wavelet distribution (GRFDW), coma patient state level, Ensemble Filter, sub-band EEG signals.

1. Introduction

Coma is a state of the deep unconsciousness with a variety of clinical conditions. For the Prediction of coma, the traditional test is done based on a set of clinical observations. Recently, some Event-Related Potentials (ERP), which is auditory, visual or tactile stimulation brief Electroencephalogram (EEG) response, has been introduced as a useful predictor of coma (i.e., appearance) and it offers a positive result.

However, such a test requires the skills of a clinical neurophysiologist, which are not commonly used in many clinical settings. In addition, there are no current standard clinical methods that have sufficient accuracy in predicting and providing a clear prognosis. Brain signals are produced by all mental states namely normal and abnormal. EEG is considered as a very powerful tool in the field of neurology and clinical neurology and can reflect all the brain's activities. Although EEG diagnosis is better, monitoring and management of diseases of the nervous system, analysis and interpretation of the relevant EEG has hindered its widespread acceptance as an important clinical tool for varying degrees of difficulty.

1. 2. Related Work

The Fuzzy multichannel EEG classifier (FMCEC) algorithm can be considered in constructing a classifier when the interaction between different signals is collected on the skull at different times and places [1].The main improvement and optimization of the Multi-View Convolutional Neural Network (MVCNN) model of the convolutional layer and stochastic gradient descent are based on the discrete Stochastic Gradient Descent (SGD) of the multi-spectral image characteristics of the EEG, and the multi-view convolutional layer structure is proposed [2].

A Robust Principal Component Analysis (RPCA) -embedded Transition Learning (TL), while avoiding intra- and intra-personal differences [3], can create a unique horizontal model of less labeled data.Relevant rational isolated short-term Discrete Short-Time Fourier Transform (DSTFT) epilepsy EEG data [4] is a novel feature extraction technique.

The Gaussian mixture hidden Markov model uses automatic feature extraction and autoregressive deep variation car encoding models to use EEG signal equipment. The second component is EEG classification and features extraction [5] to hide the Gaussian combination. Demix tries to improve each pair to use a two-dimensional rotation matrix to reduce the Within-Class Correlation Coefficient Distance (WCCD) interference between channel pairs. Therefore,

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the EEG channel to enhance the correlation coefficient is characterized by cognitive task classification [6].

A hierarchical two-way Gated Recurrent Unit (GRU) network with attention is used to extract Electroencephalogram (EEG) signals from human2. emotion categories [7]. The proposed feature deals with messy interference E Artifact Rejected Common Spatial Pattern (AR-CSP) [8].

Obscure Fuzzy Decision Tree (FDT) Classification initial data uncertainty account, which causes the loss of some information in slowing down the initial signal growth, should be considered. However, the application of fuzzy classification requires a variation according to preprocessing because it requires data in fuzzy format [9-10].

CNN (Convolutional Neural Network) contains the relevant information which is one of the main reasons behind the CNN-dependent deep learning model's success [11]. In contrast to stimulus-related activities, all EEGs have block design tracks for classification in spontaneous brain states based on volume level secular interaction [12].

The classification characteristic is complex, and the classification itself can take into account vague classification by using lightning Electroencephalogram (EEG), data loss Effective classification of stress which are the important issues in neurology [13]. So far, single task and manual classification are still the hallenges [14]. In addition, the network method has gradually evolved into the complex anatomical study of the brain, making it easier to interpret different mental states in a promising direction [15].

Hierarchical Semi-skipping Layered Gated Unit (SLGU) and Gated Recurrent Units (GRU) in the Recurrent Neural Networks (RNN) provide better performance for hidden layer [16] for Efficient Network (ENet) in addition to Layered Outsourced Units (SLU). The Convolutional Neural Network (CNN) system Image Net features the VGG-16 CNN model as a target CNN model. Its components are similar to the previous training in design other than the VGG-16 softmax output layer [17].

Frequency bands also reduce the EEG channel size by a one-dimensional layer [18] and A two-dimensional interpretation function is proposed similar to an image: Performance evaluation involves representing the information content model of the EEG signal in two different ways. The Selection Method is used to remove unwanted and inappropriate features [19] from the MWVG feature. An apartment Multiplex Weighted Visibility Graph (MWVG) maintains its time-dependent properties [20]; a graphical representation of the variable time series mapping is useful.

3. Implementation of the proposed system

Coma is defined as the state of unconsciousness, lack of response to harmful stimuli. The pathophysiology of consciousness and coma is not fully understood. On the other hand, the clinical examination does not give us enough information on the coma stage. This article introduces an EEG-based preliminary review system for brain activity functions related to Frequency domain wavelet coefficients, which extracts information from EEG clinical data recorded in the real world. Gaussian random frequency domain wavelet distribution (GRFDW) generates the best in the feature selection model.

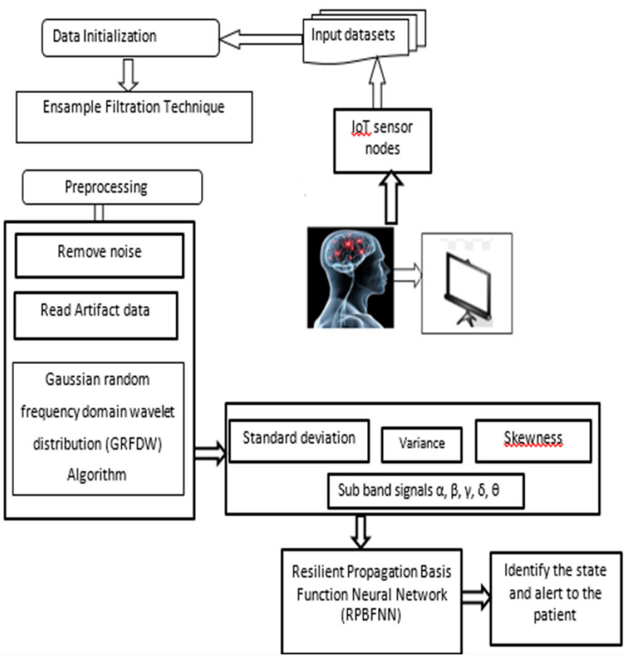

Figure 1 Proposed Architecture

In the first stage, the pre-treatment is done using a discrete wavelet transform in the input signal to remove noise or artifacts. The second stage is characterized by the use of different types of wavelet decomposition to extract the frequency domain. In the third stage, the extracted features are to train the RPBFNNcoma aberration by classifying the presence or absence.

3.1 Ensemble filter based Preprocessing of EEG Signal

During the recording of the EEG signal, the artifacts or the unwanted noises are added to the signals. The Noises are the most important features, which disturbs the EEG signal to an extent that the measurement from the original EEG signals becomes unpredictable. The major categories of noise are artifacts and external noise.

Artifacts removal: Artifacts play an important role to process EEG signals. It becomes tedious for clinicians to diagnose diseases if EEG signals are associated with artifacts. The basic EEG signal is in a frequency range of 0.1 Hz to 50 Hz. The main purpose of the preprocessing system is to remove noise from the acquired EEG signal.

External noise: These noises occur due to poor contact of electrodes or electrodes leads to low-frequency artifacts.

3.2 Gaussian random frequency domain wavelet distribution (GRFDW) algorithm based Feature selection

Extraction of facilities forms the basis of the characteristics of the original EEG, data and selection observation and EEG signal comprehension. Extractable features include first-row, second-row, and original EEG, data high-row cumulative. The importance of signal processing applications is significant using first- and second-order statistics, which trade with Standard deviation, Variance and Skewness. The above techniques determine the behavior of processed EEG signals

In this study, the Frequency domain wavelet decomposition method is used to extract the interval between sub-band EEG signals of α, β, δ, γ, and θ wave amplitudes from the feature or noise removal. Frequency domain wavelet coefficients are used to extract different features from the sub-bands of α, β, δ, γ, and θ. The extracted features are coefficient variance, standard deviation, energy and entropy for each sub-band.

Input: Artifacts or noise removed from the EEG signal dataset

Output: Different Features in EEG for every Sub bands

Start:

Step 1: The Artifacts or noise-removed EEG signal is read.

Step 2: The features which are to be extracted are chosen (Standard deviation, Variance, Skewness)

$$C(i,j) = \int_{-\infty}^{\infty} si(t)\frac{1}{i}\Psi * \left(\frac{t-j}{i}\right) \quad (1)$$

$$F\{C\ (i,j)\} = \sqrt{i\Psi * (i,\omega)si(\omega)} \quad (2)$$

Where $\Psi * (i,\omega)si(\omega)$ represents the continuous wavelet coefficients $C(i,j)$The signal si (t) and the wavelet function w (t) are the Fourier transform, respectively.

$$T(F\{C\ (i,j)\}) = \frac{1}{2\pi}\int_{-\infty}^{\infty} i(\theta,\tau)\phi(\theta,\tau)x(n) \quad (3)$$

Step 3: The sub-bands of noise removed EEG signal is extracted Subband signals are α, β, γ, δ, θ

Step 4: The Features from each sub-bands are calculated

Standard deviation

This is the distribution of the statistical feature description relative to the average data.

$$Standard\ deviation$$
$$s = \sqrt{\frac{1}{t-1}\sum_{n=1}^{t}} \quad (x[n] - \frac{1}{t}\sum_{n=1}^{t} \quad X[n])^2 \quad (4)$$

Variance

It is the square of the standard deviation.

$$variance\ v = s^2 \quad (5)$$

Skewness

It is a measure of the lack of asymmetry or the symmetry of an EEG signal data set. The data set of the EEG signal distribution extending more towards the left of the mean defines the positive skewness. The vice versa of the positive skewness defines the negative skewness.

$$Skewness\ E = D[\frac{(x-\mu)^3}{\sigma^3}] \quad (6)$$

Where E=expectancy.

Normally, different types of features are available. But in the coma patient detection process, these four features are mostly used because these features are the best measures of variation based on every item of the distribution.

The Continuous Wavelet Transform (CWT) of a signal $si(t)$ is defined as the integral and wavelet between the signals $si(t)$ is a compressed version of time translation and scale expansion/wavelet function w (t). Corresponds to a scalar production, which is calculated to produce a continuous wavelet coefficients C (i, j), which is located in a position determination signal and the "j" (time shift factor) and "i" the degree of similarity between positive wavelet scale.

3.3 Resilient Propagation Basis Function Neural Network (RPBFNN) classification

In this proposed solution, the coma state analysis framework is based on the sequence of Resilient Propagation Basis Function Neural Network(RPBFNN) and nonlinear analysis of EEG signals. Firstly, the Gaussian filtering method eliminates the signals noise from the pre-processed amplitude and then extracts the representative features of the less frequency field and non-random study highlights based on the report. Moreover, the extracted features are identified by the optimal combination and evaluated for vector decomposed function using the RPBFNN classifier to signal EEG signals. RPBFNN Classifier algorithm structure is shown in figure 2, and the activation function is represented in figure 3. The algorithm steps are discussed below.

Each hidden unit in the network has two parameters called its associated center (X_j) and width (σj). The activation function of the hidden unit is a Gaussian function, which is radially symmetric in the input space. The output of each hidden unit depends only on the radial distance between the input vector Xi and the center parameter C_i, which is the hidden unit. The response of each hidden unit is scaled to an output unit by its connected weight W_j and then summed to produce the total network output. The following formula calculates the overall network output.

3.3.1 Resilient Propagation Basis Function Neural Network (RPBFNN) Classifier

Input: Load EEG data file.

Step 1: Training and test data separation of collected data.

Step 2: All data values are adjusted.

$$S_n = \frac{(S-S_{min})\times(i_q-j_q)range}{(S_{max}-S_{min})} + Starting\ Value$$

where, S_n I = standardized value, $S_{min} and S_{max}$ = min and max values of the variable S.$i_q - j_q$ are the values as output interval of neuron activation function

Step 3: Determine the three-level vector decomposition of the RPBFNN.

$$out_i = f[\sum_{j=1}^{n} \quad w_{ij} out_j + a_i]$$

where out_i = Considered the i-th output vector decomposition.

out_j= output of the j[th]neuron, w_{ij} = Relational weight between the i-th vector and the j[th] inputs and ai = perpetual called bias.

Step 4: The bias and weight matrices are initialized

$$E(m) = \frac{1}{2}\sum_{q=1}^{n} \quad [i_q - j_q]^2 \qquad (7)$$

where i_q= qth Input system output representative of the preferred network, j_q = the actual output vector decomposing network

Step 5: Identify the number of times.

Step 6: compare the output vector decomposing with the pre-defined values.

Step 7: Finds the true positive and true negative values from the compared signal.

$$F_{PBF} = \sum_j \quad W_j \varphi_j \text{ , } j = 1 \text{ to } n \text{ (number of hidden units)} \qquad (8)$$

$$\varphi_j = e^{-|X_j - C_i|^2} \,/\, 2\sigma_j^2 (4.2)$$

Where

φ_j =Response of the j[th] hidden unit

W_j = Weight Connecting hidden unit j to output unit

X_j =Center of j[th] hidden unit

σ_j = width of j[th] hidden unit

Step 8: Repeat step 4 until the actual output vector.

Step 9: Stop the process.

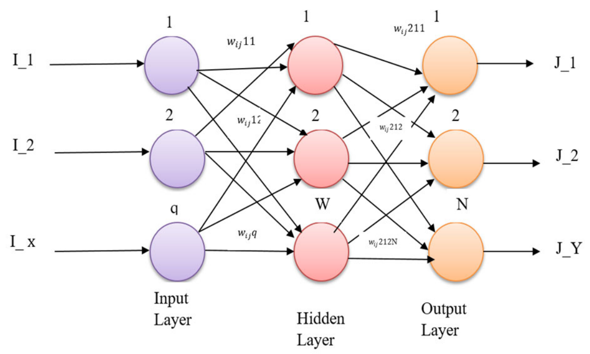

Figure 2 Resilient Propagation Basis Function Neural Network (RPBFNN) classifier structure

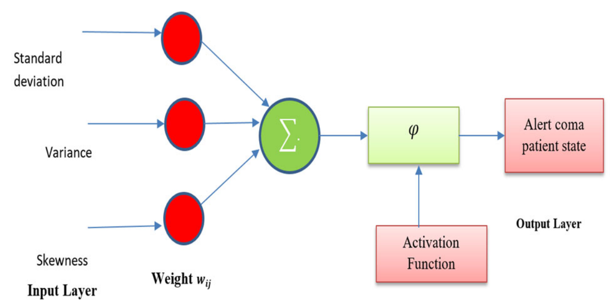

Figure 3 Activation functional block of RPBFNN

Figure 3 represents the functional activation block for the Resilient Perceptron Neural Network (RPBFNN) classifier. In this block demonstration, the system utilizes feed-forward neural formation based on the weight ratio and activation function by which the coma state level is identified.

3. Result and Discussion

The proposed method simulation has been implemented in the python framework and the brain wave signal dataset collected from the Brainwave EEG Dataset has been taken and 500 data have been taken from different coma patients.

Table 1 Simulation Parameter

Parameter	Value
Data set	Brainwave EEG Dataset
Number of Data	500
Trained data	400
Test data	100
Platform	Python
Tool	Jupyter notebook

Above table 1 presents the details of the proposed system. This section describes the proposed Resilient Propagation Basis Function Neural Network (RPBFNN)and the previous Global cortex factor-based multivariate autoregressive (GCF-MVAR), 4-D convolutional neural-network (4-D CNN), ID (Iterative Dichotomiser) -maximum posteriori Active Selection algorithm (ID-MPASA), recurrent restricted Vector Decomposed Neural Network Classifier (R2VDNN) methods.

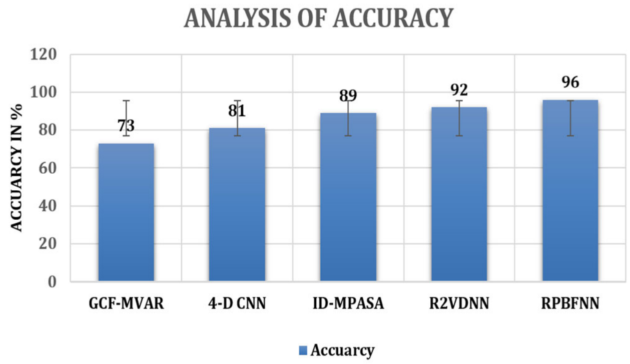

Figure 4 Analysis of Accuracy

Above figure 4 shows the analysis of the accuracy of EEG signal classification. It compares the existing GCF-MVAR which produces 73%, 4-D CNN which produces 81%, ID-MPASA which produces 89%, R2VDNN which produces 92%, with the proposed RPBFNN which proves better accuracy of analysis with 96%.

Sensitivity: The sensitivity at its ability accurately looks at the coma patient brain wave signal analysis. The classifier always determines the brain wave signal to calculate the true positive rate.

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \tag{9}$$

Specificity: Specificity is a statistical value used to evaluate classification performance. It is also known as the true negative rate that can determine the proportion of correctly identified negatives. It is usually expressed in percentage.

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{10}$$

Table 2 Analysis of sensitivity and specificity

Parameters	GCF-MVAR in %	4-D CNN in %	ID-MPASA in %	R2VDNN in %	RPBFNN in %
sensitivity	61	72	88	92	95
specificity	63	76	81	89	92

Above table 2 presents the details of the proposed RPBFNN and previous GCF-MVAR, 4-D CNN, ID-MPASA, R2VDNN method's sensitivity and specificity level.

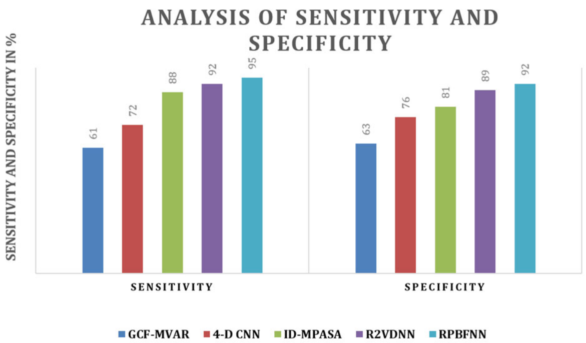

Figure 5 Analysis of specificity and sensitivity

The analysis of proposed RPBFNN based sensitivity level is 95%, specificity level is 92%, and previous GCF-MVAR based sensitivity level is 61%, specificity level is 63%, 4-D CNN based sensitivity level is 72%, specificity level is 76%, ID-MPASA based sensitivity level is 88%, specificity level is 81%, R2VDNN based sensitivity level is 92%, specificity level is 89%, and the results of the method are Presented in above figure 5.

$$\text{Error rate} = \frac{approximate\ value - exact\ value}{exact\ value} * 100 \quad (11)$$

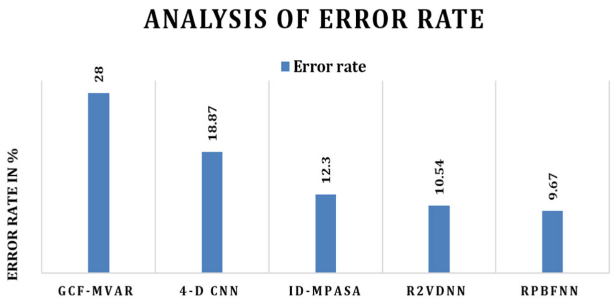

Figure 6 Analysis of Error Rate

Above figure 6 presents the detailed comparative analysis on the error rate classification ratio with different methods. The proposed RPBFNN achieves the minimum error rate of 9.67%, and the previous GCF-MVAR achieves 28%, 4-D CNN achieves 18.87%, and ID-MPASA achieves 12.3%, R2VDNN achieves the minimum error rate of 10.54 % respectively.

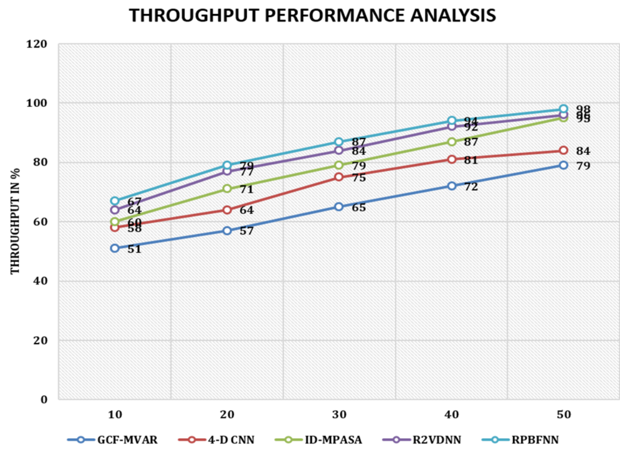

Figure 7 Throughput

Figure 7 shows that throughput of the proposed RPBFNN is 98% and the existing methods GCF-MVAR produces 79%, 4-D CNN produces 84% and ID-MPASA produces 95%, and R2VDNN produces 96% respectively.

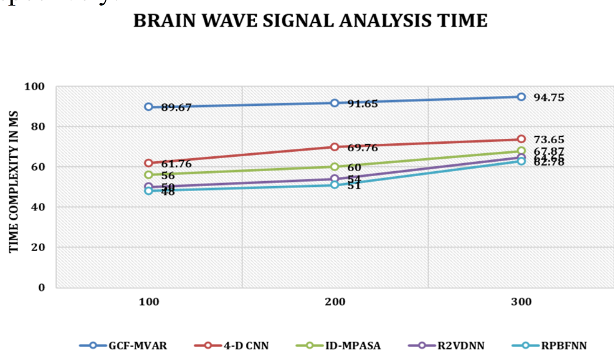

Figure 8 Analysis of Time Complexity

The time complexity analysis shows that the GCF-MVAR produces time complexity in 94.75 ms, 4-D CNN in 73.75 ms, ID-MPASA in 67.87 ms, R2VDNN produces in 64.65 ms, and the proposed RPBFNN produces time complexity in 62.78 ms.The details are presented in above figure 8.

4. Conclusion

Among the proposed method used for probing human brain dynamics, electroencephalography (EEG) provides a direct measure of cortical activity with temporal resolution in milliseconds. Early prediction and analysis of EEG data have relied upon visual inspection of EEG records. Since the introduction of EEG recordings, the volume of data generated from a study involving a single patient has increased exponentially. The feature (inputs) used were measures of dispersion – which captured the statistical variations found within the particular time series. The proposed Resilient Propagation Basis Function Neural Network (RPBFNN) accuracy analysis is 96%, sensitivity level is 95% and specificity level is 92%, the minimum error rate is 9.67%, throughput performance is 98%, and analysis of time complexity in 62.78 ms.

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