ARTIFICIAL INTELLIGENCE APPROACHES TO LIE DETECTION: A NEW FRONTIER IN DECEPTION SYSTEMS

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Abstract

This paper explores some early detection technologies, such as polygraph, and discusses the influences that lie detection initiatives have had in human interactions over the decades. It addresses the empirical issues in the context of police and educational and examination applications to identify whether special AI technologies have the capability of recognizing lying along with the related cultural concern. Lie detection is a complex problem that affects different aspects of human life. Traditional deception detection methods have limitations. One method to detect lies is through the identification of facial micro-expressions, which are involuntary expressions displayed on the face of humans when they are trying to conceal or repress emotions. Manual measurement of micro-expressions is hard, inaccurate, and time-consuming. The paper presents a review of a lie detection system using facial micro-expressions and computer vision. It is an automated vision system designed and implemented using LabVIEW. An embedded Vision System (EVS) is used to capture the subject's interview. Testing results show that this system can be used for interpreting eight facial expressions: happiness, sadness, joy, anger, fear, surprise, disgust, and contempt, and detecting microexpressions. It extracts accurate output that can be employed in other fields of study, such as psychological assessment. The results indicate high precision that allows future development of applications that respond to spontaneous facial expressions in real time.

***Keywords**: deception detection, artificial intelligence, machine learning, micro-expression, computer vision*

Introduction

Lie detection is based on the assumption that when an individual experiences fear, worries, emotional excitement, his or her respiration rate, blood pressure, and skin resistance sharply increase. The ability to know when someone is speaking the truth or a lie is critical in interpersonal communication, border security, law enforcement and criminal investigations, the job hiring process, social media and online platforms.

Traditional deception detection depends on polygraph testing (changes in heart rate and blood pressure), electrodermal (changes in the electrical property of the skin that vary with the activity of the endocrine sweat gland), and respiratory. These methods have been criticized due to a lack of accuracy and can be easily manipulated. For example, during the 2016 U.S. Presidential campaign, misleading information was released that managed to steer public opinion in society.

The advent of Artificial Intelligence (AI) has revolutionized lie detection. The AI-powered lie detector analyzes linguistic features, facial expressions, voice patterns, and physiological patterns. To improve lie detection, the AI systems leverage deep learning, machine learning, and biometric analysis to detect deception and obtain a more accurate result than traditional methods.

Despite the promise of AI-powered lie detection systems, there are several challenges and concerns that need to be addressed. This includes the need for high-quality training for a large amount of data, the ethical implications of using AI for lie detection, and the potential for bias.

This paper provides an overview of the current AI-powered lie detection systems, advantages, challenges, and limitations. It aims to provide a comprehensive review of how AI can improve lie detection and the ethical implications that come with it.

Background and Related Work

Humans have a strong “truth” default, meaning that when processing incoming information, they will passively believe statements made by others. However, naïve acceptance can put people at risk for deception (Jullian R., 2020). Research shows that 60% of people lie during a typical 10-minute conversation (Jullian R., 2020). Considering the pervasiveness of lying, it is easy to recognize deception as a challenge for individuals involved in law enforcement and the conduct of examinations because they are expected to differentiate between truth and lies daily. The introduction of Artificial Intelligence (AI) in deception detection has gained significant attention in recent years. Researchers have explored various AI methods, including natural language processing, machine learning, and deep learning, to develop more precise and efficient lie detection systems. Lie detection technologies such as the polygraph have often been controversial, facing strong criticism for bias and unfairness. Some researchers believe that AI could help improve our odds and do better than old-fashioned techniques like polygraph tests (Jessica H., 2024). An AI-based lie detector could one day be used to help us sift fact from fake news, evaluate claims, and potentially even spot fibs and exaggerations in job applications. The question is whether we will trust them. However, the perceived ease of implementing AI-related lie detector tools is making them tempting to inject into everyday workplace community situations such as educational examinations and interviews (Jo Ann O, 2024). In the field of psychological research on deception detection, the rise of artificial intelligence has resulted in discussions about its potential benefits and risks. Most researchers argue strongly for the inclusion of good theories in the design, training, and application phases of AI. In this paper, we ask an important follow-up question: what makes a good theory? And why do they matter in detecting deception? To this end, we argue that mechanism-driven and cognitively informed theories are the ones AI researchers need to be looking for. (Philip T., 2025).

Traditional Lie Detection Methods

For decades, deception detection has relied on various psychological and physiological indicators. Some common traditional methods include:

Polygraph Tests: Measure physiological responses like heart rate, skin conductivity, and respiration while a person responds to questions. However, it lacks accuracy and is susceptible to manipulation. It lacks perfection and can be deceived by a trained individual easily.

Voice Stress Analysis: This is a technique that uses inaudible voice to detect stress to produce a lie detector system.

Limitation of the traditional system

Polygraph accuracy: The traditional methods have serious limitations because there is a belief that, in the use of polygraph, deceptive answers will produce physiological responses that can be differentiated from those associated with non-deceptive answers; however, there is no specific physiological reaction associated with lying, making it difficult to identify factors that separate those who are lying from those who are telling the truth.

Voice Stress Analysis: It aims to detect deception by analyzing stress-related changes in voice patterns such as tremors, pitch, and frequency, which are thought to reflect stress associated with lying. Unlike the polygraph, VSA does not require physical sensors to be attached to the subject, which makes it less invasive. Emotional states such as nervousness or excitement, which are unrelated to deception, can also cause changes in vocal patterns, making this method unreliable (Sharma R, Et al, 2023).

Micro-expression Analysis: Involuntary facial expressions are another method of detecting deception; this method can indicate emotional concealment, but they do not definitely prove deception, as people may hide emotion for reasons unrelated to lying. These techniques require expert interpretation, which can introduce human error and bias (Tumuli et al, 2020)

Emergence in AI-Powered Lie Detector

Multimodal Analysis: This includes the integration of data from different sources to detect lies. AI tools capable of monitoring heart rate, analyzing facial expressions during video calls, and providing real-time assessment of truthfulness (Sun C. et al, 2023).

Adaptive Learning Techniques: AI systems could become more adaptive, learning from new data continuously to improve their performance in various real-world situations. This would help them adjust to different cultural contexts and individual behaviors.

Related Works
The following is a brief discussion of works related to research on lie detection using AI and machine learning.
Previous work on detection focused on a combination of various factors, including verbal and non-verbal aspects. Text/audio only approaches alone using RNN or LSTM architecture were able to achieve only moderate accuracy of 76 % -84 % (Venkatesh et al, 2019). Micro-expressions-only approaches achieved higher accuracy of 77 % -88 % (Venkatesh et al, 2019). Not immediately visible to the human eye. (Owayjan et al, 2022) developed LabVIEW computer vision software based on a mathematical algorithm to analyze the facial micro-expressions to detect lies. (Singh et al., 2015) developed an image processing method to detect lies based on eye blink rates using the Haar cascade algorithm. (Soumya Barathi, 2020) designed a lie detection system by analyzing facial microexpressions using principal component analysis.

AI-Powered Lie Detection: Concept and Working
AI solutions for deception detectors operate by processing multimodal data to detect signs of deception. These systems use machine learning algorithms to analyze inputs from multiple sources, including visual, audio, and text features, which significantly enhances lie detection accuracy, achieving an accuracy of 99 % (Sun C. et al, 2023).

Technologies
Recent developments in machine learning and computer vision have led to AI systems being capable of analyzing micro-expressions, vocal patterns, and behavioral cues. These systems aim to detect deception and assist border control officers (Liao, H.; Zhao, W.; Zhang, C.; Dong, W., 2022).

Computer vision: This technology analyzes visual data to detect micro-expressions and facial cues associated with lying. Models like ResNet-18 have been used to classify facial expressions such as fear, aiding in lie detection. Micro-expression analysis has become an extremely powerful tool and influential tool in the domain of understanding human emotions and motives. This very brief but powerful subtle facial expression, lasting for less than half a second, can actually reveal underlying deeper feelings that can be signs of stress, lying, or discomfort, feelings that people endeavor to conceal or mask from others. With recent advancements in artificial intelligence, particularly in the fields of machine learning and computer vision, there has been improvement in the capacity to recognize and analyze this method. Studies have shown that AI algorithms can achieve accuracy of over 85% in detecting microexpressions, significantly surpassing the average human accuracy of around 47%(Li, X.; Hong, X.; Moilanen, A.; Huang, X.; Pfister, T.; Zhao, G.; Pietikäinen, M.,2018). A lot of improved, advanced AI algorithms that are incorporated into systems today are capable of handling high-resolution images captured by state-of the art cameras and can identify even slight facial movements that may occur with great accuracy. However, there are technical limitations, including the need for large, labeled datasets, which are scarce due to the difficulty in capturing micro-expressions, and challenges in processing high-frame-rate video data in real time, as well as the complexity of integrating multiple streams of data such as optical flow and enhanced visual magnification to improve recognition accuracy (Liu, J.; Li, K.; Baolin, S.; Zhao, L., 2020).

Natural Language Processing (NLP) is a machine learning technology that gives computers the ability to interpret, manipulate, and comprehend human language. AI tools trained on language models, such as BERT, have been developed to identify lie statements, achieving accurate results. Vocal analysis is a very interesting field of research that fuses the study of Natural Language Processing (NLP) and advanced speech analysis techniques. These carry out a thorough analysis of several crucial aspects of spoken communication, including characteristics such as voice pitch, quality of tone, and any hesitations while speaking. All of these may be essential pointers that can indicate whether there is dishonesty in what the speaker is trying to convey. Certain technical criteria must be met to successfully implement this system. There must be the use of high-quality audio recording equipment, sophisticated signal processing algorithms, and computer resources that can perform real-time processing. Conducting an in-depth analysis of these unique vocal characteristics allows advanced artificial intelligence to pinpoint subtle yet significant changes and complex speech patterns, which may prove that an individual is not wholly honest with what they are asserting or stating. However, there is a need to employ noise mitigation measures and create a controlled recording environment. In addition, integrating advanced techniques in speaker recognition can significantly enhance system robustness against this external disturbance (Mahadeva Prasanna, S.R.; Sinha, R.; Das, R.K.,2022). The following academic paper (Sternglanz, R.W.; Morris, W.L.; Morrow, M.; Braverman, J.,2019) is a thorough review of the many techniques used in detecting deception, among which is vocal analysis. This work integrates findings from a wide range of studies to give insightful information about both the effectiveness of these techniques and their limitations when used in the field of lie detection.

Machine Learning and deep learning: Machine learning is a branch of Artificial Intelligence that allows computers to learn from data and obtain skills to work on a task without being programmed solely for it. Machine learning algorithms produce a so-called model, a general representation of the patterns in data. Each row of the dataset is an individual, while the column is a feature. Deep learning is a subset of machine learning that represents knowledge as a tree-like structure, building complex and specific representations over simpler and broader ones. It focuses on training artificial neural networks inspired by the human brain's structure and functioning. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks, are used. In deep learning, Enhanced Recurrent Neural Network (ERNN) with fuzzy logic has been proposed for deception detection.

Methodology

Data collection and Training

There are many different approaches to lie detection in videos, including uni-modal approaches such as audio, text, video (micro-expression), and multi-modal fusion of audio, text, and videos. Although a multi-modal approach would be able to use the most amount of information to detect deception in real-world situations, we often need to detect lies in real-time, and thus a micro-expression-based visual-only approach is worth exploring.

Detecting lies in videos with facial expressions requires several key building blocks, including recognizing human faces, identifying the face that we are interested in detecting lies from (in videos where more than one human face is present), recognizing the micro-expressions not immediately visible to the human eye due to the short duration of appearance and subtle facial muscle movements, and finally using time series of data to detect lies. The outcome will be a model that detects a time series of facial expressions on the target human face and uses the expression vector to categorize the video as either a lie or a truth statement.

Dataset and Features

There are two datasets required for learning this task. The first is faces labeled with corresponding expressions. The second is video clips of humans telling the truth/lies. To train the expression recognizer, we use FER-2013 ("Learn facial expressions from an image") available on Kaggle. The training set contains 28,709 examples, and the test set contains 3,589 examples. Each image is cropped to contain only the human face and is labeled using numbers 0-6, which stand for 0 - Angry, 1 –Disgust, 2- Fear, 3-Happy, 4 –Sad, 5-Surprise, 6- Neutral.

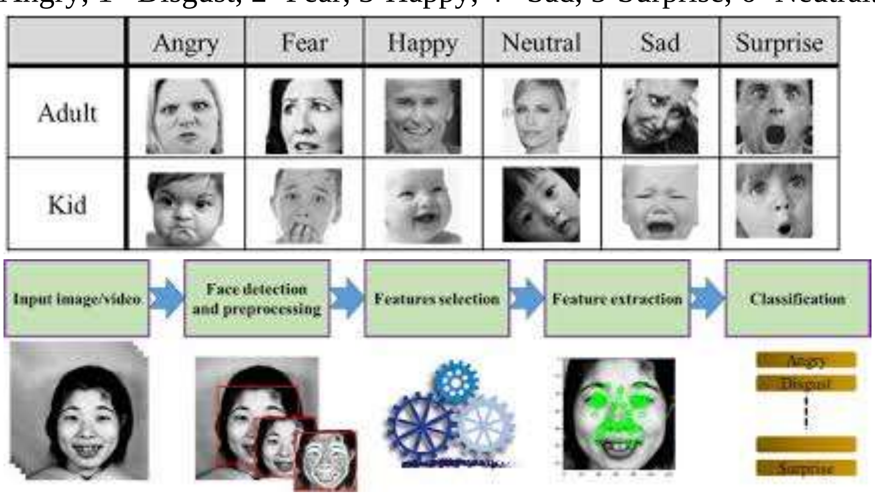

Fig 1: Image

For the video clip data, we are using a labeled video clip set consisting of 60 truths and 61 lies, which is the same dataset used by a previous paper, "Deception detection in video", in AAAI 2018(Zhe et al 2018). The average video is about 2 minutes in length, and all video files are kept in MP4 format with a frame rate of 30 frames per second. Only the person making a statement is visible in each video.

4.0 Findings

Modern computer vision approaches, especially deep learning and machine learning models, have shown vital progress in recognizing and analyzing micro-expression. Current deception detection using micro-expression and computer vision achieves accuracy rates ranging from 70% to 90%, depending on factors like dataset quality, feature extraction method, and algorithm efficiency. Polygraph tests, compared with micro-expression analysis offers non-invasion, real-time, and less intrusive approach; however, polygraphs still outperform micro-expression in controlled environments, particularly in detecting nervousness-related lies.

Results and Discussion

Using LabVIEW Vision Assistant and a CNN-Based classifier, an accuracy of 75% to 88% was obtained for lie detection. When combined with Support Vector Machine for classification, 70% to 80% was achieved due to SVM's limitations in handling deep learning features. High-speed cameras improved micro-expression accuracy by 10% when compared to standard webcams. LabVIEW's real-time processing capabilities allowed for micro-expression analysis in 50 to 100 ms per frame, making it suitable for live detection. Delays were observed when handling large datasets, particularly when integrated with deep learning.

Conclusion

The integration of LabVIEW and computer vision for lie detection reveals promising results, particularly in controlled environments. The system obtained real-time analysis with accuracy up to 88%, but faced limitations like false positives; environmental differences and processing speed remain. Future recommendations could focus on deep learning integration, optimized processing, and multi-modal analysis for improved reliability.

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