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Lie Detection and Truth Identification form EEG signals by using Frequency and Time Features

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Abstract

Electroencephalogram signals show how the brain's electricity is working. An EEG signal is a measurement of voltage changes caused by the flow of ions through the brain's neurons. They have been studied in medical research to help find out what's wrong with people with Alzheimer's and epilepsy. They have also been used in brain-computer interface (BCI) applications.This paper discusses how well the electroencephalogram (EEG) can tell the difference between the truth and a lie based on brain waves (EEG). In the past, the feature sets were introduced as part of an EEG-based identification system. In this paper, they are tested as parts of a detection system. The statistical moments serve as the foundation for the examined feature set. For classification tasks, publicly available EEG datasets like the Dryad dataset, obtained from 15 participants, are fed into a feedforward neural network classifier. The 12 channels were trained separately, where each channel was divided into a different number of blocks, and the results indicated that some channels were bad. Some were very encouraging, reaching 100% in block number 16. Comparison with other recently published efforts shows promising identification results, with a single channel and a few features achieving the best results, up to 100% accuracy.

Keywords: EEG signal processing, feature extraction, statistical moments, Neural Network.

JOURNAL OF ALGEBRAIC STATISTICS
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Introduction

There has been a lot of interest in lie detection tests and their applications in recent decades because of the increasing security threats, the state of law and order, and crime prevention and control in many countries. Numerous attempts have been made to detect deception, but none have succeeded. Scientists and researchers have expressed great interest in cutting-edge neuroscience-based methods for behavioral investigations [1].In the modern world, polygraph tests are the most common way to tell the difference between real and fake answers.[2]. EEG signals can be used to both detect and predict false positives. Even though it is mostcommonly used in medical applications for epileptic patients [3], this method is used in forensics to identify a sudden change in a person's behavior.
EEG Brain signals are one type of human electrical signal. In the brain, nerve cells send out electrical impulses that come in different wave patterns [4].

Because of advances in biomedical instrumentation, these signals can now be conveniently obtained through transportable devices equipped with dry electrodes. Electrodes are positioned on the head to measure electrical brain waves [6]. Poulos et al. 1999 [7], [8] are credited as being the first to propose and conduct research on EEG waves as a biometric. This field of study was getting much attention because of its potential in biometrics systems.

Navjot Saini et al., 2019 [5] EEG signal classification using a hybrid mix of features for lie detection has been investigated. The paper discusses the extraction of domain characteristics and uses an SVM classifier. The International 10-20 electrode placement system collected EEG data from nine electrode sites: C3, Cz, P3, Pz, P4, O1, O2, and Oz. Individual probe responses at the sole Pz electrodeposition were evaluated for participant probing responses. The features used were time, frequency, wavelet, EMD-based, and correlation coefficients. The EEG data components extracted (EMD) significantly impactclassification accuracy. EEG signal spectral content differed between those who were found guilty and those who were found innocent, according to frequency domain characteristics. The sample consists of 33 individuals (18 males and 15 females). Probe (P) stimuli, target (T) stimuli, and irrelevant (I) stimuli were used to collect the data. After combining and entering the neural information generated by 40 different features, the training accuracy is 99.94%, the testing accuracy is 98.8%, and the maximum testing accuracy is 99.44%. The unrelated responses of subjects to the probe, target, and other midline electrode placements can also help detect lies.

JOURNAL OF ALGEBRAIC STATISTICS
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Neeraj Baghel et al., 2020 [6] have discussed Employing a convolution neural network. According to the research, automated truth detection from EEG data could be achieved using deep learning. The researchers aimed to develop a deep learning-based model that could detect liars without needing emotions or physiological expressions. The Dryad dataset was used to train and validate the proposed model. Six gem images served as stimuli during the detection process for a set of thirty people who were randomly assigned to either the guilty or innocent side. AF1 through AF4 was represented by EOG in the model's final two channels, whereas the remaining 12 channels were EEG. For a total of ten seconds, the EEG signal was recorded. The Dryad dataset includes 300 samples. Each layer has a different number of neurons, and activation functions corrected linear unit (ReLU), hyperbolic shadow (Tanh), and sigmoid (Sigma) in it (Sigma). New spatial denoising methods (SDA) were presented for research and development. The proposed architecture for CNN classification and identification. Using this method, you can tell if someone is telling the truth or lying with an accuracy of up to 84.44%.

YijunXiong et al., 2020 [7], The chaotic phase synchronization (PS) method is used to investigate the differences in EEGs acquired from lie detection (LD) trials between the two groups of subjects. A three-stimulus technique was used in the LD experiment to collect EEG data from the twenty volunteers. The Phase Locking Value (PLV) was used as a statistical measure by PS for a few stimuli in the LD study. The experimental results show a distinct geographical and temporal discrepancy in PS, with a more robust and higher PLV in the guilty group than in the innocent group, which was used to analyze the distributed frontal, temporal, central, and parietal connections in an attempt to uncover their deception mechanism. They used phase synchronization patterns between 12 EEG channels to do this. The EEG data from an LD experiment using only a few stimuli was used to examine PS, and the PS between different EEG activities in various brain locations was explored. The study involved ten university students with no history of mental or neurological illness (9 males; the mean age was 22.3). (22.3 is the average) An approach utilizing three distinct forms of stimulation was used. The 10-20 system was used to set up the electrodes. This included both horizontal and vertical EOG recordings in 14 channels. Using PLV-based characteristics, it was possible to make a classification system (SVM) that can tell the difference between honest and dishonest brain activity.

On the other hand, EEG-based detection research has encountered difficulties with feature extraction and the processes necessary to pick the best features for classifiers[8].There must be as few electrodes as feasible so that the EEG signal acquisition from the user's scalp is as

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
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ISSN: 1309-3452

straightforward as possible. The system's complexity and processing time should be lowered by applying feature extraction methods and classifiers with less computational complexity[9].

In this paper, the smallest feasible number of features and channels were used in this study to achieve high detection accuracy without the requirement for expensive feature fusion and to keep the needed computing complexity at a minimum. The statistical moments are used to create independent feature sets.

The Proposed System

The workflow of the proposed system with different proposed methods is shown in Figure (1). It consists of two main stages: (i) the enrollment (training) phase; and (ii) the classification (detection phase).

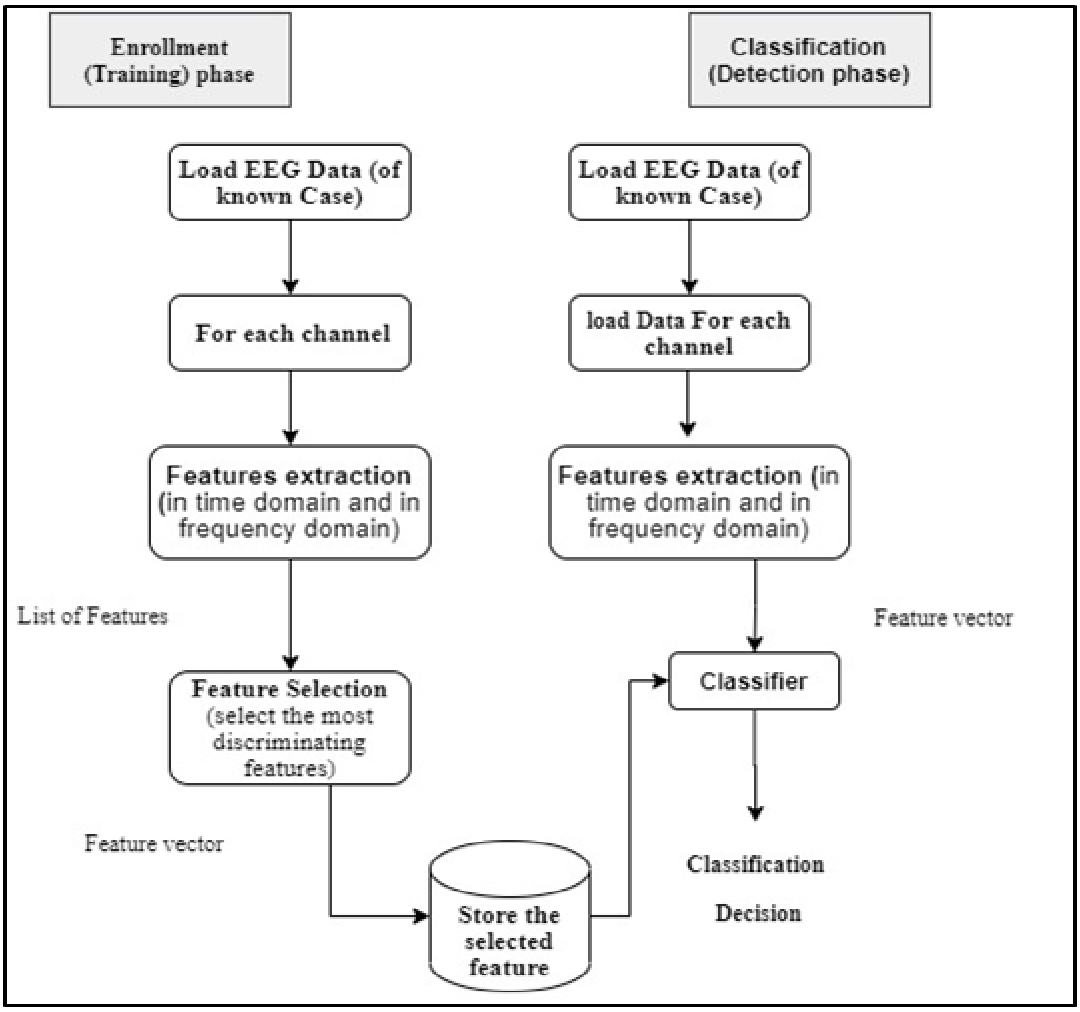

Figure (1): the detailed flowchart of the system with all proposed methods

i. Enrollment (Training phase) implies three steps:

- Load EEG data (of a known case) for each channel.
- Features extraction (in the time domain and frequency domain): this step is used to extract the main features from the EEG signal and generate the feature pool. A new type of feature is proposed (Statistical Moments).
- Feature Selection (select the most discriminating features): This step aims to combine the best set of features to generate the final feature vector.

ii. Classification (Detection phase) implies three steps:

- Load EEG data (of a known case) for each channel.
- Features extraction (in the time domain and frequency domain): this step is used to extract the main features from the EEG signal and generate the feature pool. A new type of feature is proposed (Statistical Moments).
- In the classification stage, the feedforward neural network classifier was used for classification purposes. This stage implies two steps: (i) the training step in which the system is trained using a training dataset for neural network enrollment; (ii) the testing step to check the system's performance using a test dataset and by using the set of weights generated in the training step.

EEG Signal Data Loading Step

In this paper, the EEG Dryad dataset was used. It was a public, free dataset that was used to test how well the system works at spotting lies. The number of records is pretty large. Here are some of the details about the dataset.

The first step in the proposed EEG signal polygraph system is to load the primary EEG signal, and the signals of its participants are stored in text file format. Dryad datasets[6].

The South-Central University for Nationalities' College of Biomedical Engineering's Psychology Research Ethical Committee (PREC) approved the experiment. Thirty individuals were randomly randomized into guilty and innocent groups, with six gem photographs as stimuli during the detection process. The suggested model included 14 channels, 12 of which were EEG, and the final two were EOG from AF1 to AF4. The EEG signal was captured for 10 seconds. For the EEG data, an International 10–20 system was used with 12 electrodes (Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, Oz)[10].

Detailed information about the Dryad dataset consists of:

- The dataset is divided into "lying" and "honest." Each folder contains data for 15 subjects.
- Each subject's folder has five subfolders and data files for five sessions.
- There are three files in each session's folder in 3 corresponding folders. Each folder consists of 14 channels. 12 EEG channels and 2 EOG channels. Each channel contains 16384 samples.
- One session lasts 0.5 s and includes 30 iterations.

Data Preprocessing

Preprocessing is considered the initial stage of the other stages because it involves changing or adjusting the signal to make it more suited for feature extraction [11]. In the proposed system, the preprocessing consists of two steps:

1.Feature Normalization Step

The term "normalization" refers to creating statistical data that has been shifted and scaled. This is necessary because the extracted features have different scales, so combining these characteristics is unacceptable and will adversely affect the classifier's learning process[12].

A normalization step is necessary due to the wide range of signal types. Ensure that all features fall inside the field [0–1] [12].In the simplest kind of normalization, min-max normalization scales the range of features [0, 1] by renormalizing them. [0, 1] is the most common range for a minimum and maximum, shown in Equation (1). [12] is used to normalize features to a range of [0,1]:

$$x' = \frac{(x - \mathrm{Min})}{(\mathrm{Max} - \mathrm{Min})}$$

Where x′ represents the normalized feature and x represents the original feature, all characteristics' minimum and maximum values are represented by the Min and Max values.

2.Framing step

When studied over a short period, the human brain signal exhibits time-varying characteristics and can be viewed as a stationary random process[13]. As a result, the brain signal is typically divided into small time blocks, known as frames, and the analysis is performed on these frames. It is a method used to divide the signal stream into a collection of frames with the same lengths, with each frame being evaluated independently of the others. The original signal will be framed into the N

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
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sample frame in overlapping blocks, with each block representing a single sample. Each frame has an overlap of M milliseconds in time.

In our work, each channel was divided into six blocks (512,256,128,64,32,16) to calculate several features for each of these lengths and then will be tested separately to find out which one is better to work within the proposed system.

Features Extraction Stage

The basic features required to identify lies and know the truth are extracted at this stage; these features must have a high ability to distinguish a specific element through a high ratio between the interlayers.

Some prosodic and statistical moment features are extracted and used in this stage.

Prosodic Features

Prosodic features are a type of statistical measurement feature concerned with timing, articulation, duration, and zero crossing (ZCR) is the point at which there is no voltage at all at any given time. The rate at which a signal changes from positive to zero to negative (ZCR) is the other way around [14].

Formally, ZCR is defined as [15]:

$$ZCR = \frac{1}{T-1}\sum_{t=1}^{T-1} 1_{R<0}\,(S_t S_t\text{-}1)$$

Where S is a signal of length and $1_{R<0}$ is an indicator function (is a function that maps elements of the subset to one and all other elements to zero).

Statistical Moments Features

In distribution characteristics, they are expressed in terms of Power's rolling or rotating effects, whereas in physics, this concept refers to Power's rolling or rotating effects. For example, moments refer to how much a given quantity differs from its mean or any pivot point in terms of mass, force, histogram intensity, frequency transform coefficients, and other kinds of coefficients with certain geometrical distributions [16].

Moments can be classified into many categories. Mathematically, moment features for a frame are calculated to characterize its behavior and extract critical features. These features can be expressed as follows:

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
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ISSN: 1309-3452

1. The first-order moment is the mean. It is the most common measure of the location of a set of points. It represents the average of a set of data points. Generally, it is denoted by μ[17]:

$$\mu= \frac{1}{N}\sum_{i=1}^{N}(x_i)$$

Where N denotes the total number of samples and is the number of samples.

2. The second order moment is standard deviation as a measure of value spread: it represents the degree to which data points spread around the mean, as denoted by the following definitions[16]:

$$\sigma=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Where N is the total number of samples, x_i is the sample, and $\mu$is themean.

3. The three-order skewness moment can indicate the degree to which a random variableis symmetrical around its mean. Negative, positive, or undefined skewness values are all possible, as denoted by the following definitions[18]:

$$\text{Skew}=\frac{\sum_{i=1}^{N}(x_i - \mu)^3}{N\sigma^3}$$

Where N is the total number of samples, x_i is the sample, μ is the mean, and σ is the standard deviation.

4. In the four-order moment, Kurtosismeasures the total size of the tails about the entire distribution. There are several ways to measure this, but the fourth standardized moment is the standard one, denoted by the following definitions[19]:

$$\text{Kurt}=\frac{\sum_{i=1}^{N}(x_i - \mu)^4}{N\,\sigma^4}$$

Where N is the total number of samples,x_i is the sample, μ is the mean, and σ is the standard deviation.

5. Higher moments high-order moments are moments beyond those of the fourth order. The 5th-order moment can be thought of as a measurement of the "relative importance of tails relative to the center (mode and shoulders) in contributing to skewness" (for a given amount of skewness, a higher 5th moment means more skewness in the tails and less skewness in the mode, while a lower

5th moment means more skewness in the shoulders).The five-order moment is denoted by the following definitions[20]:

$$\mu 5=\frac{1}{N}\sum_{i=1}^{N}(x_i \ - \mu)^5$$

Where N is the total number of samples, x_i is the sample, μ is the mean.

6. Power: Power is the likelihood that a hypothesis test will discover an effect if one exists. Power analysis can determine the minimum sample size needed for an experiment using the desired significance level, effect size, and statistical Power. The sex order moment (Power) is denoted by the following definitions[21].

$$p=\frac{1}{N}\sum_{i=1}^{N}(|x_i|)^2$$

Where N is the total number of samples, x_i is the sample.

Classification Stage

At this stage, feature patterns should be assigned to a category. Using a neural network classifier is an excellent classification method since it can categorize dynamic data and is resistant to partial input unpredictability. This is because there are only a handful of distinct feelings.

In our work, we use a feedforward backpropagation algorithm to classify features. The MATLAB environment is used to train a feedforward backpropagation algorithm for detection classification.

The proposed system uses a feedforward neural network with two layers. Input layer nodes vary from case to case, but there is a total of seven features employed. The index numbers of emotion classes are encoded using binary coding [0,1], which means that two output bits have been employed. In the output layer, there is one node. The sigmoidal activation function is used to update the output of the hidden signal, which is then sent to the system's output nodes.

Two phases comprise the applied classification process stage: (i) the training step and (ii) the testing step. Training a neural network is determining an optimal set of weights for the network's nodes, enabling them to make classification judgments that are close to the goal values. Backpropagation is the most frequent algorithm used to train feedforward neural networks. Utilization of supervised learning for training purposes has occurred. A collection of feature patterns from all classes was used to train the neural network.

In the testing step,the trained neural network is evaluated using the training and testing set of extracted feature vectors. The purpose of the conducted test is to evaluate the system's performance.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
https://publishoa.com
ISSN: 1309-3452

Artificial Neural Network Typologies

(ANN): Artificial neurons are more sophisticated classifiers, and they're supposed to mimic the action of biological neurons [22]. The ANN function was used in our research. Feedforward neural networks, RBF networks, and recurrent networks [23] are only a few examples of the many ANN types.Feedforward A backpropagation algorithm is implemented in our work for feature classification. An Antenna Network (ANN) comprises three layers: input, output, and a hidden layer. The three layers are in the following order: the input layer, consisting of input neurons; the optimal neural network setup parameters in the input layer; the learning rate (LR=0.01); momentum (Mom=0.9), and the number of trains. The hidden layer (the RBF layer) consists of RBF neurons, and the output layer consists of RBF output neurons.

Each layer can have any number of nodes. The connections between the input layer, the RBF layer, and the output layer are weighted, meaning they only transmit the input. The links between the RBF and output layers are weighted [24]. In our work, 12 channels were trained separately. In each channel, there is a set of ready-to-train features. The training file is divided into three subsets: 50% of the files were used for training, 25% for validation, and 25% for testing. In the output layer, there is one layer. The sigmoidal activation function is used to update the output of the hidden signal, which is then sent to the system's output nodes. Figure 2 shows the neural network representation of the input, hidden layer, output layer, and output topology.

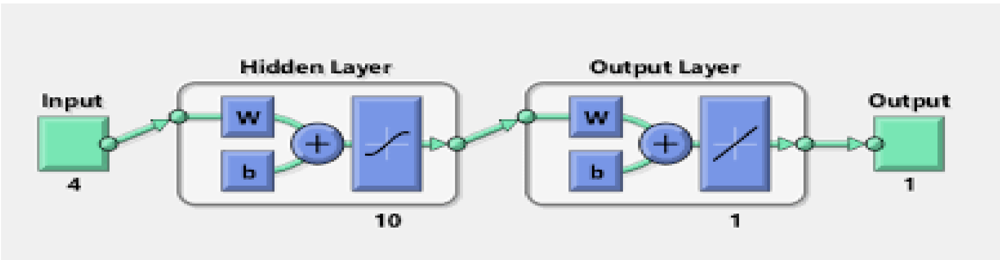

Figure (2): Neural Network Architecture representation

Experimental Results

This paper presents and discusses the findings of a few tests run to assess the established system's performance. The Microsoft Visual Studio 2012's C# programming language and MATLAB were used.

Dryad datasets were used to test the proposed system's accuracy with all the proposed feature extraction methods. Dryad datasets are relatively large (12 EEG channels and two EOG channels),

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
https://publishoa.com
ISSN: 1309-3452

where each set of features is extracted from a single channel. The best attained system recognition rate was 100% for some feature sets and channels for each proposed feature extraction method using all the datasets.

The purpose of the training phase is to establish the optimal neural network setup parameters, which include the number of nodes in the input layer, the number of nodes in the hidden layer (HL), the learn rate (LR), momentum (Mom), and the number of trains. Numerous permutations of these factors have been examined to determine the optimal detection rate.

Table (1) This table shows these parameters' values when tested with features from different block sizes and channels for each case when training the system with dataset samples. In the following sections, you can read more about how the training and tests turned out:

- When we test only one feature, accuracy is in the following table:

Table (1):the result of the train and test only one feature in block size is 16

Channel number	Channel name	Block size	Features number	Features set	Successful samples	Failed samples	Accuracy
11	FC6	16	1	Zero crossing	32	0	100%
11	FC6	16	1	power	31	1	96.9%
8	O2	16	1	Mean	31	1	96.9%
9	P8	16	1	Mean&Power	31	1	96.9%
12	F9	16	1	Mean	31	1	96.9%
8	O2	16	1	Power	30	2	93.8%
12	F9	16	1	StdDev	30	2	93.8%
8	O2	16	1	Kurtosis &pow5	29	3	90.6%
10	T8	16	1	Mean&Power	29	3	90.6%
11	FC6	16	1	Mean	29	3	90.6%
12	F9	16	1	Skew&Power	29	3	90.6%

- When we combine two features,or three or four, the results of accuracy are encouraging and are represented in the following tables:

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
https://publishoa.com
ISSN: 1309-3452

Table (2):the result of train and testing two features in block size is 16

Channel number	Channel name	Block size	Features number	Features set	Successful samples	Failed samples	Accuracy
11	FC6	16	2	Power, Zero Crossing	32	0	100%
12	F9	16	2	Mean, Std	32	0	100%
8	O2	16	2	Mean, Power	31	1	96.9%
9	P8	16	2	Mean, Power	31	1	96.9%
10	T8	16	2	Mean, Power	29	3	90.6%

Table (3):the result of train and testing three features in block size is 16

Channel number	Channel name	Block size	Features number	Features set	Successful samples	Failed samples	Accuracy
11	FC6	16	3	Mean, Power, Zero Crossing	32	0	100%
4	FC3	16	3	Mean, Power, Zero crossing	29	3	90.6%

Table (4):the result of train and testing four features in block size is 16

Channel number	Channel name	Block size	Features number	Features set	Successful samples	Failed samples	Accuracy
12	F9	16	4	Mean, StdDev, Skew, Power	32	0	100%
8	O2	16	4	Mean, Power, Kurtosis, Pow5	31	1	96.9%

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
https://publishoa.com
ISSN: 1309-3452

9	P8	16	4	Mean, Power, Kurtosis, Pow5	31	1	96.9%
10	T8	16	4	Mean, Skew, Power, pow5	30	2	93.8%

- When we combine all the features in the block, the results of accuracy are more encouraging and are represented in the following table:

Table (5):the result of train and testing two features in block size is 16

Channel number	Channel name	Block size	Features number	Features set	Successful samples	Failed samples	Accuracy
8	O2	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	32	0	100%
11	FC6	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	32	0	100%
12	F9	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	32	0	100%
9	P8	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	31	1	96.9%
10	T8	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	31	1	96.9%
1	AF3	16	7	Mean, Std, Skew, Kurt,	30	2	93.8%

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
https://publishoa.com
ISSN: 1309-3452

				Power, Zero, Pow5			
4	FC3	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	30	2	93.8%
5	T7	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	30	2	93.8%
3	F3	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	29	3	90.6%

- The best result and the high accuracy in each case arein the following table:

Table (6):the result of train and testing all features in block size is 16

Channel number	Channel name	Block size	Features number	Features set	Successful samples	Failed samples	Accuracy
11	FC6	16	1	Zero crossing	32	0	100%
11	FC6	16	2	Power, Zero Crossing	32	0	100%
12	F9	16	2	Mean, Std	32	0	100%
11	FC6	16	3	Mean, Power, Zero Crossing	32	0	100%
12	F9	16	4	Mean, StdDev, Skew, Power	32	0	100%
8	O2	16	7	Mean, Std, Skew, Kurt, Power, Zero,	32	0	100%

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
https://publishoa.com
ISSN: 1309-3452

				Pow5			
11	FC6	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	32	0	100%
12	F9	16	7	Mean, Std, Skew, Kurt, Power, Zero, Pow5	32	0	100%

- All lengths were tested in different cases; for all channels, some cases succeeded, and others failed. The best results were in the size of block 16. We will show some samples from other block cases in the following table:

Table (7):the result of training and testing different cases of features in different block size

Channel number	Block size	Features number	Features set	Successful samples	Failed samples	Accuracy
1	512	7	All Features	858	166	83.8%
1	128	1	zero crossing	170	86	66.4%
1	64	4	Mean,StdDev, power,Zero Crossing	111	17	86.7%
2	512	1	power	640	384	63.5%
2	256	7	All Features	420	92	82%
2	32	4	Mean, Power, Zero crossing,Kurtosis	52	12	81.3%
3	128	2	Power, Zero Crossing	230	36	85.5%
3	64	7	All Features	120	8	93.8%
4	512	1	power	690	334	67.4%
4	128	3	Mean, Power,Zero	211	45	82.4%
5	64	7	All Features	115	13	89.8%
5	32	3	Mean, Power, Zero	60	4	93.8%

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
https://publishoa.com
ISSN: 1309-3452

6	128	2	power, zero crossing	180	76	70.3%
6	32	1	Power	45	19	70.3%
7	256	7	All Features	410	102	80.1%
7	32	3	Mean, StdDev,Power	48	16	75%
8	512	2	Mean, Power	892	132	87.1%
8	128	1	Mean	234	22	91.4%
9	64	7	All Features	124	4	96.9%
9	32	4	Mean, Power, Kurtosis, Pow5	59	5	92.2%
10	512	2	Skew,Power	843	181	82.3%
10	256	1	Power	425	87	83%
11	128	7	All Features	238	18	93%
11	64	3	Mean, Power,Zero	123	5	96.1%
12	128	2	Mean, Power	246	10	96.1%
12	32	1	Power	63	1	98.4%

In general, the results presented in the above tables show that there are 12 channels tested separately. The test results indicate three of them were bad, such as (F7, P7, and O1), and six of them were good, such as (AF3, F3, FC5, T7, P8, T8), and (O2, FC6, F9) were the best channels, as their test results reached 100%, and these results considered are very competitive and encouraging to use one channel.

Comparison with Recent Related Works

Many published studies on EEG-based lie detection systems have shown promising results, although many utilized more than one channel or feature to detect the deceptions. Table (8) shows that this paper's results are comparable to those of other papers published on the Dryad dataset. This is because the proposed methods in this paper have low computational complexity and require very little execution time because the system uses a single channel, fewer features, and a fast algorithm.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 4102-4121
https://publishoa.com
ISSN: 1309-3452

Table (8): Comparisons of Dryad datasets are based on the number of channels and features employed.

Authors	No. of channel	No. of features	Accuracy
Neeraj Bagheli et .al [6]	12 channels	Four discriminative features are used	84.44%
Junfeng Gao and et.al [10]	12 channels	Three groups of features And all are eight features	96.11%
Proposed work	One channel	Only one or merge (2 or 3 or 4) and all 7 Features tests, in some cases, give	100%

Conclusion and Future Work

In this research, the proposed feature extraction approaches for purposes were tested. The system was fast, simple, and achieved encouraging outcomes. The conducted tests showed that the best achieved in block size 16 for the statistical moments feature set when it was applied to the Dryad database. Block size 16 showed performance better than (32,64,128,256,512). Because of the block-based approach, more statistical traits can be pulled out and used more effectively.

The test results demonstrated the efficacy of the suggested system:

- Which provided a detection rate of 100% when trained with all featuresin a single channelsuch as (O2, FC6, and F9).
- Which provided a detection rate of 100% when trained with a subset of features in a single channelsuch as (FC6, F9).
- Which provided a detection rate of 100% when trained with a single feature in a single channelsuch as (FC6).

The computational complexity of this method is relatively insignificant. Using only one or two EEG channels, this study found that the proposed methods could find distinguishing features and spot lies in the given data sets.

This research used dryad data, and the results were encouraging, reaching 100%. It is assumed that another data set will be tested on the system to ensure that the number of applicable features is sufficient or that the system needs to extract a new set. New features are recommended for lie detection and EEG-based truth determination based on new types of statistical moments.

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