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A Survey for Lie Detection Methodology Using EEG Signal Processing

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ABSTRACT

Electroencephalography (EEG) is a hot topic all around the world. EEG signals, a series of measurements taken using electrodes on the scalp, can indicate brain activity. They are more private, sensitive, and difficult to steal and recreate. EEG data are increasingly commonly employed in diagnosing brain illnesses and the field of Brain-Computer interfaces thanks to advancements in biomedical signal processing techniques (BCI). BCI is a brain-computer interface that uses electrical impulses from the brain to communicate. EEG signals are used to interpret the electrical activity of the brain. The electrical activity of the brain is read using EEG signals. Many studies are being conducted in many fields to benefit from this technology. Studying EEG gives a solid understanding of how brain signals function in various moods and activities. Lie detection is a new technology that is being used to combat crime. Traditionally, this has been accomplished by language analysis, face and body movement recognition, training observation, and voice stress analysis. EEG analysis provides a better understanding of brain activity thanks to advances in cognitive science and neuroscience. Deception identification has become a severe issue as crime has increased. Previous surveys have discussed numerous approaches supported with experimental outcomes and compared them. This paper addressed each direction and offered different sets of characteristics and electrodes, EEG signal preprocessing, feature extraction, feature selection, and classification. Also, it discusses many methods which may need some adjustments at each phase of brain signal processing for lie detection.

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1. Introduction

In recent decades, lie detection tests, and their applications have received much attention due to rising security threats and the state of law, order in many nations, and crime prevention and control. Many attempts have been made to detect lying accurately. State-of-the-art neuroscience-based methodologies for behavioral investigations have sparked much interest among scientists and researchers [1]. Polygraphs, or lie detectors, are the most commonly used method for

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detecting the truthfulness of concealed information. This method is based on the premise that lying can elicit a wide range of physiological responses that can be observed and recorded using the appropriate tools. Involuntary changes in the body are studied through physiological reactions [2].

Body functions like blood pressure, heart rate, respiration, and skin conductivity were initially measured using the polygraph [3]. The examiner compares the measured physiological values to predicted normal levels after the experiment to determine the subject's level of honesty, but that lying beats the test because the expert liars can fool those previous techniques by manipulating physiological factors that have long been known. As a result, the polygraph test result is neither legal nor credible [4]. However, in the recent decade, new technologies have been created beyond the EEG-based polygraph for detecting lies [5][6]. Falsehood detection and prediction are both possible with the help of EEG signals. This method is utilized in forensics to identify a sudden change in a person's behavior, even though it is most commonly used in medical applications for epileptic patients [6].

One of the human electrical signals is EEG Brain signals. Electrical impulses are generated by nerve cells in the brain, which vary regularly in unique wave patterns [7]. EEG is a recording of electrical activity monitored by electrodes placed on the scalp. (Hans Berger,1873–1941), a German scientist and psychiatrist recorded the first human EEG in 1924. The five primary rhythms of the EEG signal (delta, theta, alpha, beta, and gamma) fall into distinct frequency ranges ranging from low frequency (delta) to high frequency (gamma) [8].

Electroencephalography (EEG) detects falsehoods and verifies facts using changes in brain waves. Because these signals are nonstationary and have a poor signal-to-noise ratio, classifying them is difficult [7]. After that, the key objective is to read, analyze, and transform these waves into a human-readable format before using them as input to various devices. For deception detection, a collection of questions relating to crime are asked of the subject to determine the subject's conduct. These questions serve as a stimulant for the topic [9].

The main objectives of this systematic review are to explore the methods and techniques used to detect lies and find out the truth using EEG technology in addition to reviewing articles on the proposed strategies and mechanisms, collecting various information to reach a clear understanding of the available studies, developing, improving, and employing them, and making recommendations to enhance their efficiency.

2. EEG characteristics

EEG is recorded using electrodes placed on the scalp above the brain by the 10–20 international standards shown in Fig. 1. The frequency bands of the EEG waveform are classified (alpha, beta, theta, delta, and gamma waves)[9]. The five frequency bands are briefly described below [9]:

- Delta waves (0.5–4 Hz): The slowest EEG waves are frequently observed during deep and unconscious sleep. Delta waves have significant amplitudes (75–200 V) at this stage. As a result, it is believed to reflect the unconscious brain of the individual. When our perception of the physical world diminishes, delta waves grow[10].
- Theta (4–8 Hz) waves are most noticeable while in a state of peaceful concentration. Additionally, they can be observed during memory retrieval and several short-term memory tests. Typically, theta waves have an amplitude of 100 volts[11].
- Alpha waves (8–14 Hz) are the most common rhythms in healthy people. They are seen as a peak in the frequency spectrum of sound. Alpha waves have been detected on a few occasions during periods of relaxation, with the eyelids closed (E.C.s) but the subject still awake (E.C.s)[12].
- Beta waves (frequency range 14–30 Hz): Beta waves are associated with an enhanced state of alertness, worried thought, and concentrated attention. The amplitude of these waves is ten volts.
- Gamma waves (above 30 Hz) are produced during prolonged information processing. These waves have incredibly small amplitudes (less than 2 V). Additionally, it is known that gamma waves have more significant electrical impulses in response to visual inputs and picture comprehension [10].

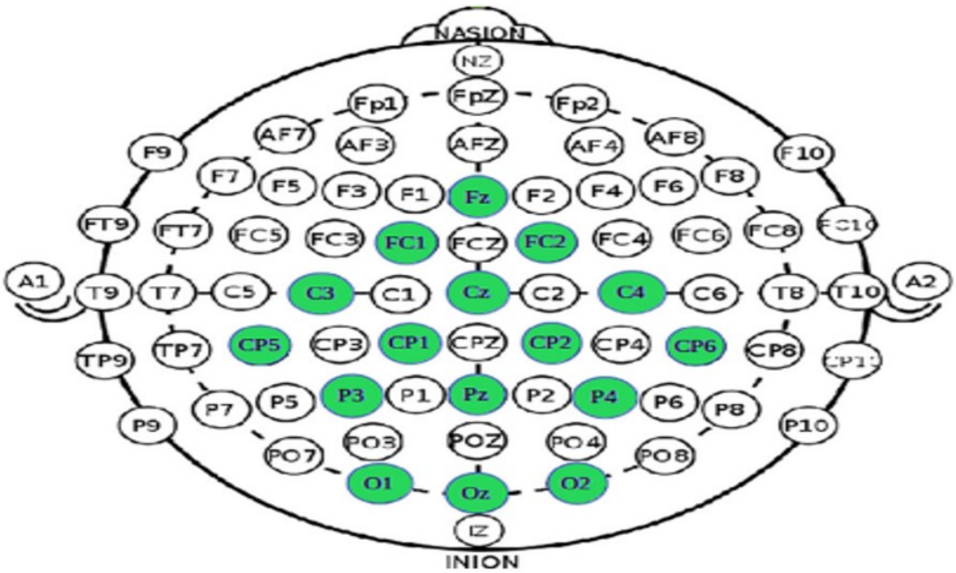

Figure (1): Electrode placement based on 10-20 international system[12]

3. **Literature review of EEG lie detection Technologies.**

This section discusses earlier techniques and algorithms. The methods of EEG polygraph examination are examined and contrasted. This is an overview of the contents. So far, it has been accomplished in this field. Data collecting, preprocessing, feature extraction, and final classification are the four fundamental components of electroencephalogram-based polygraph systems. EEG acquisition technique (protocol in EEG data recording), preprocessing technology, features retrieved from EEG signals, and classification system all play a role in the performance of an EEG polygraph system. These features will be discussed in greater detail further down.

Vahid Abootalebi et al., [13]2009, have discussed concerning the extraction of EEG features in P300-based lie detection, an innovative technique based on specific characteristics, and a statistical classifier was established. Ag/AgCl electrodes were implanted at the Fz (Frontal), Cz (Central), and Pz (Parietal) locations (10–20 system) to capture the (EEG). Only Pz's results are included. At a rate of 256 samples per second, electrical processes in the brain were amplified and digitized. The best feature set for data classification was determined using a genetic algorithm. To select the best subset of characteristics, a G.A. approach was utilized. G.A. is based on biological organisms' genetic processes. Feature set that included some morphological, frequency, and wavelet characteristics. Morphological (ALAR, SSA), Frequency (f median, f mean), Wavelet (A(0–125), A(250–375), A(375–500), A(500–625), A(875–1000), B(500–625), B(625–750), B(750–875), C(0–62), C(63–125), C(188–250), C(313–375), C(375–437), C(500–562), C(625–687), C(813–875), C(938–1000)). Correct detection rates in both the guilty and the innocent participants were 86%. The main objective of this study was to find out how well a new classification approach performed in the P300-based GKT. It should be noted that the methods used were tested on several data sets. The absolute accuracy achieved is determined by the type of subject, the protocol used, and the processing technique. As a result, the results of such studies may aid the development of more reliable P300-based models for lie detection.

Samreen Amir et al., 2013 [4] discussed Lie detection in interrogations using digital signal processing of brain waves. EEG technology is used to detect lying. The feature extraction method extracts information from brain signals like band frequency. Morphological features such as amplitude, peak to peak readings, zero crossings, latency, and other parts extracted information from brain signals. The study focused on the band frequency. In a 10-20 system, the motion of interest was only collected by five electrodes. Focus is on beta waves, which can be seen when a person is alert, anxious, or alert. Any deviations are identified as a shift in the mental state during questioning. Based on EEG waves, a system for lie detection is being created. It features an analog section used to amplify and filter the data obtained. The DSP board is then used to analyze the data further and compute the correlation between the signals in the relaxed state and the data received during questioning. This investigation supports the subject's assertions. Adding more electrodes improves the raw EEG, making it better and more acceptable.

Anjali Arya et al., 2013 [14] have discussed how EEG and facial EOG can research and analyze human emotions when lying. The experiment included ten participants, ages 18 to 28. EEG electrodes were inserted onto the patient's scalp using the 10-20 electrode placement technique. Used the sampling rate set was 2000 samples per second per channel. For data collection, an RMS-32 polysomnography hardware system with 32 channels for EEG recording. The frequency, amplitude, and shape of EEG waves and the locations on the scalp where they were recorded were used to classify them. In this study, a delta wave is most effective while lying down. It spans 67.02% of EEG wave patterns, with theta wave covering 15.52%, alpha wave covering 10.55 percent, beta wave covering 6.79%, and gamma wave covering 0.13%. They concluded that electroencephalography (EEG) is an accurate and sensitive approach to measuring emotional expression. They may record the reaction using an EEG even when individuals are asked to suppress their emotions while lying.

Junfeng Gao et al., 2014 [15] have discussed the investigation of P300-based lie detection techniques and created a new way to improve the signal-to-noise ratio (SNR) of P300, which was used to improve the accuracy of lie detection. Each patient was given one of two groups: guilty or not guilty. The EEG data from 14 electrodes was recorded on 34 patients. A new spatial denoising method (SDA) used independent component analysis to get a good picture of the P300. After three features were found in the denoised waves, the best parts were found using the F-score method. Finally, three different conventional classifiers were fed selected feature data to compare performance. The SDA and classifier parameters were optimized using a grid-searching training method with cross-validation. Because the support vector machine (SVM) approach outperforms the F-score, it was combined. For P300, the suggested model F-score SVM achieves a significantly greater classification accuracy (specificity). Compared to SDA and other classification models, the given F-score SVM obtains much greater classification accuracy for P300. (96.05 % specificity) and non-P300 (sensitivity of 96.11 %). Compared to prior techniques, the presented method achieves a higher individual diagnosis rate, and it only requires a minimal number of stimuli in the real-world testing application. EEG data were acquired using An International 10–20 system was employed with twelve electrodes (Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, Oz). There are three types of characteristics. 1-Features in the time domain (1) Maximum amplitude, (2) Latency, (3) Peak-to-Peak, and (4) Positive area are all factors to consider. 2-features in the frequency domain (2) Mean frequency, (1) maximum frequency (3) The primary frequency's power. Features of the 3-Wavelet features. This study used the dryad data.

Artha Ivonita Simbolon and et. al., 2015 [16]. Discussed An EEG-P300 Experiment using Lie Detection the SVM Algorithm was used to classify the data. The ERP technique is used to evaluate whether a person is lying or not. Eleven males between the ages of 20 and 27 were involved in the study. ElectroCap, Fz, Cz, Pz, O1, and O2 were among the channels employed. These channels are for sighting-related actions. The stimuli P, T, and I were displayed repeatedly in random order. The time difference between each stimulus is around 1.1 s with a 2 s delay. Based on the P300 signal, the SVM algorithm can differentiate between fraudulent and non-fraudulent threads. Using feature extraction, it is possible to determine the signal P300's minimum, maximum, mode, median, and mean amplitudes. Extraction of the signal Using SVM, it was narrowed down to the most accurate and efficient results. Although the final model had a low Precision, it could distinguish between all subjects. It is most likely the 70.83 % exact SVM model, with a computation time of only 0.0283 seconds.

S. Kamran Haider and et.al, 2017 [17]. They created a stand-alone technology that uses EEG to detect brain waves. Various extraction approaches extract the desired information from the brain impulses collected from sixteen electrodes. The channel names utilized are (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T 8, FC6, F4, F8, AF4). The Pz is the primary site where P300 may be monitored the most. Therefore, visual studies were limited to Pz data. Those who took part in This study included twenty individuals (15 men and five females, ages 20 to 25), all of whom were university students (undergraduate and postgraduate). All of them were in good health with stable psychological conduct. In this assessment, two sorts of characteristics were discovered. 1. Shape-based morphological features were retrieved and assessed (latency time, maximum peak signal value, positive signal value, and total area). 2. Frequency Characteristics (frequency mode, median, and mean). The linear peak discriminant analysis (LDA) technique performs component analysis on the P300. A distinction must be made between positive and negative samples. Signals acquired from sensors were used to determine whether a person is guilty or innocent. In both the guilty and the innocent, 85% of deception detection is correct.

Arjon Turnip et al., 2017 [18], The components of brain signal activity (EEG-P300) that reveal whether or not someone is telling the truth or lying have been examined. Twelve healthy adults (ten men and two women, ages 19 and above) participated in the study. The Mitsar 202 EEG device recorded EEG data from five Ag/AgCl electrodes in an elastic cap. Frontal, central, parietal, and occipital electrodes were used (O1 and O2). In advance of the experiment, the participants were given step-by-step instructions on conducting one. In this exercise, participants were divided into two groups based on whether they were telling the truth or lying. Each stimulus (P, T, and I stimuli) has to perform a specific task during its display. A two-second delay separates each stimulus one second apart. Brain waves were filtered and extracted using a bandpass filter and independent component analysis (ICA). During the signal processing, It is possible to remove low, medium, and high amplitudes from a P300 signal using feature extraction. Extraction was carried out using the discrete wavelet transform (DWT). After obtaining EEG-P300 signal information, the next step is to classify the EEG data. EEGP300 participants who are lying must be categorized to identify them from those telling the truth. A MATLAB-based method named Adaptive neuro-fuzzy inference system (ANFIS) was utilized in the classification stage. The ANFIS uses a combination of neural networks and fuzzy features to learn the system, enabling it to digest data quickly. The ANFIS approach can distinguish between liars and honest participants with an accuracy of 64.27% based on EEGP300 readings. In response to the provided stimuli, a significant spike in the EEG-P300 amplitude is observed on a lying individual, according to the findings. Using an EEG-P300 as a lie detector was effective in these trials.

Tanushree Bablani et al., 2018 [19] have discussed the Deep Belief Network Deceit Identification Test on EEG Data. The primary goal is to categorize the acquired EEG data to identify lies. This study subjected CIT-based EEG data to an unsupervised technique employing a deep belief network. DBN comprises four limited Boltzmann (Restricted Boltzmann Machine is a generative model that operates as an unsupervised technique for classification) machines stacked on top of each other, with softmax regression at the output layer. EEG time-frequency components contain more information than raw EEG data. Hence, they are used for learning. Using the 10-20 international system, Ag/AgCl electrodes are placed at Fz, FC1, FC2, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, Pz, P4, O1, Oz, and O2 locations to capture EEG data. A wavelet with DBM was utilized, with four RBMs aggregated together using 16 channel EEG data. The average accuracy of 81.03 % is achieved. Feature Extraction (Wavelet transform) is a transformative feature. When the DBN findings are compared to supervised algorithms like LDA (uses three channels (Cz, Fz, Pz) and an average accuracy80.0%is achieved, it is shown that DBN has a greater accuracy rate than LDA. The procedure for determining guilt should be substantially more precise than now.

Syed Anwar et al., 2019 [20] have discussed using a wearable EEG headset for Lie Detection using Event-Related Potential (ERP) data. In this study, researchers investigated brain activity to identify confidential information as an alternative to the polygraph test. In this investigation, 14 channels and 10-20 systems were used in the experiment. The first two primary channels account for more than 80% of data variation, producing the best results. The classification algorithm (SVM) for lie detection is designed to improve the system's accuracy by using fewer EEG channels. An enhanced deception detection system based on a portable EEG recording system with a low channel commercially available EMOTIV headset is shown. Peak-to-Peak, Peak-to-Peak Slope, Time Window, and the Amplitude and Absolute Amplitude (AAMP) are all frequency characteristics extracted (deleted the zeros). Advantage vectors benefit from including ENT and A.P. and several other metrics. Using a group of students close to each other, the testing set was designed to be as realistic as possible. The system has an accuracy rate of 83%. Changing the SVM's cost parameters with a specific training sequence can yield more advantages.

Navjot Saini et al., 2019 [21] have explored the classification of EEG signals using a hybrid mix of features for lie detection. The paper presented a technique for extracting domain characteristics and merging them with an SVM classifier. The EEG data were obtained at nine electrode sites using the International 10-20 electrode placement system: C3, Cz, C4, P3, Pz, P4, O1, O2, and Oz. The probing responses of the participants at the Individual probe responses were assessed at the only Pz electrodeposition. The features utilized were a mix of time, frequency, wavelet, EMD-based, and correlation coefficients. The components extracted from (EMD) of the EEG data significantly boost the classification accuracy. Frequency domain characteristics demonstrated changes in the spectral content of EEG signals between guilty and innocent persons. There are thirty-three participants in the dataset (18 males, 15 females). The data was acquired utilizing three categories of stimuli: Probe (P) stimuli, target (T) stimuli, and irrelevant (I) stimuli. Training accuracy of 99.94 percent, testing accuracy of 98.8 percent, and maximum testing accuracy of 99.44 % are reached when the neural information created by 40 unique features is merged and entered into SVM. Subjects' unrelated responses to the probe, target and other midline electrode placements can also provide helpful information in detecting lies.

D.H. Yohan Kulasinghe, 2019 [22], discussed detecting lies using EEG technology and machine learning. SVM, k-Means, ANN, and Linear Classifier are machine learning algorithms that may evaluate EEG data. The technology known as the 10-20 system is used to capture scalp EEG. When someone talks about a mixture of truth and lies, it may take some time, which can be advantageous. Signal amplitude, wavelength, frequency, and voltage were used as characteristics of the classification model to analyze EEG signals. It used cues from the frontal pole (Fp) and the temporal region (T) to detect deception. Since those areas are in charge of logical thinking, reasoning, judgment-related processes, emotional reactions, and emotional memory. The complicated EEG waveforms are translated into a modest waveform using the Fast Fourier Transform (FFT) approach. Use the algorithm to tell the difference between the truth and the lie. SVM works nicely on a single data point. According to the most convenient feature for spotting falsehoods, the approach's accuracy is 86%.

Shubham Dodia et al., 2019 [23] have recommended an ELM-based lie detection system. For extraction, the STFT and BBAT optimization methods were used. EEG brain signals were first evaluated using an acquisition device tested on various patients. The Ag/AgCl electrode mode's preparative setup contains 16 channel configurations: Fz, FC1, FC2, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, Pz, P4, O1, Oz, O2 sites. For the trials of the guilty and the innocent, Channel 12 (Pz) conducts independent analysis. The signals were preprocessed to eliminate noise. The Fourier transform method was applied to extract features from the electroencephalogram signals in a short amount of time. The collected feature set was placed into an extreme learning machine classifier to train the guilty and innocent samples. The proposed polygraph system has an 88.3% result accuracy. ELM was chosen because it allowed fast network learning, concealed nodes, and weights to be assigned at random. Features that have been extracted are (mean, variance, maximum amplitude, minimum amplitude, skewness, kurtosis, power, S.D.). Anjali Arya et al., 2013 [14] have discussed how EEG and facial EOG can research and analyze human emotions when lying. The experiment included ten participants, ages 18 to 28. EEG electrodes were inserted onto the patient's scalp using the 10-20 electrode placement technique. Used the sampling rate set was 2000 samples per second per channel. For data collection, an RMS-32 polysomnography hardware system with 32 channels for EEG recording. The frequency, amplitude, and shape of EEG waves and the locations on the scalp where they were recorded were used to classify them. In this study, a delta wave is most effective while lying down. It spans 67.02% of EEG wave patterns, with theta wave covering 15.52%, alpha wave covering 10.55 percent, beta wave covering 6.79%, and gamma wave covering 0.13%. They concluded that electroencephalography (EEG) is an accurate and sensitive approach to measuring emotional expression. They may record the reaction using an EEG even when individuals are asked to suppress their emotions while lying.

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Navjot Saini et al., 2019 [21] have explored the classification of EEG signals using a hybrid mix of features for lie detection. The paper presented a technique for extracting domain characteristics and merging them with an SVM classifier. The EEG data were obtained at nine electrode sites using the International 10-20 electrode placement system: C3, Cz, C4, P3, Pz, P4, O1, O2, and Oz. The probing responses of the participants at the Individual probe responses were assessed at the only Pz electrodeposition. The features utilized were a mix of time, frequency, wavelet, EMD-based, and correlation coefficients. The components extracted from (EMD) of the EEG data significantly boost the classification accuracy. Frequency domain characteristics demonstrated changes in the spectral content of EEG signals between guilty and innocent persons. There are thirty-three participants in the dataset (18 males, 15 females). The data was acquired utilizing three categories of stimuli: Probe (P) stimuli, target (T) stimuli, and irrelevant (I) stimuli. Training accuracy of 99.94 percent, testing accuracy of 98.8 percent, and maximum testing accuracy of 99.44 % are reached when the neural information created by 40 unique features is merged and entered into SVM. Subjects' unrelated responses to the probe, target and other midline electrode placements can also provide helpful information in detecting lies.

D.H. Yohan Kulasinghe, 2019 [22], discussed detecting lies using EEG technology and machine learning. SVM, k-Means, ANN, and Linear Classifier are machine learning algorithms that may evaluate EEG data. The technology known as the 10-20 system is used to capture scalp EEG. When someone talks about a mixture of truth and lies, it may take some time, which can be advantageous. Signal amplitude, wavelength, frequency, and voltage were used as characteristics of the classification model to analyze EEG signals. It used cues from the frontal pole (Fp) and the temporal region (T) to detect deception. Since those areas are in charge of logical thinking, reasoning, judgment-related processes, emotional reactions, and emotional memory. The complicated EEG waveforms are translated into a modest waveform using the Fast Fourier Transform (FFT) approach. Use the algorithm to tell the difference between the truth and the lie. SVM works nicely on a single data point. According to the most convenient feature for spotting falsehoods, the approach's accuracy is 86%.

Shubham Dodia et al., 2019 [23] have recommended an ELM-based lie detection system. For extraction, the STFT and BBAT optimization methods were used. EEG brain signals were first evaluated using an acquisition device tested on various patients. The Ag/AgCl electrode mode's preparative setup contains 16 channel configurations: Fz, FC1, FC2, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, Pz, P4, O1, Oz, O2 sites. For the trials of the guilty and the innocent, Channel 12 (Pz) conducts independent analysis. The signals were preprocessed to eliminate noise. The Fourier transform method was applied to extract features from the electroencephalogram signals in a short amount of time. The collected feature set was placed into an extreme learning machine classifier to train the guilty and innocent samples. The proposed polygraph system has an 88.3% result accuracy. ELM was chosen because it allowed fast network learning, concealed nodes, and weights to be assigned at random. Features that have been extracted are (mean, variance, maximum amplitude, minimum amplitude, skewness, kurtosis, power, S.D.).Participants' EEG signals were recorded in the brain using a BrainVision recorder. On 20 people, a novel CIT was performed (18 men and two women). The participants were between the ages of 20 and 30. To receive their brain signals, all subjects who took part in the study were required to submit a no-objection certificate. Participants in the survey are physically and intellectually well, and they do not have any visual impairments. The experiment was carried out in complete silence.

Yijun Xiong and et.al, 2020 [24], analyzed the difference of electroencephalograms (EEGs) recorded from lie detection (LD) experiments between the truth and lying responses from the two types of subjects is investigated using the chaotic phase synchronization (PS) method. The LD experiment, which was based on the conventional three stimulus procedure, was used to collect data on the EEG of the twenty volunteers. For a few stimuli in the LD experiment, the Phase Locking Value (PLV) was used as a statistical measure from PS. The experimental results reveal a distinct geographical and temporal discrepancy in PS, with the guilty group having a stronger/higher PLV than the innocent group, having high accuracy of up to 88.05%; they analyzed the distributed frontal-temporal-central-parietal connection based on the phase synchronization patterns between 12 EEG channels in an attempt to uncover the underlying deception mechanism. For this, examined PS with the EEG signals which are collected by LD experiment based on a few stimuli, and investigated the PS between EEG activities from different brain regions. Ten university students with no history of psychiatric or neurological disorders participated in the study (9 males, the age between 20 and 23 years, and the mean is 22.3). The three-stimulus procedure was utilized. The electrode configuration was done using the 10-20 system. EEG signals were recorded in 14 channels, including horizontal and vertical EOG. The suggested a classification method based on machine learning (SVM) to discriminate deceit from truthful brain activities using PLV-based characteristics.

Neeraj Baghel et al., 2020 [25] have discussed Employing a convolution neural network. The study proposed using deep learning for automated truth detection from EEG data. The goal was to create a deep learning-based model that solves the problem of lying detection without emotions or physiological expression control. The suggested model's training and validation were carried out using the Dryad dataset. Thirty individuals were randomized into guilty and innocent groups at random, with six gem photographs serving 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. There are 300 samples in the Dryad dataset. Where low-level features were extracted for the first layers, each layer contains a different number of neurons and Activation functions corrected linear unit (ReLU), hyperbolic Shadow (Tanh), and sigmoid (Sigma). It was proposed that a new spatial denoising method (SDA) be developed. The suggested CNN classification and identification architecture. The recommended technique has achieved up to 84.44% accuracy in determining whether someone is lying or speaking the truth.

Table (1): Comparison between different approaches to EEG lie detection

Authors	Name & number of channels	Feature extraction	Classification algorithm OR Technique	Accuracy

Vahid Abootalebi and et.al. [13]	Ag/AgCl electrodes were implanted at the Fz, Cz, Pz. Only Pz's results are included. At a rate of 256 samples, ps	Included morphological, frequency, and wavelet characteristics. Morphological (ALAR, SSA), Frequency (f median, f means).	genetic algorithm (GA)	86%
Samreen Amir et. [4]	In a 10-20 system, just five electrodes were employed to gather the signal of interest. They concentrated on beta wave activity.	Morphological features such as amplitude, latency, negative area, peak to peak values, zero crossing, and other features are used.	------------------------	------------
Anjali Arya and et.al. [14]	Using the 10-20 electrode placement technique. The sampling rate was set to 2000 samples per second per channel.	The frequency, amplitude, and shape of EEG waves.	------------------------	------------
Junfeng Gao and et.al. [15]	EEG Data Acquisition Twelve electrodes (Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, Oz) from an International 10–20 system used	There are three groups of features.1-Time-domain features (1) Maximum amplitude, (2) Latency, (3) Peak-to-Peak, (4) Positive area. 2-frequency-domain features (1) Maximum frequency, (2) Mean frequency. (3) The power of the primary frequency.3-Wavelet features.	F-score SVM	Accuracy for P300 (specificity of 96.05%) and non-P300 (sensitivity of 96.11%)
Artha Ivonita Simbolon and et. [16]	ElectroCap, Fz, Cz, Pz, O1, and O2 were several channels utilized.	Lowest amplitude, maximum amplitude, mode amplitude, median amplitude, and mean amplitude	SVM (support vector machine)	70.83%
S. Kamran Haider and et.al. [17]	The Pz is the primary site where P300 may be monitored the most. Therefore, visual studies were limited to Pz data	Morphological features: latency time, maximum peak signal value, positive signal value, and total area. 2. Frequency Characteristics: frequency mode, median, and mean.	LDA	85%
Arjon Turnip and et.al. [18]	Frontal (Fz), central (Cz), parietal (Pz), and occipital (Oz) electrodes were used (O1 and O2)	Feature extraction: lowest amplitude, mode amplitude, maximum amplitude, median amplitude, and mean amplitude	ANFISA	64.27%
Tanushree Bablani et. al. [19]	Ag/AgCl electrodes are placed at Fz, FC1, FC2, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, Pz, P4, O1, Oz, and O2 locations to capture EEG data	Feature Extraction (Wavelet transform)	DBN is made up of four limited Boltzmann (Restricted Boltzmann Machine is a generative model that operates as an unsupervised technique for classification)	81.03 %

Syed Anwar et. al. [20]	Used 14 channels and 10-20 systems. The first two primary channels account for more than 80% of data variation	(AAMP), (P2P), (P2PT), (P2PS), mean frequency, and average frequency are all frequency characteristics. Entropy (ENT), (A.P.)	SVM	83%
Navjot Saini and et. al. [21]	EEG data were recorded at nine electrode sites. The probing responses were evaluated at the just Pz electrodeposition.	The features mix time, frequency, wavelet, EMD-based, and correlation coefficients.	SVM	Training accuracy of 99.94 %, testing accuracy of 98.8 %, and maximum testing accuracy of 99.44%.
D.H. Yohan Kulasinghe. [22]	The frontal pole (Fp) and the temporal region(T)	Signal amplitude, wavelength, frequency, and voltage	SVM	86%
Shubham Dodia and et.al. [23]	Fz, FC1, FC2, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, Pz, P4, O1, Oz, O2. Channel 12 (Pz) conducts independent analysis	Mean, variance, maximum amplitude, minimum amplitude, skewness, kurtosis, power, S.D.	ELM	88.3%
Yijun Xiong and et.al. [24]	Based on phase synchronization patterns between 12 EEG channels, a frontal-temporal-central-parietal relationship was discovered.	------------------------	SVM	88.05%
Neeraj Baghel et. [25]	Fourteen channels, 12 of which were EEG, and the final two were EOG from AF1 to AF4. the EEG signal is captured for 10 seconds	------------------------	CNN	84.44%

4. Disadvantage of each method

1- **genetic algorithm (GA):** the major disadvantages of genetic algorithms is that they are very slow[26].
2- **SVM (support vector machine):** The computational complexity is high[27].
3- **LDA(Linear Discriminant Analysis):** It fails when the discriminatory function is based on the variance of the characteristics rather than the mean and It is possible that the complex structures will not be preserved for non-Gaussian distributions[27].
4- **ANFISA(Adaptive neuro-fuzzy inference system):** Understanding and developing a fuzzy system involves skill, developing fuzzy rules takes time, and is its enhanced performance degradation in comparison to other ways[28].
5- **DBN(Deep Belief Network):** Choosing the most sensitive features in various diagnosis concerns is a time-consuming and labor-intensive task[29].
6- **CNN (convolutional neural network):** A high number of labeled training samples are required for weight parameter learning, and a strong GPU is required to expedite the learning process. People who lack such processing capacity, time, and a large-scale training set are sometimes unable to take advantage of the strong CNN[30].

5.Classification techniques

A classifier system's primary purpose is to build linear or non-linear boundaries between features belonging to different classes in the feature space. Appropriate classifier selection necessitates fitting the distribution of characteristics to discriminate across categories. Many categorization approaches were employed in EEG lie detection systems. In, a multi-class support vector machine (SVM) was used in [16] [20] [21] [22] [24] [15], SVM (supervised learning method) is a machine learning methodology for assessing and categorizing data that uses supervised learning methods. With SVM-based categorization, it has been possible to find the optimal balance between accuracy gained from a small amount of training data and generalized test data. [12]. whereas in [17] linear discriminant analysis (LDA) was used, in [13] genetic algorithm (G.A.) was employed, in[19] Boltzmann Machine was used, in[23] extreme learning machine classifier(ELM) was applied, and in[25] CNN algorithm was used and in[18] neural networks and fuzzy features(ANFIS) was used.

6. Feature Extraction

The preceding portion of this research presented a literature review and a comparative evaluation of several techniques and algorithms for EEG lie detection systems. The lie detection challenge is complicated by extracting and accurately selecting discriminative elements from EEG data. After essential characteristics from the brain, signals were retrieved when the noise-free data from the signal amplification phase were obtained, use techniques to extract features from EEG waves. EEG characteristics have been extracted in a variety of areas. There are two types of features used in previous studies, statistical and Time-domain features. Because the suggested statistics are so dissimilar, the statistical characteristics allow for separation across feature types. Except for the first difference in the time series, none has a very high weighted relative frequency score. The signal's statistical feature power has a high score. This does not mean to be a highly valued feature. In [13][4] [16] [23] [14] [20] used statistical features. Although EEG time-domain features aren't widely used, various methods for identifying time-series properties differ between emotional states. The most commonly used characteristics in EEG lie detection are features from various frequency bands. The fast Fourier transform (FFT) is the most often used technique for computing the discrete Fourier transform (DFT) (FFT). The short-time Fourier transform is a popular option (STFT). In [15] [19] [21] [17] [22] [18] used Time-domain features.

7.EEG Databases

There are two categories of datasets used in published researches: (1) Public dataset and (2) private dataset; some studies have used the public database such as The Dryad dataset is freely available to the public and may be found on the dryad database. This dataset is utilized for the proposed model's training and validation. Thirty individuals were randomly separated into guilty and innocent groups, and six gem photographs were provided as stimuli during detection. The experiment included three types of stimuli (irrelevant, probe, and target). EEG signals were obtained on 14 electrodes. used in [25] [15]. MI BCI EEG and EMG datasets were collected concurrently from 52 healthy subjects in two groups (100 or 120 trials for each class). The electrode placements for 3D EEG and non-task-related EEG were recorded (resting state, eyeball and head movements, and jaw clenching). Validation of the datasets was accomplished using the fraction of trials, spectrum analysis, and classification analysis. GigaDB, a GigaScience database, was used to store these datasets. [31], and used in [19]. Other studies have been used private datasets.

8.Conclusions

All previous attempts to use EEG signals have revealed that brain waves include unique properties, making them suitable for applications such as human lie detection. Much research covered in this study has offered different sets of characteristics and electrodes for lie detection using EEG. We provided a comprehensive comparison of the various feature extraction approaches available using machine learning techniques.EEG signal preprocessing, feature extraction, feature selection, and classification methods have all been studied in the literature. The SVM approach is the most widely used in studies and performs well on a single data point. On the other hand, the signal Generations when lying cannot be considered private information. Further experiments in preceding signal processing and the requirement to discover the best appropriate classification algorithm are required to construct a more complicated and reliable polygraph system employing EEG and machine learning. In the future, we will concentrate on enhancing the system's classification accuracy by using feature extraction algorithms that are tailored to EEG data, resulting in more robust feature vectors.

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