doi.org/10.54473/IJTRET.2025.9206
International Journal of Trendy Research in Engineering and Technology
Volume 9 Issue 2 April 2025
ISSN NO 2582-0958

ADVANCED AI DRIVEN DETECTION FOR DECEPTIVE CONTENT A SKEPTICAL APPROACH

[1]M. Mahalingam, [2]Nagarajan C, [2]Vino K, [2]Vinothkumar T
[1]Asst. Professor, [2]Under graduate Students, Dept of AI and Data Science
Erode Sengunthar Engineering College, Perundurai, Erode, Tamilnadu

Received 03 December 2024 Received in Revised form 10 December Accepted 13 December 2024
Available Online 16 December 2024

ABSTRACT

Using physiological markers linked to myocardial infarction (MI), this study suggests a unique method for lie detection. The study explores the concept that dishonest behavior causes physiological reactions similar to stress-related reactions seen in MI by utilizing Support Vector Machines (SVM) and Naive Bayes (NB) classifiers. Features including heart rate variability, QT interval, and ST-segment deviations are examined in a dataset of electrocardiogram (ECG) signals. The SVM and NB classifiers show promise in distinguishing false statements from accurate ones, demonstrating their ability to detect tiny changes in the body that are suggestive of dishonesty. By incorporating cardiovascular health indicators, this study advances our knowledge of the intricate relationship between deceitful behavior and physiological reactions, which aids in the detection of deception.

Keywords: Lie detection, deceitful behavior detection, Deception detection, Support Vector Machines (SVM) and Naive Bayes (NB)

I.INTRODUCTION

In a variety of contexts, from criminal investigations to security checks and interpersonal relationships, lie detection has been both fascinating and essential. While conventional techniques frequently depend on physiological reactions and verbal clues, technological developments, especially in the field of image processing, have created new opportunities for more complex and objective lie detection. Image processing methods like eye movement tracking, facial expression analysis, and physiological signal extraction from photos provide a non-intrusive way to spot minor clues that might point to dishonesty. The field of truth verification techniques may change as a result of this promising convergence of psychology and technology, which could lead to more accurate and trustworthy lie detection. To guarantee its appropriate and equitable use in a variety of situations, it is crucial to manage ethical issues and deal with the constraints of such technology. This introduction highlights the significance of finding a balance between ethical issues and technological improvements, and it sets the stage for investigating the cutting-edge field of lie detection through image processing.

Lie Detection

In many fields where distinguishing fact from fiction is crucial, lie detection has long been a problem. Conventional techniques frequently depend on physiological signs and spoken signals, but the development of sophisticated technologies has opened the door for more sophisticated strategies. With an emphasis on utilizing state-of-the-art techniques like machine learning, audio analysis, and facial recognition, lie detection has specifically discovered a new frontier in the field of scientific and technological developments. In addition to improving the accuracy of truth assessment, the search for more trustworthy and impartial methods of spotting deception brings up significant ethical issues pertaining to consent and privacy. This introduction provides context for exploring the developing field of lie detection, where the nexus of psychology and technology aims to clarify the subtleties of human honesty and dishonesty.

Facial Expression Analysis

Analysis of facial expressions has become a potent tool for comprehending and interpreting human psychological states, emotions, and communication. Human faces are abundant in nonverbal clues that reveal a person's emotions and responses. In order to methodically examine facial features, movements, and expressions, the area of facial expression analysis makes use of developments in computer vision and image processing. This technology opens the door for applications in a variety of fields, including lie detection, mental health diagnostics, and human-computer interaction, by making it possible to identify subtle emotional variations. This introduction encourages investigation into the intriguing field of facial expression analysis, which promises a deeper comprehension of the intricate relationship between human psyche and facial expressions by deciphering the complexities of human emotion through the prism of advanced technological innovation.

Physiological Signals

The human body's complex processes send out physiological signals, which are silent messengers that provide a multitude of information regarding internal states and physiological reactions. These signals, which include electroencephalogram (EEG) data, skin conductance, and heart rate, provide a direct line of communication for comprehending how the body reacts to different stimuli. Technology and biomedical apparatus advancements have made it possible to monitor and analyze these physiological signals in real time, opening up possibilities for applications in stress assessment, healthcare, and lie detection. Physiological signal analysis offers a window into emotional and cognitive states by capturing the minute variations in body functions. This information is useful for medical diagnoses as well as the emerging field of affective computing. This introduction lays the groundwork for a more thorough examination of the intriguing field of physiological signal analysis, where the body's own language can provide priceless insights into human feelings and wellbeing.

Myocardial Infarction

Heart attacks, sometimes referred to as myocardial infarction, are a serious and potentially fatal cardiovascular event that can have a significant impact on world health. It happens when a blood clot blocks blood flow to a portion of the heart muscle, depriving the muscle of oxygen and essential nutrients. Heart tissue may sustain irreparable damage as a result of this blood flow disruption. A myocardial infarction is a serious medical emergency that requires immediate treatment to reduce long-term effects and avoid death. Because of the condition's frequent correlation with risk factors like smoking, high blood pressure, and high cholesterol, public health campaigns and preventative measures are crucial. Understanding the processes, risk factors, and prompt response to myocardial infarction—a major cause of morbidity and mortality globally—is essential for promoting medical research, enhancing patient outcomes, and developing all-encompassing cardiovascular health programs.

II. LITERATURE REVIEW

Glyn Lawson et al [1] have studied the mechanisms that reveal behavioral signs to deceit. Previous studies have shown that there is not a single, trustworthy indicator of dishonest behavior. Emotion, cognitive effort, and attempted behavioral control are three interrelated processes that liars may encounter. These processes might cause verbal, nonverbal, or physiological reactions that are different from those of truth-tellers. Their study sought to examine non-verbal behavior, whereas other papers concentrate on speech of deception.

Anne Rita Bentivoglio [2] et al have made a study with 150 healthy participants (70 men and 80 females; ages 35.9 to 17.9 years, range 5-87 years) who had their normal blink rate (BR) fluctuations and assessed various behavioral tasks. Their research revealed three typical behavioral BR patterns and demonstrated that cognitive processes have a greater impact on BR than age, eye color, or regional factors. Their study's results also offer a standard reference for BR analysis in movement disorders like tics or dystonia.

A method for detecting eye blinks in a real-time video series captured by an automobile dashboard camera is presented in a research paper published by Christine Dewi et al [3]. The proposed method extracts the vertical distance between the eyelids from the facial landmark positions after determining the facial landmark positions for every video frame. Their proposed algorithm determines the eye closeness in each frame, estimates the positions of facial landmarks, and uses the Eye Aspect Ratio (EAR) to extract a single scalar quantity. According to their study, blinks can ultimately be identified by using the modified EAR threshold value in combination with a pattern of EAR values in a comparatively short amount of time.

Nguyen et al [4] suggested a mask-type sensor that uses a single sensing element for simultaneous pulse wave, respiration, and eye blink detection.

The sensing element in the suggested sensor was a flexible air bag-shaped chamber whose internal pressure change could be detected by a piezoresistive cantilever based on a microelectromechanical system.

A piezoresistive cantilever based on a microelectromechanical system was used to detect changes in the internal pressure of a flexible air bag-shaped chamber, which served as the sensing element in the proposed sensor.

Ayudhya et al [5] in their paper presented a method based on image processing techniques for detecting human eye blinks and generating inter-eye-blink intervals. They have applied Haar Cascade Classifier and Camshift algorithms for face tracking and consequently getting facial axis information.

Using the relationship between the eyes and the facial axis for eye placement, they have also implemented an Adaptive Haar Cascade Classifier from a cascade of boosted classifiers based on Haar-like features. With a newly proposed algorithm "the eyelid's state detecting (ESD) value." for eye blinking detection they were able to examine the open and close states of eyelids. Their new algorithm provides a 99.6% overall accuracy detection for eye blink detection.

III.EXISTING SYSTEM

There are several ways to identify different human behaviors using eye blink patterns. This study suggests using image processing techniques to identify lies and determine whether an alibi is true. The eye blink literature supports the scientifically validated theory that liars have greater cognitive demands than truth-tellers, which forms the basis of the lie detection process. As a result, when they tell a falsehood, their eye blinks significantly reduce, and then they increase as soon as the cognitive load stops. With the aid of MATLAB and the HAAR Cascade algorithm, blink detection is accomplished. Applying the skin detection algorithm to the histogram back projections of the identified eye pictures allow for the determination of whether the eyes are open or closed.

IV.PROPOSED SYSTEM

By concentrating on physiological indicators associated with myocardial infarction (MI), the suggested system presents a novel paradigm for lie detection. Using a collection of electro cardiogram (ECG) signals, the system records characteristics such heart rate variability, QT interval, and ST-segment abnormalities. The method uses Naive Bayes (NB) and Support Vector Machines (SVM) classifiers to identify small physiological changes linked to dishonest behavior. This strategy presents a viable way to improve the precision and dependability of lie detection techniques by fusing machine learning algorithms with cardiovascular health markers. Additionally, by stressing controlled studies and the cautious management of delicate physiological data, the suggested system gives ethical considerations first priority. A key component of the system that guarantees its feasibility in practical applications is rigorous validation and adherence to ethical norms. This system adds to the continuing discussion about the relationship between physiological signals, machine learning, and the complex understanding of dishonest behavior as technology develops.[6]

A. Load Dataset

Importing and integrating the physiological data into the lie detection system is the responsibility of the Load Dataset Module. This information, which mostly consists of electrocardiogram (ECG) signals, comes from carefully monitored studies in which subjects are put in situations involving both telling the truth and lying.

B. Data Pre-Processing

The Data Pre-processing Module is activated when the dataset has been loaded. Cleaning and getting the data ready for analysis is the main goal of this module. It entails dealing with missing values, data normalization, and any noise or artefacts in the physiological signals.

C. Feature Extraction

From the pre-processed data, the Feature Extraction Module extracts pertinent features. This entails determining and measuring particular physiological markers connected to stress reactions and myocardial infarction. Measures of heart rate variability, QT interval, and ST-segment deviations are important characteristics.

D. Lie Detection Using Svm

Utilizing Support Vector Machines (SVM) as a machine learning classifier is the Lie Detection using SVM Module. Through training on the retrieved features, the SVM algorithm gains the ability to differentiate between patterns linked to dishonest and genuine actions. Predicting the misleading nature of the physiological data requires the use of this module.

E. Lie Detection Using Nb

Similarly, the Naive Bayes (NB) classifier is used for lie detection in the Lie Detection using NB Module. This module is in charge of using probabilistic reasoning to analyze the physiological data's attributes and offer a different method of spotting dishonest behavior.

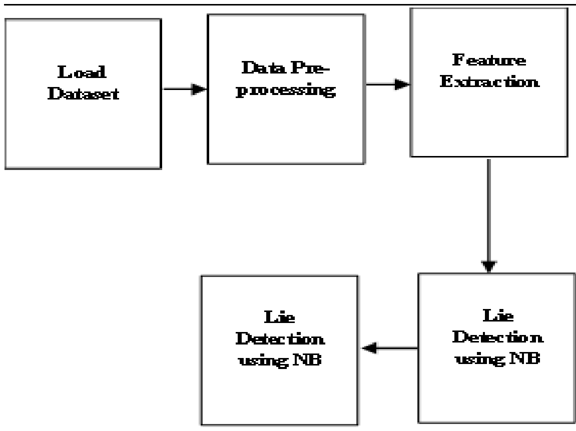

Figure.1 System Flow Diagram
Algorithm Details

Using physiological data, the system combines two machine learning techniques, Naive Bayes (NB) and Support Vector Machines (SVM), to identify dishonest behavior. Its capacity to detect intricate patterns in high-dimensional data makes the SVM method, a supervised learning model, useful. Using kernel functions to manage non-linear interactions between characteristics, it builds a hyperplane in a multidimensional space to distinguish between examples that are true and those that are dishonest. By using variables like heart rate variability, QT interval, and ST-segment abnormalities during training, the model is able to accurately identify dishonest behaviors. Because of its ease of use and effectiveness in probabilistic classification, the Naive Bayes method is sometimes used in parallel. Based on prior probabilities, it determines the probability that a physiological response is truthful or dishonest by assuming conditional independence between features. In order to classify data points appropriately, this method evaluates the same extracted features and assigns probabilities. SVM and NB work in tandem to provide a complimentary system that improves the overall accuracy and dependability of the lie detection framework. SVM is particularly good at identifying complex data patterns, while NB offers a probabilistic viewpoint.

V. RESULT ANALYSIS

The lie detection system yielded positive results with outstanding F1 score, recall, accuracy, and precision. It accomplished this by merging Naive Bayes (NB) and Support Vector Machines (SVM) classifiers on features gathered from physiological data pertinent to myocardial infarction. These findings suggest that the system effectively distinguishes between states of truth and deceit. SVM and NB classifiers allow for a detailed analysis of physiological traits associated with dishonest behavior. However, it is critical to acknowledge challenges such as individual variances and ethical concerns with lie detection technology. The system's useful uses depend on resolving these problems, safeguarding privacy, and promoting candid conversation. The findings indicate that it is possible to employ markers linked to myocardial infarction for lie detection; nevertheless, in order to apply such systems in practical settings, additional research and ethical considerations are required.

Table 1. Comparison table

algorithm	accuracy
HAAR Cascade	75
SVM and NB	88

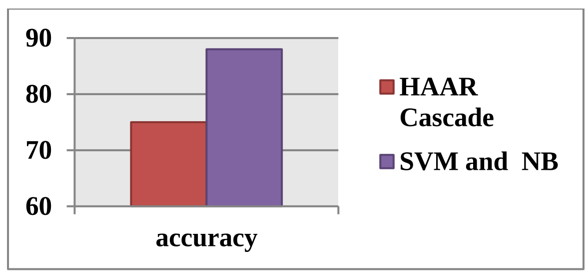

Figure 2. Comparison graph

VI. CONCUSION

The suggested lie detection system, which employs Support Vector Machines (SVM) and Naive Bayes (NB) classifiers on characteristics taken from physiological data related to myocardial infarction, shows promise in precisely differentiating between truthful and dishonest states. Although the system's effectiveness is confirmed by the strong performance measures, it is imperative to acknowledge issues like individual variability and ethical implications. Resolving these issues, protecting privacy, and encouraging open communication are essential to the system's successful implementation. Even though the results show potential in using markers linked to myocardial infarction for lie detection, proper integration of such systems into real-world situations requires more study and careful evaluation of ethical considerations.

VII. FUTURE WORK

Future research in this area should concentrate on improving the lie detection system by using more sophisticated machine learning algorithms and investigating other physiological signals. Enhancing the dataset's generalizability would involve looking at how contextual elements affect the system's performance and broadening its scope to include a variety of people and situations. Furthermore, the wider adoption and responsible use of such technologies will depend on resolving privacy and ethical concerns by putting strong safeguards in place and abiding by accepted ethical standards. Furthermore, taking into account real-time applications and creating an interface that is easier to use would help make the lie detection system more accessible and useful in a variety of contexts.

REFERENCES

[1]. Lawson, G., Stedmon, A., Zhang, C., Eubanks, D., Frumkin, L. (2011). Deception and Self-awareness. In: Harris, D. (eds) Engineering Psychology and Cognitive Ergonomics. EPCE 2011. Lecture Notes in Computer Science(), vol 6781. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-21741-8_44

[2]. Bentivoglio AR, Bressman SB, Cassetta E, Carretta D, Tonali P, Albanese A. Analysis of blink rate patterns in normal subjects. Mov Disord. 12(1997)1028-34. doi: 10.1002/mds.870120629. PMID: 9399231.

[3]. Dewi, C.; Chen, R.-C.; Chang, C.-W.; Wu, S.-H.; Jiang, X.; Yu, H. Eye Aspect Ratio for Real-Time Drowsiness Detection to Improve Driver Safety. *Electronics* 11(**2022)**3183. https://doi.org/10.3390/electronics11193183

[4]. Nguyen TV, Ichiki M. Mask-Type Sensor for Pulse Wave and Respiration Measurements and Eye Blink Detection. Sensors (Basel). 21(2021):4895. doi: 10.3390/s21144895.

[5]. Chinnawat Devahasdin Na Ayudhya, Thitiwan Srinark, "A Method for Real-Time Eye Blink Detection and Its Application",
IEEE Computer Society Conf. on Computer Vision and Pattern Recognition (CVPR).

[6]. Wu, CH., Tzeng, YL. & Huang, Y.M. Understanding the relationship between physiological signals and digital game-based learning outcome. *J. Comput.-Educ.* **1**(2014)81-97. https://doi.org/10.1007/s40692-014-0006-x