A Review of Lie Detection Techniques

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Abstract –*A claim that is thought to be untrue and is often made with the intent to deceive someone is called a lie. The lie is challenging to distinguish from the truth as the variations between true and false claims are so negligible. Lying requires more cognitive effort than stating the truth because the liar must work hard to close all the gaps in the lie. When feeling fear, anxiety, or extreme excitement, a person's oxygen consumption rate, BP, galvanic skin resistance, etc. will significantly increase. This is the basis of lie detection. Lies can be detected psychologically by probing for details, asking unexpected questions, and exerting cognitive strain on the subject. Recently, deception detection has advanced beyond polygraphs to include electroencephalography, eye blink patterns, voice signals, etc. This paper presents the various advanced lie detection techniques and their comparison.*

Key Words: ***DIFCW, Machine learning, Extreme learning machine (ELM) and SLFN (Single layer feed-forward network), Electrooculogram (EOG), Electroencephalograph (EEG), Convolutional Neural Network (CNN), Discrete Wavelet Transform (DWT), Bi-directional Long Short Term Memory (Bi-LSTM),) Principal Component Analysis (PCA)***

1. INTRODUCTION

A lie implies conduct in which a person makes a conscious decision to deceive another person without revealing the intent behind the lie [1][2]. Lie detection aims to uncover hidden facts known to one individual but kept from others. It is difficult to know if somebody is lying. The task of accurate lie detection is intriguing for scientists working in several disciplines. It is essential to spot lies in several areas, including law, medicine, and criminal justice. Despite its reliance on polygraphs as an alternative method for detecting lies, this method has serious reliability issues. Observation and comparison of physiological activity are typically made during a question-and-answer session [3]. Several researchers have sought to identify lies using measures of brain activity, eye blink patterns, and voice signals.

This article examines various techniques for lie detection besides polygraph and the different methods presented in chapter 3. Their comparative Analysis is shown in Chapter 4. The conclusion of this article is presented in Chapter 5.

2. LITERATURE REVIEW

An extreme learning machine (ELM) and SLFN (Single layer feed-forward network) based machine learning have been applied to lie detection tasks in [4]. The system makes use of the Vertical and horizontal Electrooculogram (EOG), and Electroencephalograph (EEG) signals for lie detection. This method achieves maximum classification accuracy of 97% with a very short training and testing period. Based on deep learning, a multimodal fusion network detects lies by combining text, audio, and visual information [5]. Visual attributes are collected from the videos by employing a 3D CNN. This system provides higher accuracy of 92% and 96% respectively for late and early fusion approaches. A Lie Detection System based on Machine Learning is built using a wearable EEG headset in [6]. Feature extraction of signals is done using a 3-level Discrete wavelet transform and classification of features is done using a Support Vector Machine. This lie detection approach gives an accuracy of 83%.

Another EEG signal-based lie detection method using CNN has been proposed in [3]. The suggested model is trained and evaluated using data from the Dryad dataset and a newly created EEG lie dataset. The CNN employed in this system consists of 4 Convolutional layers. The suggested model performed well on the Dryad dataset with an accuracy of 84.44%, whereas it performed poorly on the EEG lie detection dataset with an accuracy of 82.00%. A deep learning approach has been developed to detect lies by leveraging microfeatures and audio features in [7]. This system was based on using a Deep Neural network for lie detection. Audio data was collected by conducting interviews. Real-time facial feature detection is performed by asking a predetermined list of questions. This system achieved an accuracy of 98.45%.

[8] proposed a lie detection system based on DIFCW radars with machine learning. A machine learning algorithm for detecting lies is built based on features extracted from respiratory and heartbeat signals. The system provides 63.2% and 61.5% accuracy for respiratory and heartbeat signals respectively. Another lie detection approach that classifies lies using EEG, auditory, and visual inputs has been proposed in [9]. There are three units in this novel design, one for each data type in the Bag-of-Lies dataset. EEG classification unit consists mainly of a Bi-directional LSTM network. This novel lie detection system has 83.5% accuracy in the lie detection problem.

3. METHODOLOGY

3.1 F-Score and Extreme Learning Machine-based system

EEG data of individuals are considered for lie detection in this approach [4]. Three types of features are extracted from subjects' P response EEG data. They are the time domain, frequency domain, and time-frequency domain features. Two methods were done for performing the lie classification i.e., F SCORE-ELM, and PCA-ELM. F score and PCA methods were used for extracting the dominant features from the P response data. Then these features are fed to the Extreme Learning Machine for training. The generated prediction model is used for identifying lies.

3.2 Deep CNN- based approach

This approach makes use of a fusion of textual, audio, and visual features [5]. The spatial and temporal data are retrieved from video using a three-dimensional CNN. Another CNN model extracts textual features. Audio features are extracted utilizing an open-source program known as open SMILE. Following that, features are merged and fed into an MLP classifier to classify the multimodal into either of the two classes (Truthful or deceptive). The benefit of feature level fusion is that it takes advantage of early feature correlation, which frequently leads to improved task completion.

3.3 DWT & SVM- based approach

The deception detection approach uses portable EEG recording equipment that is easily accessible on the market, including a low channel EMOTIV headset [6]. Feature extraction is performed using 3-level DWT. Initial calculations are based on DWT and time division, resulting in 20 features. It works well for removing features with low values (zero), demonstrating its utility as an initial feature selection method. Data projection onto a statistically independent space is achieved by the principal component analysis (PCA). Data patterns are detected using SVM, which are then used to categorize lies. The Gaussian kernel is used here.

3.4 DNN & Bio Signal-based system

Real detection of the interviewee's faces and identification of their facial landmarks commences the process of creating the dataset [7]. The micro-expressions and features of the eye, nose, jawline, etc. are monitored by asking questions. Additionally, the variance in auditory features is recorded. These audio and facial features were then used to train the prediction model. The algorithm examines two specific features. First, check for eye-rolling, furrowing, and lip movement when the interviewee responds to questions. During the testing phase facial cues are mapped and a person's face is recognized when they are being interviewed. Following the extraction of AV features, a probabilistic value or rating is computed.

3.5 DIFCW Radar with Machine Learning-based system

This system uses DIFCW radar to measure a person's heartbeat and respiratory signal without making physical contact with them [8]. A continuous wave signal received from the radar is reflected from the chest wall, modulating respiratory and heartbeat signals. After that, baseband signals are produced using intermediate frequency modulation. Then, from these signals, a total of 10 features (Time domain, Frequency domain, Nonlinear domain) were extracted. Extracted features are used to generate a prediction model using a machine learning algorithm which is used to detect the lie.

3.6 EEG-guided Multimodal system

To classify truths and lies, this system relies on EEG, acoustic, and visual information [9]. An n-channel EEG device is employed to acquire EEG signals. The EEG data is subsampled by t units. Every EEG sample is depicted as a constant dimensional sample with zero padding. To detect lies, two-dimensional feature vectors are fed to bidirectional LSTMs. The suggested method additionally uses an LSTM network to handle inverted EEG data in order to recall information from future predictions. To boost the efficiency, LSTM and Bi-LSTM run simultaneously with training data. To categorize an EEG as genuine or deceptive, the size of the output feature vector is decreased from 1468 to 2. For performing lie classification using audio signals, features extracted from audio signals are fed to an attention CNN architecture. For lie detection using visual signals, frame-by-frame sequence videos are used for feature extraction. Then the extracted features are fed to a two-stream CNN for the classification task.

4. COMPARISON

The comparison analysis of the above-discussed lie recognition techniques is shown in Table 1. A deep neural network-based system that is based on audio and visual data provides higher accuracy in the lie classification task.

No	Title	Technique	Data	Accuracy
1	A novel lie detection method based on an extreme learning machine using p300 [4]	ELM and SLFN	EOG and EEG signals	97%
2	Deep learning-driven multimodal fusion for automated deception detection [5]	Deep CNN 3DCNN MLP classifier	Audio+ Visual+ Textual data	92% for late fusion 96.4% for early fusion
3	Event Related Potential (ERP) based Lie Detection using a Wearable EEG headset [6]	DWT + PCA+ SVM	EEG data	83%
4	Deep Neural Networks for Lie Detection with Attention on Bio-signals [7]	DNN	Facial features Audio features	98.45%
5	Lie Detection Based on a DIFCW Radar with Machine Learning [8]	DIFCW	Respiratory signal Heartbeat signals	61.5% 63.2%
6	EEG Guided Multimodal Lie Detection with Audio-Visual Cues [9]	Bi-LSTM LSTM	EEG Audio-Visual Cues	83.5%

Table 1: Comparison of Various Lie detection Methods

5. CONCLUSION

The detection of lies has been studied in criminology, psycho logy, and behavioral science research. Throughout history, scientists and forensic science professionals have made numerous efforts to detect lies in the legal and criminal arenas [11][9]. Psychological lie detection has existed for a very long time. Polygraphy tests monitor skin sensitivity, breathing rate, heart rate, etc. The results of polygraphy tests can vary due to various factors. Other than the polygraph, many lie-detection methods have emerged as a result of technological innovation. In this paper, some lie detection methods based on EEG signal, audio, visual and textual features have been reviewed. It is found that a deep learning-based system based on audio and visual data outperforms all other methods by providing 98.45% accuracy in the lie classification task.

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