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Overview of the Electroencephalogram (EEG) signals

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Abstracts: In recent years the algorithms of machine learning were used for brain signals identification as a useful technique for diagnosing diseases like Alzheimer's and epilepsy. In this paper, the Electroencephalogram (EEG) signals are classified using an optimized Quantum neural network (QNN) after normalizing these signals. The wavelet transform (WT) and the independent component analysis (ICA) were utilized for feature extraction. These algorithms were used to reduce the dimensions of the data, which is an input to the optimized QNN for the purpose of performing the classification process after the feature extraction process. This research uses an optimized QNN, a form of feedforward neural network (FFNN), to recognize the EEG signals. The Particle swarm optimization (PSO) algorithm was used to optimize the quantum neural network, which improved the training process of the system's performance. The optimized QNN provided us with somewhat faster and more realistic results. According to simulation results, the total classification for ICA is 82.4 percent, while the total classification for WT is 78.43 percent; from these results, using the ICA for feature extraction is better than using WT.

Keyword: Diagnosing,Electroencephalogram

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Introduction

The biomedical engineering interested dramatically in the automatic classification of Electroencephalogram (EEG) signals. Because the biomedical signals, inherently unstable and randomly change over time depending on the change and mental health conditions and situations of tension for the same person, and one of these signals is brain signal that varies according to the psychological state of the person himself and changed depending on the circumstances, all of this has paid great attention to the analysis of brain signals. The EEG is the registration of electrical activity on the scalp. Current flow due to firing of nerve cells in the brain results in a voltage wiggle that measured as EEG [1].

Measuring the brain'sresponse to a stimulus is called event-related potential (ERP). The stimuluscan be motor, sensory, or cognitive naturally. Human ERPs are usually recorded from electrodes placed on the human scalp.

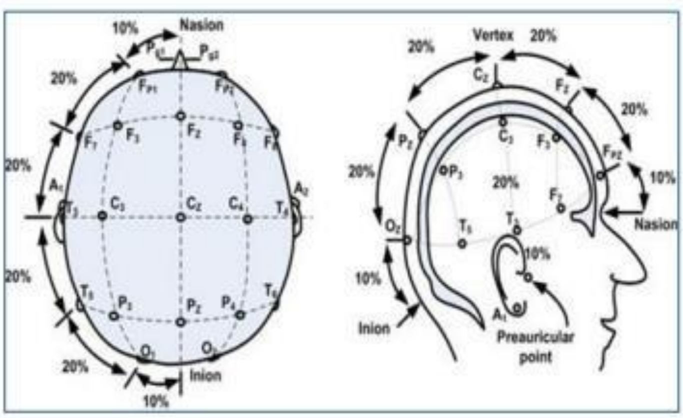


Fig. 1. The placement of electrodes on the scalp according to the international (10-20)standard.

The placement of electrodes on the scalp according to the international(10-20) standard is shown in fig. 1 [2]. The popular way of analyzing event-related EEG signals is the computation of ERPs. This can be done by repeating an event of interest such as a visual stimulus of a computer screenand analyzing a small fraction of the EEG activity that is evoked by this event [3]. The feature extraction technique of EEG signals provides an accurate feature in which would to classify between any event related potentials of the brain using QNN. Five types of EEG signals are used. Each type of these signals is a mental task assigned to a particular person to perform it. These tasks are (baseline, multiplication, letter composing, rotation, counting).

Overview of the EEG Device.

An electroencephalography is a test that measures electrical activity in the brain using small metal discs (electrodes) attached to the scalp. Brain cells communicate through electrical impulses and are active all the time, even during sleep. This activity appears as wavy lines in an EEG recording. An electroencephalogram is one of the main tests for diagnosing epilepsy.An electroencephalogram can also play a role in diagnosing other brain disorders.

Why is it done

An electroencephalogram can detect changes in brain activity, which may be useful in diagnosing brain disorders, especially epilepsy or other seizure disorders. An EEG may also be helpful in diagnosing or treating:

- Brain tumors
- Brain damage due to a head injury
- Brain dysfunction that can have a variety of causes (encephalopathy)
- Sleep disorders
- Encephalitis (encephalitis caused by the herpes virus)
- Stroke
- Sleep disorders
- Creutzfeldt-Jakob disease

An EEG may also be used to confirm brain death in a person in a persistentcoma. A continuous EEG is used to help find the right level of anesthesia for a person in a medically induced coma.

Risk.

EEG tests are safe and painless. Sometimes seizures are deliberately triggered in people with epilepsy during the test, with appropriate medicalcare available in case they are needed.

How does the patient prepare before being examined by thedevice?

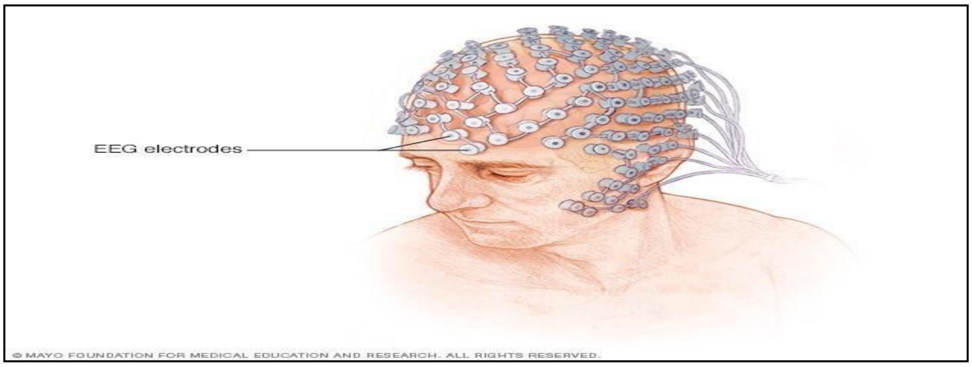
1. Food & Medicines
2. Take your usual medications unless otherwise instructed.

Other precautions

- Be sure to wash your hair the night before the test or on the day of the test, but do not use conditioners, hair creams, sprays or styling gels. Hair care products can make it difficult for the skinattach to your scalp.
- If you're supposed to fall asleep during an EEG test, your doctormay ask you to sleep less or avoid sleeping the night before thetest.

What you can expect:

During the test



Electrodes for EEG

You'll feel little or no discomfort during an EEG. The electrodes do nottransmit any sensations. They only record your brain waves.

Here are some things you can expect to happen on an EEG:

- **A competent technician will take the measurement of your head and mark your scalp** with a special pen to indicate wherethe electrodes are connected. A cream may be applied to these dots on your scalp to improve the recording quality.
- **The technician will fix discs (electrodes) on your scalp** using a special adhesive. Sometimes, a flexible headdress equipped with electrodes is used instead. The electrodes are connected via a set of wires to a device that amplifies brain waves and records them on a computer.

Once the electrodes are held in place, an EEG usually takes between 20 and 40 minutes. There are tests for specific medicalconditions that require you to sleep during the test. In that case,the test may take longer.

- **You will relax in a comfortable position with your eyes closed during the test.** At multiple times, the technician may ask you to open and close your eyes, perform simple calculations, read a paragraph, look at a picture, breathe deeplyfor a few minutes, or look at a flashing light.
- **A video will usually be recorded during an EEG.** A video camera captures your body movements while an EEG records your brain waves. This bulk recording can help your doctor diagnose and treat your condition.

A mobile EEG allows longer monitoring outside of the clinic or hospital. But these types of EEG devices aren't always an option. This test can recordbrain activity over several days, increasing the likelihood of recording during epileptic seizure activity. But compared to video EEG follow-up done in the hospital, a mobile EEG isn't as efficient at determining the difference between epileptic seizures and other seizures.

After the test

The technician removes electrodes or headdress. If you haven't received asedative, you won't feel any side effects after the procedure. And you can go back to your usual routine.

But if you receive a sedative, it will take time for the medication to wear off. Arrange with someone to take you home. When you get home, rest anddon't drive for the rest of the day.

Results

Trained doctors analyze EEGs, interpret the recording, and send the resultsto the doctor who ordered EEGs. You may need to schedule an appointment to discuss the test results in the office.

Ask a family member or friend to come with you to the appointment, if possible, to help you remember the information you'll receive.

Write down questions to ask your doctor, such as:

- Based on the results, what are my next steps?
- What kind of follow-up, if any, do I need?
- Are there any factors that might affect the results of this test insome way?
- Do I need to repeat the test?

EEG SIGNAL CLASSIFICATION SYSTEM PROPOSED

1. Methodology for the feature extraction.

The working method is summarized in the existing diagram No. 1

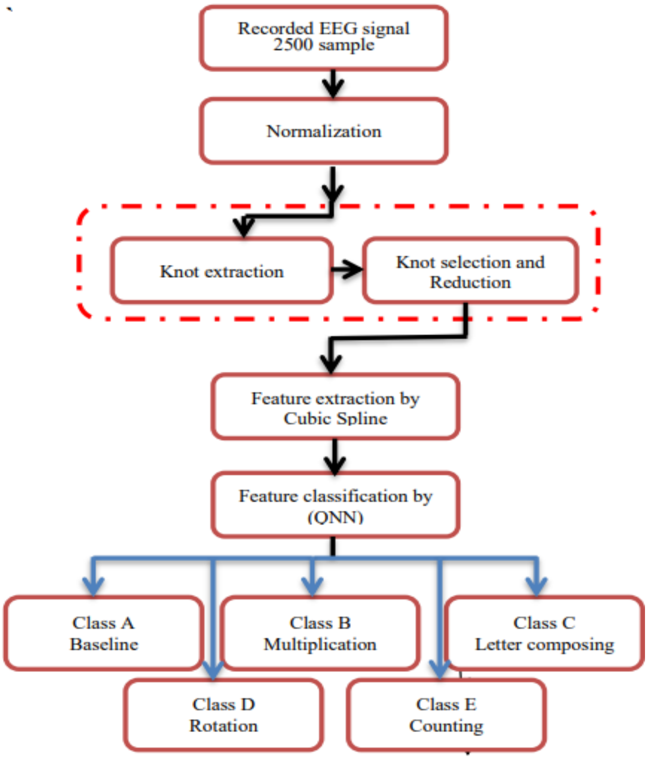


Fig.2. Structure of EEG Classification System.

1.1. Wavelet Transform

If a signal does not change considerably over time, it is considered to be stationary. The stationary signals can be subjected to the Fouriertransform [11]. However, many signals, like EEG, can have non stationaryor transient features. As a result, applying the Fourier transform directly tosuch signals is not recommended [12]. The approaches of the time frequency, like the wavelet transform, should be utilized in this case. A different of probing functions can be utilized in wavelet analysis. The continuous wavelet transform's defining equation is derived from this concept (CWT).

Where the variable a modifies the function over x(t) and variable bmodifies the temporal scale of the probing function w. The wavelet function, φ, is stretched down the time axis if an is larger than one, and it touches the function if an is less than one (but still positive) [13]. The probing function w can be any of a variety of functions, but it always takes on an oscillating form, hence the word "wavelet." For all values of a. and the term 1 $\sqrt{a}$ is the normalization factor which ensures the energy is the same [14]. In DWT signal analysis, choosing the right wavelet and the rightnumber of layers of decomposition is crucial [15]. The signal's principal frequency components influence the number of stages of decomposition. The wavelet coefficients are changed so that those components of the signal that correlate well with the frequencies required for signal categorization are retained [16]. Because there are no meaningful frequency components in EEG signals above 30 Hz, the number of levels was set to 5. As a result, the signal is divided into D1–D5 details and a finalapproximation.

2.1. **Independent Components Analysis**

Using the ICA, feature extraction based on a multivariate random signal is turned into a signal with mutually independent components. Frommixed signals, this approach can be utilized to isolate independent components. In this context, independence refers to the fact that the information that carried by the one component cannot be deduced from information carried by the others. This means that the combined independent probability of the values is estimated as a product of their individual probabilities in statistical terms [17]. Suppose that c is a scalar source signals xi(t) for $i = 1, \ldots, c$, where t is a time index of $1 \leq t \leq T$. We combined the c values at a given time into the vector x(t) for notational simplicity and assumed the vector has a zero mean. We may write the multivariate density function because of our independence assumption and the assumption of no noise:

$$B(x(t)) = \prod_{i=1}^{c} B(x_i(t)) \qquad (2)$$

Assume that at each moment, a d-dimensional data vector is.

$$Y(t) = A\,x(t) \qquad (3)$$

Where A is a c x d scalar matrix, and we'll need d ≥ c. The Independent component analysis is used to reconstruct the source signals from detectedsignals. We're looking for an actual matrix W that looks like this:

$$z(t) = WY(t) = Wax(t) \qquad (4)$$

Where z denotes an estimated at the sources x (t), we're looking for $W =$

$A - 1$, but neither A nor its inverse exist. We use maximum-likelihood approaches to figure out what A is. We employ a density estimate parameter by a $B\hat{}(Y, A)$ and look for a vector parameter that minimized a difference between the estimated and source distributions [18].

3.2 Classification Process by Optimized

QNN The proposed system's main purpose is to analyze EEG data using ICA and wavelet transforms as an alternative technique to extract signal features, and to use an efficient optimized QNN for classification. Each EEG signal is made up of 2500 samples, each representing a vector pattern. The data set's vectors will be normalized. Knots are recovered after normalization, and the best knot is chosen to represent the essential characteristics of EEG signal shape and its specific points [19]. The feature vectors will be formed and then applied to the optimized QNN for classification or training. A three-layer (L) QNN is employed as an EEG signal classifier, with the retrieved features used for training and testing. The training process was repeated until the maximum number of iterations was reached. The output layer of QNN has (5) output neurons (no), and the input layer has 40 input neurons (ni). A scalar variable represents each signal, a vector of variables represents a collection of signals, and the processing for generating signals mixes from signal from the source using a sets of the mixing coefficients. The ICA shows how to represent a group of signals as a scattergram, with each point corresponding to the signals' values at a certain time, and how to apply a geometric transformation to each point using a set of mixing coefficients [20].

$$x_1 = as1 + bs2 \qquad (5)$$

$$x_2 = cs2 + ds2 \qquad (6)$$

Where the coefficients a , b, c and d sets of the mixing coefficients. The resulting "mixing" points that are added can be combined with the original "source" points. To construct "signal" points, unmixing coefficients are utilized, which reversed the original signal's effect. The signal-to-signal source mixtures are transformed geometrically [21].

$$s_1 = \alpha 1x1 + \beta 1x2 \qquad (7)$$

$$s_2 = \alpha 2x1 + \beta 2x2 \qquad (8)$$

Where $\alpha 1$, $\alpha 2$, $\beta 1$ and $\beta 2$ are unmixing coefficients set while s1, s2 represents original signals. A signal $x's$ discrete wavelet (DWT) which is obtained by running it through filters [22]. Following that, the samples were run through a low pass filter with a g impulse response; the two are convolutional:

$$y[n] = (x * g)[n] = \sum x[t]g[n - t]$$

At the same time, a high-pass filter h is utilized to deconstruct the signal. The approximation coefficients and detail coefficients (from the high-pass filter) are outputs (from the lowpass) [23]. The fact that the two filters are connected is crucial, as they are referred to as a quadrature's mirrors filter. According to Nyquist's rule, half of the samples can now be discarded because half of the signal's frequencies have been deleted [10]. Following that, the outputs of the filter are subsampled by two g- high passand h- low pass:

$$yL = \sum x[t]g[2n - t] \qquad (10)$$

$$yH = \sum x[t]h[\,(2n + 1) - t] \qquad (11)$$

Where yL and yH represent the outputs in (g) high pass and (h) low pass sequentially. Because only half of each filter's output is used to separate the signal, this decomposition reduces the time resolution by half. However, each output frequency range is half that of the input [24]. The

frequency accuracy has been increased by a factor of two. With the downsampling operator

$$\downarrow:\ (y \downarrow t)[n] = y[tn] \qquad (12)$$

The preceding summary might be written in a simpler manner.

$$yL = (\ x * g) \downarrow 2 \qquad (13)$$

$$yL = (\ x * h) \downarrow 2 \qquad (14)$$

Results.

In this work, we compared the WT, ICA, using optimized QNN utilizing EEG signals from normal and abnormal patients. Wavelet transform and ICA were used for feature extraction and the dimensions arethen reduced. These data were used as inputs in a classification system based on improved QNN. The introduced recognition system is designed by using MATLAB 2020b, estimated with 5 - classes for the EEG signals. This section shows the results of experimental classification on the EEG data set, which is used in Optimized QNN by PSO. The obtained results by combining the ICA, WT, and two distinct scalp electrodes. as in Table 1 -4.

Table 1. Classification results using ICA an optimized QNN no.1

	Tp	**Fn**	**Fp**	**Se**	**Pp**	**TNR**
Class 1	25	1	3	0.98	0.887	0.892
Class 2	24	2	4	0.943	0.889	0.8571
Class 3	24	2	3	0.922	0.866	0.888
Class 4	25	2	2	0.856	0.857	0.9259
Class 5	21	4	3	0.857	0.864	0.875
TCA			84.4%			

Table 2. Classification results using ICA an an optimized QNN no.5

	Tp	**Fn**	**Fp**	**Se**	**Pp**	**TNR**
Class 1	25	0	5	0.99	0.887	0.833
Class 2	24	0	7	1	0.821	0.744
Class 3	24	0	3	1	0.876	0.888
Class 4	25	2	11	0.998	0.677	0.6944
Class 5	21	0	7	1	0.764	0.75
TCA			78.43%			

Table 3. Classification results using WT an optimized QNN no.1

	Tp	**Fn**	**Fp**	**Se**	**Pp**	**TNR**
Class 1	25	0	3	0.931	0.899	0.874
Class 2	24	0	5	0.921	0.789	0.744
Class 3	24	0	3	0.897	0.876	0.98
Class 4	25	2	4	0.828	0.862	0.944
Class 5	21	0	7	0.867	0.864	0.825
TCA			77.8%			

Table 4. C Classification results using WT an an optimized QNN no.5

	Tp	**Fn**	**Fp**	**Se**	**Pp**	**TNR**
Class 1	24	0	6	1	0.874	0.82
Class 2	24	2	5	0.896	0.966	0.844
Class 3	21	6	2	0.746	0.887	0.88
Class 4	23	4	3	0.828	0.862	0.8944
Class 5	20	8	4	0.712	0.864	0.725
TCA			75%			

Where, Tpi is positively true classification for ith class and Fni is negatively false classification for ith class. Fpi is positively false classification for ith class. The sensitivity which is also called true positiveis defined as :

$Se = Tpi\ Tpi + Fni$ (20)

$Pp = Tpi\ Tpi + Fpi$ (21)

Where Pp is the positive productivity. The specificity value (true negative) is derived by dividing the total number of diagnoses by the total number of diagnoses reported by the expert neurologists. The true negative ratio, also known as specificity, is determined using the formula:

$TNR = Tni\ Tni + Fpi$ (22)

According to simulation results in Table 1 - 4, the total classification for ICA is 82.4 percent, while the total classification for WT is 78.43 percent; from these results, using the ICA for feature extraction is better than using WT. Figure 1 below represents the simulation of the EEG signals and the difference between the normal EEG and the abnormal one.

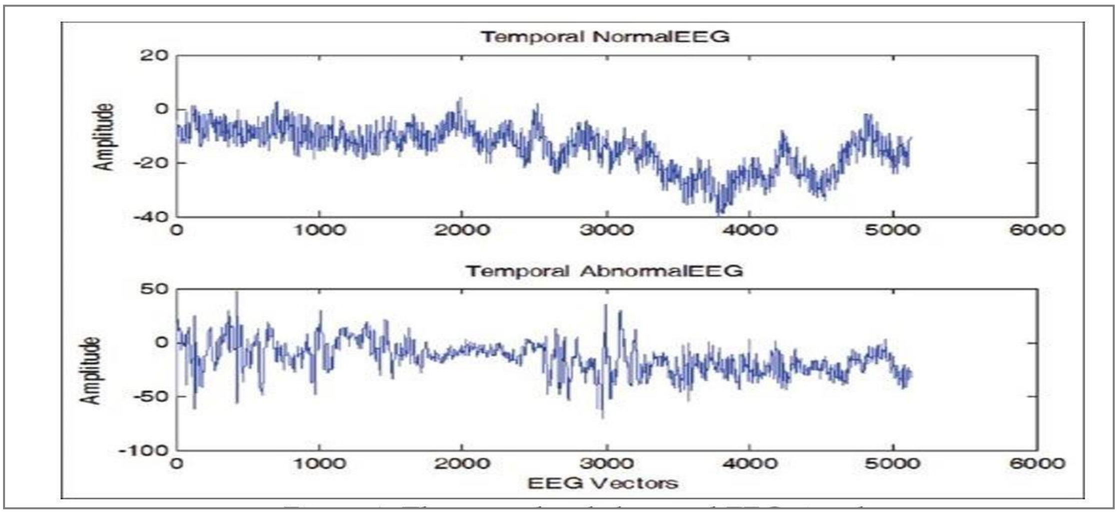


Fig 3. The normal and abnormal EEG signal**.**

Disscusion

To circumvent this problem, improved QNN is used in this study. Second, in prior studies, the algorithms immediately sent all of classifiers collected features. However, there is a mixed distributionbetween classes in general due to a large variance in the EEG pattern distributions. However, the mixed distributions between the different classes in a general due to the large variance in the patterndistribution of the EEG. If a feature modification method that minimizes within-class scatter while maximizing scatter between classes is applied in the system. The size of the overlap zone between classes should be lowered greatly, and classification performance should be improved. To achieved this, the WT, ICA which are used in the proposed structures. Based on the simulation result for the proposed and experiences in the classification problems in the signals of EEG. I would like to make some of the following important points:

The enhanced QNN classifier's excellent classification accuracy provides insight into the features utilized to define EEG signals. The concluded applications of the coefficients of ICA are featuresthat accurately reflect EEG signals, and that using the features, abetter difference between the classes may be achieved as compared to WT.

1. When compared to the ANN, the classification results and statistical parameter values showed that the optimized QNN with the ICA, WT had a lot of success in classifying EEG signals, the suggested combined ICA and WT approaches with optimized QNN approach can be evaluated.

2. The optimized QNN diagnostic system's testing performance hasbeen determined to be satisfactory, and we believe that once developed this system has the potential to be employed in clinical. This tool makes evaluating EEG signal's objective, and its automated nature makes it simple to utilize in clinical practice. Asidefrom the capability of a real-time deployment of the expert diagnostic system, increasing the diversity and quantity of parameters can improve diagnosis accuracy.

Conclusion

As a result of this study, several electrodes yielded various results and different mental tasks for various brain positions. The results from the first electrode were generally best from the fifth electrode, And the performance of the system by using ICA is betterthan WT in feature extraction of the EEG signals. Furthermore, class

(4) classification from the first electrode is superior to class (5) fromthe fifth electrode. The simulation results show a high accuracy after QNN optimization by PSO. The optimized QNN provided us with somewhat faster and more realistic results. According to simulation results, the total classification for ICA is 82.4 percent, while the total classification for WT is 78.43 percent; from these results, using theICA for feature extraction is better than using WT.

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