

Lie Detection System using Multimodal Biometric Analysis

Gargi Phadke*, Aditi Chhabria, Reshma Gulwani, Yogita Mistry, Shivangi Agarwal, Ritika Thusoo, Siuli Das

Ramrao Adik Institute of Technology, DY Patil Deemed to be University Nerul Navi Mumbai, India, Country

E-mail: gargi.phadke@rait.ac.in, aditi.chhabria@rait.ac.in, reshma.gulwani@rait.ac.in, yogita.mistry@rait.ac.in,

shivangi.agarwal@rait.ac.in, siuli.das@rait.ac.in, ritika.thusoo@rait.ac.in

ARTICLE INFO

Received: 29 Dec 2024

Revised: 17 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

Polygraphs and other conventional lie detection techniques have come under fire for their inaccurate results, which are attributed to individual physiological variations and anxiety. To deal with these restrictions, the innovative method known as multimodal biometric analysis was proposed. This cutting-edge technique combines physiological and behavioral indicators, such as skin conductance, facial expressions, and eye movements, to identify dishonesty. The system analyses many data streams at once in an effort to spot tiny patterns linked to lying, such altered facial expressions or an increased blink rate. Human communication relies heavily on emotions, and nonverbal clues like facial expressions have a big influence on how people connect with one another. These discoveries have been integrated into computer vision and other emotion identification technologies. Combining sentiment analysis with emotion detection Physical characteristics are also utilized to identify lies. Heart rate and skin resistance changes are used as another type of signals in proposed method. This paper explores the potential of such technologies to enhance investigative practices. It is verified by visual and graphical methods using different conditions. The proposed method also uses changes in skin resistance and heart rate as signals. The potential of these technologies to improve investigative techniques is examined in this research. It is confirmed using graphical and visual techniques under various circumstances.

Keywords: Computer vision, media pipe, Arduino controller, pulse sensor, Galvanic Skin Response (GSR) Sensor.

INTRODUCTION

Detecting lies with reliability and accuracy has been a challenging task across various fields, including criminal investigations and security screenings. Traditional methods, such as polygraphs, have been subject to criticism for their limitations. Often, inaccurate results are produced due to anxiety or inherent physiological variations between individuals. To overcome these shortcomings, researchers are exploring a new frontier in lie detection known as multimodal biometric analysis. This innovative approach promises a more comprehensive and nuanced understanding of deception by analyzing a combination of behavioral and physiological cues exhibited by a person [1, 2, 14, 15]. Facial expression emotion recognition is an intuitive reflection of a person's mental state, which contains rich emotional information, and is one of the most important forms of interpersonal communication [11]. Facial emotion recognition uses Computer Vision technology to decipher facial patterns to recognize emotions from a video input source, such as a camera on the device, or any connected external Camera [12, 13]. Different sensors are used to collect the physical data are used in this paper

LITERATURE SURVEY

Insaf Ajili et al., [1] Human motions and emotions recognition inspired by lma qualities. In [2], E. P. Bareeda [2] proposed speech processing technique for Lie detection. Zhao et al. [3] explored a new approach to lie detection systems, in this system, investigation into the potential of using eye blinks, measured through electroencephalography (EEG), as a tool for lie detection. EEG measures electrical activity in the brain, and traditionally, polygraphs haven't focused on eye blinks and this paper likely explores the physiological basis for this connection. In the paper [4] Tran-Le et al. explored the possibility of using facial expressions for lie detection in real-

time, their study investigates an automated approach that could potentially be faster than traditional methods. In the paper [5] J. Immanuel et al. investigated into the potential of using eye blinks, measured through electroencephalography (EEG), as a tool for lie detection, these study has the potential to offer new insights into the detection of deception and improve our understanding of the human brain.

E.P.F. Bareeda et al., [6] proposed speech patterns for deception detection. The traditional methods of lie detection such as polygraphs rely on physiological measures, whereas this paper investigates the possibility of using speech processing techniques to identify deception. N. Rodriguez-Diaz, et al. [7] explored a novel approach to lie detection using machine learning. The machine learning model was able to identify patterns associated with lying within the game. F. M. Talaat et al [8] delved into a cutting-edge technique for detecting lies that emphasizes the importance of explaining its reasoning.

S. A. Prome et al. [9] presented a critical analysis of the current state of using Machine Learning (ML) and Deep Learning (DL) techniques for deception detection. The review examines various approaches used for lie detection, and it is likely to explore techniques that analyze different data sources, such as speech patterns, facial expressions, and even text. X. Li et al., [10] explores a novel approach to polygraph technology. The study focuses on the ballistocardiogram (BCG) signal, a signal that is not commonly measured in traditional polygraphs, as a potential tool for deception detection. Erlina et al., [16] proposed the A Microcontroller-based Lie Detection System Leveraging Physiological Signals.

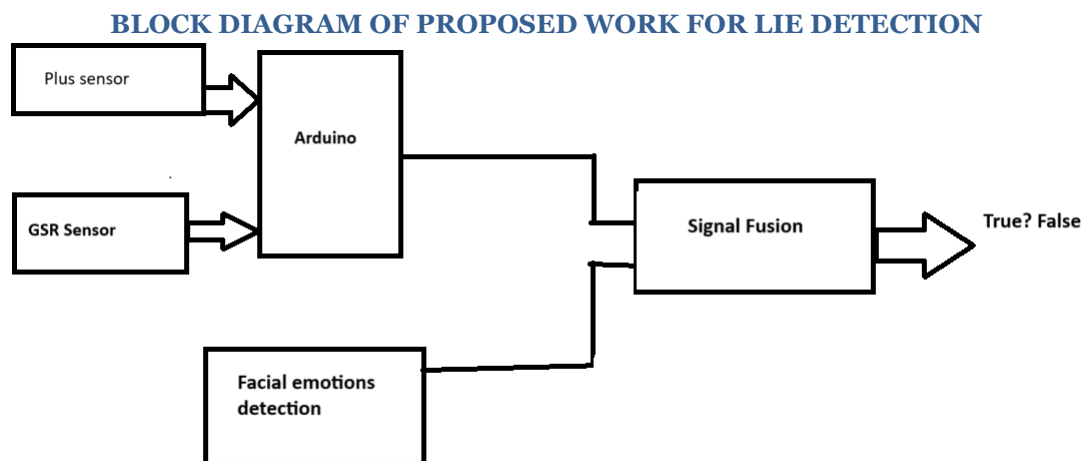


Fig 1. Block Diagram of Propose system for Multi modal Lie Detection

Figure 1 shows block diagram of proposed method. With Proposed system, the aim is to make the system easier to set up and ready for use as quickly as possible. Two different signals are used for lie detection. To achieve same, utilizing a live camera feed and computer vision system to record facial data. Another Signal employ two sensors, namely Pulse sensors, to record heart rate data, which will then be used to detect any changes in heart rate when the suspect is answering questions. Alongside the pulse sensor, we will also utilize a Galvanic Skin Response Sensor to record skin conductivity and any changes due to increased sweat gland activity, indicating nervousness and potential untruthfulness. Next section, gives all signal processing in details.

MULTI MODAL SIGNAL ACQUISITION AND PROCESSING

Figure 2 shows detail processing all different signal. First Signal Visual Signal acquisition and processing and another signals from sensor acquisition.

1. Visual Signal Processing

In this section visual signal acquisition and processing are examined. Computer vision tools are used for processing. Through the integration of advanced algorithms, machine learning models, and image processing techniques, computer vision systems can analyze and extract meaningful insights from images and video streams.

Computer vision tools such as Mediapipe, OpenCV, and FER are utilized. For Facial data, Multiple computer technologies like Mediapipe, OpenCV, mss (Multi Screen Shot), FER (Facial Emotion Recognition) along with computational and mathematical techniques are used.

2. Body Signal Processing

Figure 3 shows hardware inference of sensors with arduino. Details of hardware components are given below.

- **Arduino:** Arduino is an open-source electronics platform based on easy-to-use hardware and software. It consists of a microcontroller board (in our case Arduino Uno) and a development environment for writing, compiling, and uploading code to the board. Arduino boards are widely used for prototyping and building interactive electronic projects due to their simplicity and versatility. The Arduino serves as the central control unit for interfacing with sensors and processing data [18]. The two sensors used are the Pulse sensor for heart rate monitoring and the Galvanic Skin Response (GSR) sensor for detecting changes in skin conductance. These sensors are connected to the Arduino board, typically via analog or digital pins, depending on the sensor type and interface, let us look into these sensors further. In proposed work two types of sensors with Arduino: the Pulse sensor for measuring heart rate and the Galvanic Skin Response (GSR) sensor for detecting changes in skin conductance.

- **Pulse Sensor:** The Pulse sensor is a Photoplethysmography (PPG) sensor. It typically consists of an infrared LED and a photo detector placed on a fingertip or earlobe. The sensor measures changes in blood volume by illuminating the skin with infrared light and detecting the amount of light absorbed or reflected by the blood vessels. The Pulse sensor provides realtime data on heart rate, which is a crucial physiological parameter for assessing truthfulness. Changes in heart rate, such as increases or decreases, can indicate emotional arousal or stress, which may correlate with deceptive behavior [17].

- **Galvanic Skin Response(GSR) Sensor:** The GSR sensor [19] measures the electrical conductance of the skin, also known as skin conductance or skin resistance. Changes in emotional arousal or stress cause variations in skin conductance due to changes in sweat gland activity. The sensor detects these changes in skin conductance. GSR provides insights into the subject's emotional state, arousal level, or stress response. Significant changes in GSR may indicate psychological arousal associated with deception, making it a valuable indicator for truthfulness assessment.

2.1 Data Preprocessing and Feature Extraction

Data Acquisition means Reading Sensor Values. The analog inputs ('PULSE INPUT' for the heart rate sensor and 'GSR INPUT' for the GSR sensor) are sampled to read the sensor values. These values represent the analog signals generated by the sensors in response to physiological changes [20].

- **Heart Rate Calculation:** The heart rate is calculated using inbuilt function. This function processes the raw pulse signal to detect heartbeats and compute the heart rate in beats per minute [20].

- **Data Filtering and Smoothing:** The raw sensor values and heart rate readings are filtered and smoothed using moving average and exponential smoothing techniques, respectively, as described earlier.

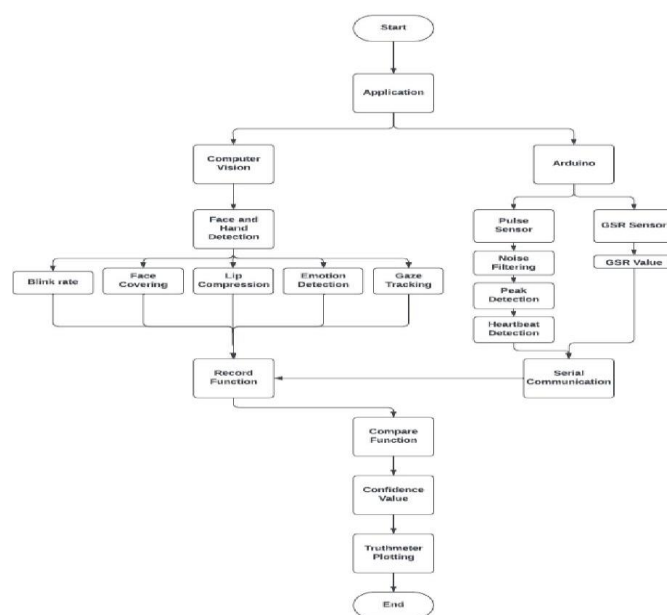


Fig 2. Process flow diagram for multimodal Signal Processing

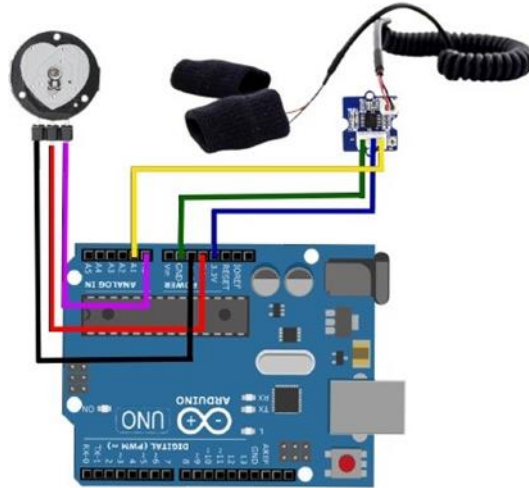


Fig 3. Hardware connection of Arduino with sensors

2.2 Data Transmission

The preprocessed sensor data, including the smoothed heart rate and raw GSR values, is transmitted over the serial port ('Serial') to an external device for further analysis or visualization. The data is sent as comma-separated values (CSV) to facilitate parsing and processing on the receiving end. By implementing these preprocessing steps, the Arduino code ensures that the sensor data is cleaned, filtered, and smoothed to minimize noise and artifacts, enabling more accurate interpretation and analysis of physiological signals such as heart rate and galvanic skin response [17].

2.3 Data Aggregation

Combining data from physiological measurements taken by sensors with information from visual observations is data aggregation. Visual observation is known as computer vision. Visual data and sensor data integration gives a more thorough comprehension of human behaviour and reactions. By identifying both overt and covert indicators of dishonesty or truthfulness, this integration improves the capabilities of lie detection systems.

- **Synchronization:** Data from both the computer vision system and the sensors are synchronized in time to ensure that observations correspond to the same temporal context. This synchronization facilitates accurate correlation between visual cues and physiological responses.
- **Alignment:** To guarantee that observations relate to the same temporal context, data from the sensors and the computer vision system are time-synchronized. Accurate connection between physiological reactions and visual signals is made possible by this synchronization. [9]. After Signal acquisition important features are used for further processing.

Table 1. Arduino Signal base Decision making Approach

| Pluse change | GSR Change | Result |
|--------------|------------|--------|
| F | F | Truth |
| F | T | LIE |
| T | F | LIE |
| T | T | LIE |

Table 2. Computer Vision Base Decision Making Approach

| Change in Blink Rate | Change in Gaze Direction | Face covering | Lip compression | Result |
|----------------------|--------------------------|---------------|-----------------|--------|
| F | F | F | F | TRUTH |
| F | F | F | T | TRUTH |
| F | F | T | F | LIE |
| F | T | F | F | TRUTH |

| | | | | |
|---|---|---|---|-------|
| F | T | T | T | LIE |
| T | F | F | F | TRUTH |
| T | F | F | T | LIE |
| T | F | T | T | LIE |
| T | T | F | F | LIE |
| T | T | F | T | LIE |
| T | T | T | F | LIE |
| T | T | T | T | LIE |

3. Feature Extraction

Different types of signals are used for processing. • Multi-modal Features representing both visual and physiological aspects of human behavior are extracted from the integrated data. These features may include facial expressions, hand gestures, heart rate variability, and skin conductance levels. Techniques such as principal component analysis (PCA) are applied to reduce the dimensionality of the feature space while preserving relevant information. This step enhances computational efficiency and reduces the risk of overfitting [2].

4. Contextual Analysis

Visual observations and sensor data are analyzed jointly to identify congruent or conflicting cues. For example, discrepancies between facial expressions and physiological responses may indicate deceptive behavior. The temporal dynamics of visual and physiological signals are analyzed to detect changes over time and assess their significance about specific events or stimuli [3].

5. Real-time Processing

Integration algorithms are designed to operate in real time, leveraging optimized processing techniques and parallelization to handle the computational demands of concurrent data streams. Low-latency Feedback in Real-time feedback generated from integrated data enables timely responses and interventions in interactive applications, such as deception detection during interviews or interrogations. Combining computer vision with sensor data enhances the effectiveness, reliability, and interpretive capabilities of lie detection systems. This integration enables more precise evaluations of human behavior and honesty, leading to improved outcomes in security, law enforcement, and human-computer interaction contexts. Understanding human intentions and truthfulness becomes an more crucial with this integrated approach, opening doors to advanced applications in various domains. Table 1 and 2 describe the decision making approach of the application, Here few defined changes in values recorded by either True (T) or False (F), Here for analysis, the approach in case of boolean values such as Face covering and Lip compression.

RESULTS AND DISCUSSION

The lie detection proposed system leverages computer vision techniques like facial landmark detection, blink rate analysis, gaze tracking, and lip compression analysis, along with physiological data from an Arduino-based heart rate and galvanic skin response (GSR) sensor [19]. The fusion of these multimodal data sources through synchronization, interpolation, and a weighted scoring mechanism achieved an overall accuracy of 82 percent in distinguishing truthful and deceptive responses across a diverse set of 13 participants. Notably, the system exhibited high precision in detecting deception cues from heart rate changes, underscoring the significance of integrating Arduino biometric data.

While blink rate and gaze shift cues contributed moderately, lip compression analysis had a lower impact on the final deception score. The system's performance highlights the potential of multimodal lie detection, paving the way for further exploration of advanced machine learning techniques and additional modalities to enhance accuracy and real-world applicability [12].

In the graph output of the heart rate and GSR sensor, we observe stable values without significant fluctuations even after asking the question. This indicates the absence of detected nervousness or changes in emotion, as no notable physiological responses are recorded. In this scenario, the heart rate calming down from previous question being asked, hence representing calmness or reduced nervousness from being asked a new question and hence decreasing

the Lie meter. In this the figures both the heart rate and GSR fluctuating rapidly, meaning after calming down it climbed and lie meter can used for visualization of system output. Figure 4 shows when the person is neutral.

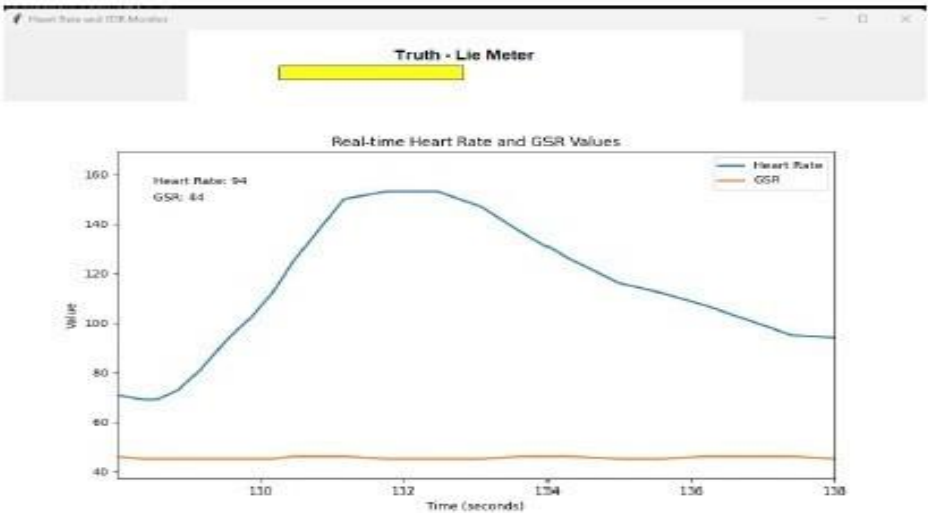


Fig 4. Result: Graphical output of proposed method when condition is neutral

The the lie meter bar is at neutral position. Peak at middle condition. Figure 5 shows when the person is true. The the lie meter bar is at 100 percent, true position. Signal are represented by flat line. Figure 6 shows when the person is true. The the lie meter bar is at 100 percent, true position. Signal are represented by flat line.

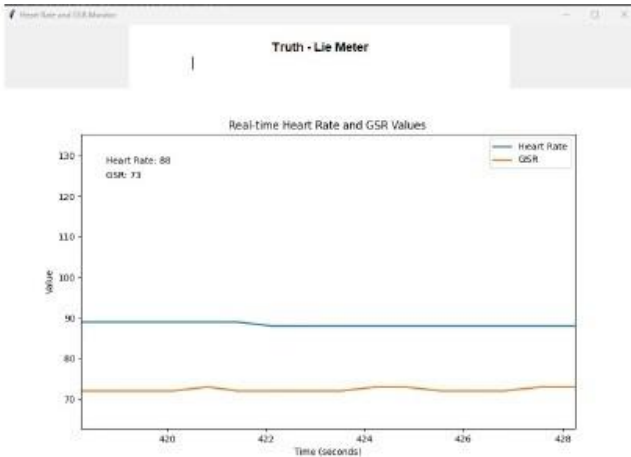


Fig 5. Result: Graphical output of proposed method when condition is true

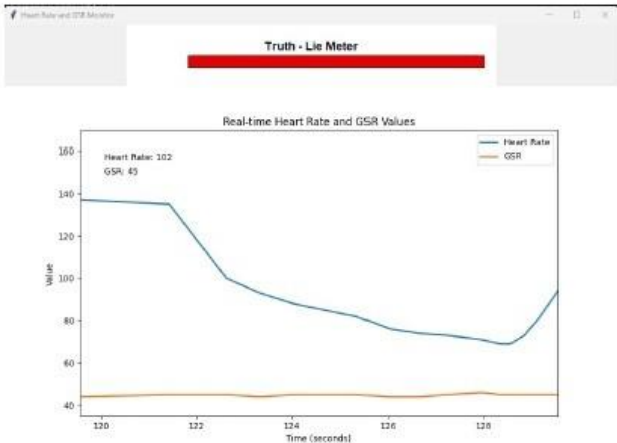


Fig 6. Result: Graphical output of proposed method when condition is lie

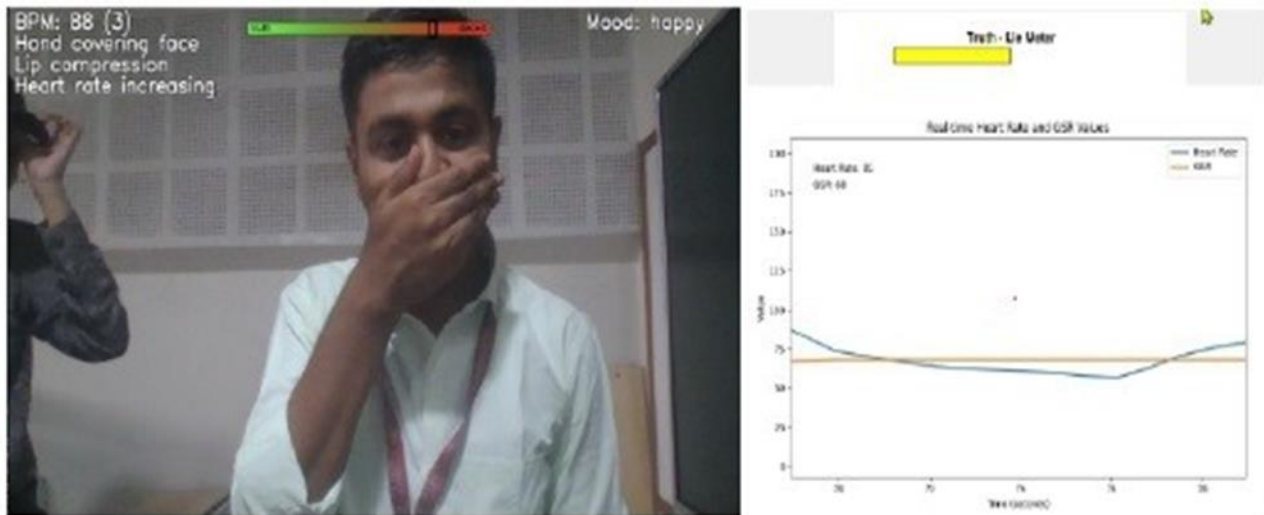


Fig 7. Result: Person is shocked as detected as neutral statement

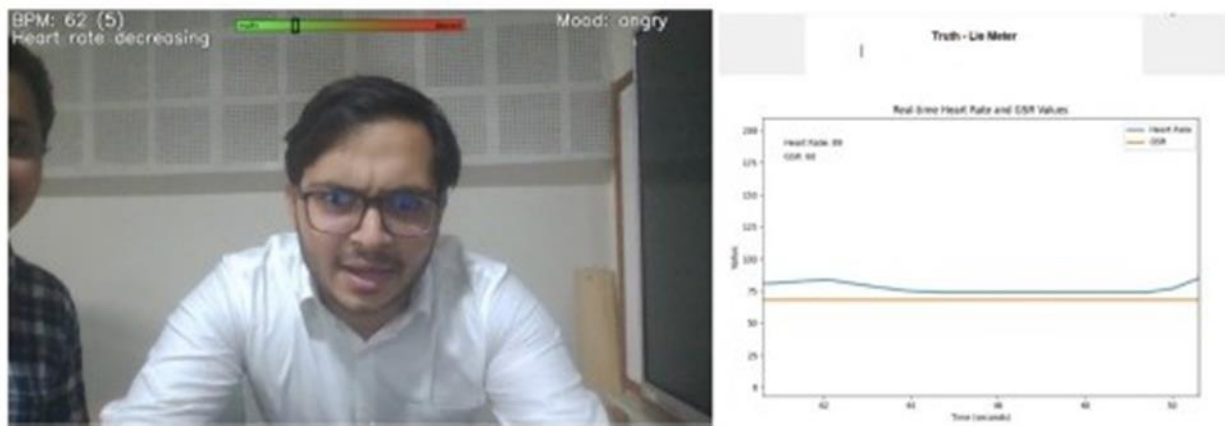


Fig 8. Result: Person is Angry but truth statement



Fig 9. Result: person statement was lie with its activity and expressions

Different conditions are considered to verify the proposed system, Camera output also shown in the figures. In figure 7 the person condition is Neutral, being shocked after displaying a lot of signs of nervousness and lying, those being Face covering, change in gaze direction, increase in heart rate and the Galvanic skin Resistance. In the figure Skin resistance variation also displayed. Fig 8 shows the Arduino data taking dictating the truthfulness, even if the emotion being displayed can be considered negative, since there is no significant change in heart rate or GSR values we can

conclude that the participant is saying the truth. Fig 9 shows the person statement was lie. Deceit level going up as we can see the indications of nervousness although it can be very helpful in determining the truthfulness, it is also highly complex and it will prove to be more beneficial to use quantifiable data rather than arbitrary ones. In this section different signals lie detections are explained using different conditions.

CONCLUSION

In this paper, Multi modal Lie detection system is proposed over traditional methods. The multimodal biometric analysis, which combines data from various physiological and behavioral sources. It presents a promising direction for advancements in lie detection. This approach leverages the strengths of different modalities. Physiological data like heart rate, Skin resistance and Additionally, facial expression analysis, while requiring consideration of cultural variations, can provide valuable information when integrated with other data sources. The proposed method more holistic approach to lie detection. Predicting algorithms can analyze the vast data collected through multimodal analysis and identify complex patterns that can potentially lead to improved accuracy in lie detection compared to traditional methods.

REFERENCES

- [1] Insaf Ajili, Malik Mallem, and Jean-Yves Didier. Human motions and emotions recognition inspired by lma qualities. *The Visual Computer*, 35(10):1411–1426, 2019.
- [2] E. P. F. Bareeda, B. S. S. Mohan, and K. V. A. Muneer. Lie detection using speech processing techniques. *Journal of Physics: Conference Series*,
- [3] X. Zhao, S. Liu, C. Ge, and W. Huang. Intelligent polygraph based on fusion of electrocardiogram and electroencephalogram sensors, *International Conference on Machine Learning, Control, and Robotics (MLCR)*, pages 153–157, 2022
- [4] M.-T. Tran-Le, A.-T. Doan, and T.-T. Dang. Lie detection by facial expressions in real time. In *2021 International Conference on Decision Aid Sciences and Application (DASA)*, pages 787–791.
- [5] J. Immanuel, A. Joshua, and S. T. George. A study on using blink parameters from EEG data for lie detection. In *2018 International Conference on Computer Communication and Informatics (ICCCI)*, pages 1–5, 2018.
- [6] E. P. F. Bareeda, B. S. S. Mohan, and K. V. A. Muneer. Lie detection using speech processing techniques. *Journal of Physics: Conference Series*, 1921:012028, 2021.
- [7] N. Rodriguez-Diaz, D. Aspandi, F. M. Sukno, and X. Binefa. Machine learning-based lie detector applied to a novel annotated game dataset. *Future Internet*, 14(1):2, 2022..
- [8] F. M. Talaat. Explainable enhanced recurrent neural network for lie detection using voice stress analysis. *Multimedia Tools and Applications*, 2023.
- [9] S. A. Prome, N. A. Ragavan, R. Islam, D. Asirvatham, and A. J. Jegathesan. Deception detection using ml and dl techniques: A systematic review. *Natural Language Processing Journal*, page 100057, 2024.
- [10] X. Li, C. Deng, Q. Wu, R. Cui, J. Tang, and Y. Zhang. Research on polygraph technology based on ballistocardiogram signal. In *2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*, 2020.
- [11] Roman Bednarik, Jani Koskinen, Hana Vrzakova, Piotr Bartczak, and Antti-Pekka Elomaa. Blink-based estimation of suturing task workload and expertise in microsurgery. In *Proceedings of the 31st IEEE International Symposium on Computer-Based Medical Systems (CBMS 2018)*, 2018.
- [12] Linlin Chao, Jianhua Tao, Minghao Yang, Ya Li, and Zhengqi Wen. Multi-scale temporal modeling for dimensional emotion recognition in video. In *Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge*, pages 11–18, 2014.
- [13] Samira Ebrahimi Kahou, Xavier Bouthillier, Pascal Lamblin, Caglar Gulcehre, Vincent Michalski, Kishore Konda, Sebastien Jean, Pierre Froumenty, Yann Dauphin, and Nicolas Boulanger-Lewandowski. Emonets: Multimodal deep learning approaches for emotion recognition in video. *Journal on Multimodal User Interfaces*, 10:99–111, 2016.
- [14] Jad Haddad, Olivier Lezoray, and Philippe Hamel. 3d-cnn for facial emotion recognition in videos. In *Advances in Visual Computing: 15th International Symposium, ISVC 2020, San Diego, CA, USA, October 5–7, 2020, Proceedings, Part II*, pages 298–309. Springer, 2020.

- [15] Andre Teixeira Lopes, Edilson De Aguiar, Alberto F. De Souza, and Thiago OliveiraSantos. Facial expression recog- nition with convolutional neural networks: coping with few data and the training sample order. *Pattern Recognition*, 61:610–628, 2017.
- [16] Erlina, Tati, Ferdian, Rian, Rizal, Alvin, Aisuwarya, Ratna. (2023). A Microcontroller-based Lie Detection System Leveraging Physiological Signals. 163-168. 10.1109/IoTaIS60147.2023.10346078.
- [17] <https://github.com/WorldFamousElectronics/PulseSensor>
- [18] <https://www.arduino.cc/en/software>
- [19] Yekta Said Cana, Bert Arnrichb "Cem ErsoyaStress detection in daily life scenarios using smart phones and wearable sensors: A survey", *Journal of Biomedical Informatics*,2019.
- [20] Manav Seth, Vanshika Patel, Ankit Mishra Measuring heart rate using the pulse sensor, *International Journal of Advance Research, Ideas and Innovations in Technology*,2021