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The use of artificial intelligence in interrogations: voluntary confession

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ABSTRACT

Interrogation is a crucial step in the investigation of criminal acts. Artificial intelligence has been used to increase the efficiency of interrogation. In this study, we developed a confession probability identification system to help investigators analyze the emotions of their interrogees while they are answering questions and determine the probability of them confessing. Based on these analysis results along with their own experience, investigators may adjust the content and direction of their interrogations to penetrate the interrogees' defenses. The proposed system uses OpenFace and FaceReader to capture data and incorporates the multi-grained cascade forest (gcForest) and long short-term memory (LSTM) algorithms for deep learning. Our results indicated that the recognition accuracy of the gcForest algorithm exceeded that of the LSTM algorithm, which is consistent with the fact that the gcForest algorithm is more suitable for smaller sample sizes. In addition, heart-rate-based assessment may lead to erroneous determination of whether an interrogatee is telling the truth or lies because their heart rate may increase as a result of emotional responses.

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1. INTRODUCTION

During a case investigation, the law enforcement agency notifies relevant individuals to appear for interrogation to clarify certain details and collect relevant evidence. Through this interrogation process, the truth of the incident can be clarified by the interrogees, and further information and leads can be gleaned from their statements. However, even though the interrogees are not necessarily the perpetrators, they may conceal the truth for certain reasons, especially if they are the actual perpetrators. In this case, the interrogators must rely on their past experience, observe and make judgments depending on the tone and attitude of the interrogees, and, if necessary, conduct polygraph tests as a reference. However, polygraph testing requires professional personnel and the consent of the interrogee, which is time-consuming and may result in a missed opportunity to collect evidence. Additionally, some objections have been raised against the use of polygraph results in judicial trials. Consequently, law enforcement agencies no longer consider polygraph results as valid evidence in court.

Law enforcement agencies primarily focus on clarifying cases and obtaining evidence during investigations. Physical evidence, documentary evidence, and relevant individuals are interconnected. Investigators must utilize existing clues to reconstruct the incident. Many breakthroughs are achieved through the statements of the interrogees. Therefore, interrogating relevant individuals is essential to gather additional information about the case. In 2016, Keli [1] investigated the influence ratios (with vs. without influence) of 17 factors affecting a suspect's decision to confess voluntarily as shown in Table 1. They reported that the fear of being caught lying ranked fifth. However, when the situation in which the investigators have already obtained concrete evidence of crime was excluded, the same factor ranked fourth. These results suggest that if the lies of the interrogees can be immediately detected during the interrogation, then 75% of the interrogees are expected to tell the truth. Such voluntary confessions from the actual perpetrators greatly affect the investigation.

Table 1. Factors affecting the voluntary confession of a suspect

	Factor	Influence ratio	
		Yes	No
1	The investigators already had evidence of the crime, so resistance was meaningless.	17	3
2	Others involved in the case have already confessed, so I did to.	12	8
3	I confessed to receive a lenient punishment.	18	2
4	I must take responsibility for my own actions.	9	11
5	I was caught lying, so I had to tell the truth.	15	5
6	I felt that it is better to confess than to remain silent.	17	3
7	I confessed to thank the investigators for their assistance.	7	13
8	I confessed to leave this place (interrogation room) as soon as possible.	16	4
9	I felt a pressure to confess.	14	6
10	I told part of the truth and concealed other parts to cover up other crimes.	12	8
11	My actions will eventually be revealed, so it is better to confess early.	10	10
12	I confessed to show that I was willing to cooperate.	15	5
13	I do not know why I impulsively confessed.	4	16
14	I cannot conceal the truth, so I have no choice but to confess.	14	6
15	The investigators were kind to me, so I confessed.	6	14
16	I confessed to get released on bail sooner.	14	6
17	I confessed because I thought the investigation unit had evidence of my crime, which turned out to be untrue.	7	13

With the continuous advancement of technology, digital imaging systems and big data have found extensive applications in the field of artificial intelligence (AI) recognition. Numerous studies have focused on the applications of image recognition, including facial and speech recognition for Internet of things (IoT), virtual reality, medicine, and license plate recognition [2]–[11]. These applications have substantially expanded and enriched various aspects of life.

Emotion recognition is a popular area in facial image recognition that is extensively used in fields such as telecommunication, gaming, animation, psychiatry, automotive safety, and computer-based educational systems [12]. Initially, emotion recognition training relied on manual labeling. However, with the integration of systems and information technology, machine learning techniques have gained prominence, leading to the development of deep learning techniques [13], [14]. The advantage of deep learning lies in its ability to achieve training and verification with a small sample size within a short time [15].

In some countries, law enforcement agencies have incorporated facial recognition into the interrogation process to reduce racial and gender bias [16]. In this study, we used the digital cameras and computers that are already installed in interrogation rooms for protecting the rights of the interrogees to gather objective reference information for investigators by using a confession probability identification system. Our system is strategically integrated into preexisting cameras and computers, ensuring that it remains inconspicuous and minimally intrusive. This approach reduces the likelihood of arousing suspicion among the interrogees and facilitates the capturing of their genuine emotions without being detected.

Although polygraph testing and AI image recognition operate on distinctly different principles, they both involve predictions based on individual behavior. Therefore, to realize a more effective and legally sound interrogation method, we attempted to replace conventional polygraph testing with noncontact methods and provide real-time assistance during the investigation process by leveraging the computational and logical capabilities of deep learning algorithms. The rest of this paper is organized as follows. Section 2 introduces the research methods utilized, including how data were retrieved and how useful information was extracted for further analysis. Section 3 presents the results and discussion. Finally, section 4 outlines our conclusions.

2. METHOD

To find solutions, investigators must analyze the deceptive information gathered from the responses of the interrogees to elicit a confession. However, given the need to scrutinize a large amount of relevant information within a limited time frame, lowering the threshold for identification is crucial to avoid overlooking critical details in investigations. With the popularization of digital imaging systems, image recognition has witnessed substantial advancements through machine learning in AI. In addition, with the advent of advanced deep learning techniques, time-consuming manual labeling processes, and slow machine learning processes have been revolutionized into a new computational process [14], [17]. Deep learning can autonomously derive features and learn independently from only the raw data provided by the operators.

Conventional polygraph testing primarily relies on physiological responses, such as blood pressure, brainwaves, and heart rate, to determine whether the examinees are being truthful [11]. Noncontact polygraph testing incorporates parameters such as skin color to determine the examinee's blood pressure and heart rate; other parameters adopted include voiceprint, facial expressions, language patterns, and eye movements [11], [18], [19]. Unlike conventional polygraph testing, whose accuracy may be undermined when the examinee is nervous or adopts countermeasures, noncontact polygraph testing reduces the influence of said situations and has therefore become mainstream [20].

Since the introduction of the Facial Action Coding System in 1976, which enabled the identification of microexpressions [21], and the emergence of deep learning in AI, substantial advancements have been made in the field of noncontact polygraphy. Currently, various deep learning frameworks, such as deep neural networks (DNNs), convolutional neural networks, and recurrent neural networks (RNNs), are used in image recognition, speech recognition, and bioinformatics. In this study, we integrated microexpression recognition, photoplethysmography (PPG), and deep learning, namely multi-grained cascade forest (gcForest) and long short-term memory (LSTM), into a confession probability identification system to conduct real-time tests on the probability of lies and confessions. Figure 1 depicts the framework of the proposed system. Overall, the system enabled noncontact detection and prompt notification during interrogations, thereby facilitating immediate detection and presentation of results.

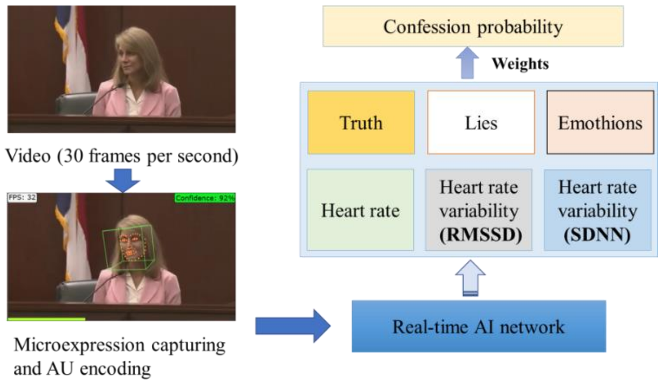

Figure 1. Process of the confession probability identification system

2.1. Microexpressions

Microexpressions are brief unconscious facial expressions that occur when an individual attempts to conceal certain emotions. The facial action coding system is a widely used protocol that identifies and labels facial expressions by describing the movement of facial muscles. It objectively measures the frequency and intensity of facial expressions and analyzes emotions. In this protocol, facial expressions are divided into action units (AUs), each of which displays changes in a certain facial characteristic (e.g., raised eyebrows, wrinkled nose). This protocol has been used in psychological research to address various research questions pertaining to socioemotional development, neuropsychiatric disorders, and deception. Through AI facial recognition and model learning techniques, AUs can be immediately labeled and used to penetrate the defenses of interrogees [22], [23].

2.2. Remote PPG

PPG is an optical technology used for measuring biomedical signals to analyze human skin at a low cost and interpret pulse information through skin reflectance variations due to changes in blood volume. Remote PPG is an advanced noncontact method for examining the skin surface of the face. When the face is properly illuminated, changes in blood volume due to pulse pressure can be detected, and the amount of reflected light can be measured. With reflectance mapped over time, each cardiac cycle is displayed as a peak. The data can then be converted into average heart rate and variability [24], [25].

2.3. Deep learning

Despite its wide use in various fields, emotion recognition remains an unresolved problem. Deep learning is a framework based on artificial neural networks. A deep learning algorithm is an algorithm that learns features from data. It mimics the functions of the human brain to represent complex data from real-world scenarios and to facilitate informed decision-making. Deep learning has been widely used in the field of computer vision, including in image classification and object detection. It has also been used in biometrics to represent unique biometric data and enhance the performance of many identity verification and recognition systems, thus increasing the accuracy of facial recognition.

DNNs are simply regarded as stacks of multiple layers of nonlinear functions. In situations where one wishes to eliminate manual determination of the nonlinear mapping relationship between two objects or where the relationship is difficult to determine, additional layers can be stacked to allow the machine to learn the relationship on its own, which is the original idea behind deep learning. Figure 2 shows the difference between a simple neural network and a DNN [26]. A simple neural network has a single hidden layer, whereas a DNN has two or more hidden layers.

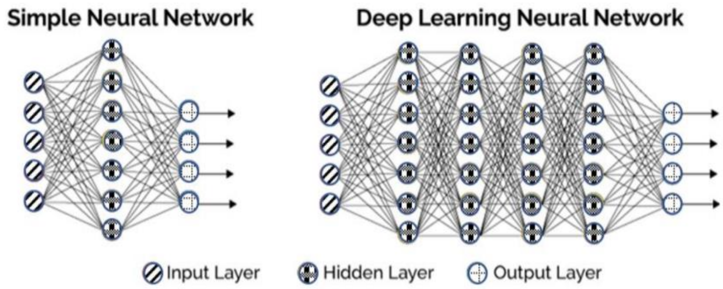

Figure 2. Difference between a simple neural network and a DNN

2.3.1. gcForest

Originally developed by Zhou and Feng [15], gcForest was established by stacking multiple layers of random forests in a cascading manner to achieve advanced feature representation and high learning performance. Unlike DNNs, gcForest requires a small volume of training data to achieve satisfactory performance. In addition, because it includes fewer hyperparameters, it does not require extensive tuning. It also incorporates adaptive tree-structured clustering, which reduces the need for a large number of computational resources and facilitates the training process [27]. The source code of gcForest is publicly available. The model is currently designed for labeled sequence data with a length of 80. Hence, gcForest can detect 20 microexpressions and 60 movements exhibited by interrogees each time they are questioned, with an output of either "Truth" or "Lie."

2.3.2. LSTM

LSTM is an RNN that was first introduced in 1997. It addresses the problems of long-term memory and vanishing or exploding gradients in RNNs [28]. As a nonlinear model, LSTM serves as a complex nonlinear unit for constructing larger DNNs. It has already been used in multiple fields [29]–[31].

In this study, three datasets were used for model training, namely the Real-Life Trial dataset [32], the Miami University Deception Detection Database [33], and the Bag-of-Lies dataset [34]. The Real-Life Trial dataset contains actual high-risk courtroom videos, whereas the Miami University Deception Detection Database and Bag-of-Lies dataset contain experiment low-risk videos filmed under laboratory conditions. The level of risk refers to the responsibility and potential consequences that interrogees may face as a result of lying. A high risk indicates that if an interrogee lies, they may face real-life consequences such as criminal charges and imprisonment.

The confession probability identification system was trained during the preprocessing stage. The videos in the datasets were split into frames at a rate of 30 frames per second. Subsequently, the datasets were divided at a ratio of 7:3, with 70% of the samples used for training and the remaining 30% used for testing the training results [35]. Facial landmark detection was then performed using a constrained local neural field model. The model provided more than 700 features, with 35 related to facial AUs. However, because the *p*-values of AU01_r, AU23_r, and AU17_C were below the required threshold, the three AUs that were presumed to lead to false judgments were excluded to increase the identification success rate [35].

3. RESULTS AND DISCUSSION

The purpose of an interrogation is to compel the interrogees to tell the truth or glean information from their statements to clarify a case or uncover leads. The key to solving many cases lies in the statements provided by the interrogees. Therefore, interrogation is an essential process for investigation units to reveal criminal facts. Although the interrogees are not necessarily the perpetrators, they may conceal the truth for certain reasons. However, lies can also serve as leads. In this study, we developed a confession probability identification system to help investigators detect lies immediately during an interrogation and penetrate the interrogees' defenses to elicit a confession.

Figure 3 shows the deep learning framework of the proposed system, which uses OpenFace to capture facial AU signals and FaceReader to detect heart rate variability through facial skin analysis. Deep learning algorithms, namely gcForest and LSTM, were used to estimate the probability of confession on the basis of weighted factors, such as truth, lies, emotions, heart rate, and heart rate variability (the root mean square of successive differences between normal heartbeats and the standard deviation of the interbeat intervals of normal sinus beats). An initial value of 100% indicates the highest level of credibility. As the interrogation proceeds, the credibility of an interrogee's statement may decrease to 0%.

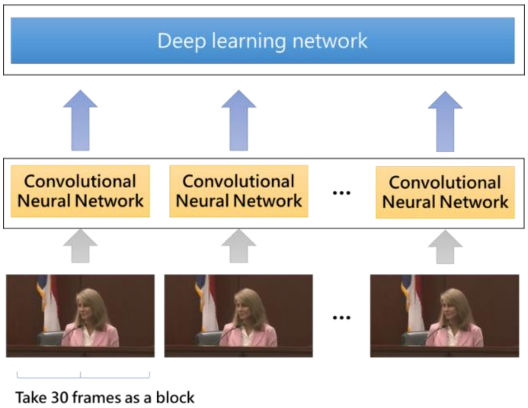

Figure 3. AI learning framework of the confession probability identification system

To differentiate between participants telling the truth and those telling lies, we conducted a pretest to observe the variations in heart rate and distribution of emotions. For this test, we used the Miami University Deception Detection Database [33] to determine the maximum heart rate of the participants both while telling the truth and while telling lies as shown in Figure 4. The results revealed an increase in heart rate when the participants told lies.

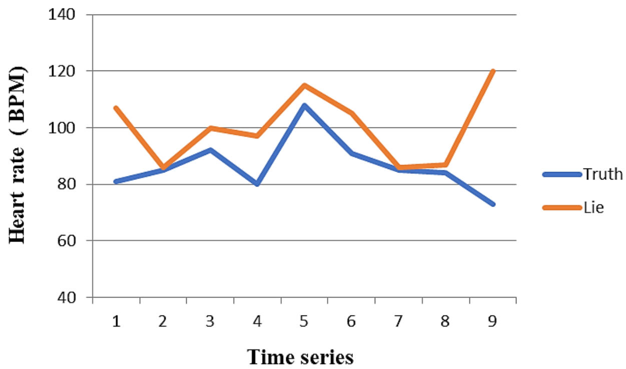

Figure 4. Maximum heart rates of the participants while telling the truth and while telling lies

We also used the Miami University Deception Detection Database [33] to investigate the distribution of emotions. After examining the maximum intensities of facial expressions as shown in Figure 5, we discovered that the participants exhibited more intense facial expressions associated with sadness, anger, and contempt when telling the truth, while when telling lies, their facial expressions associated with surprise and fear were more intense.

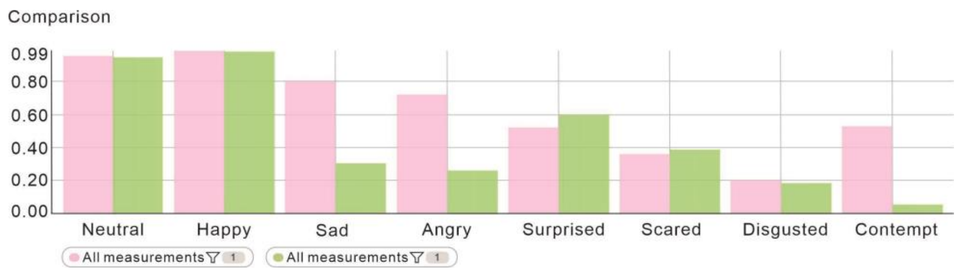

Figure 5. Maximum intensities of facial expressions: truth (pink) and lies (green)

After completing the microexpression recognition system, we used gcForest and LSTM to analyze the three datasets. Table 2 lists the recognition accuracies for the three datasets. Notably, the recognition accuracy of gcForest exceeded that of LSTM for the three datasets. These recognition results are consistent with the fact that the gcForest algorithm is more suitable than the LSTM algorithm for small sample sizes.

Table 2. Recognition accuracies of the three datasets

Algorithm	Real-Life Trial Dataset	Miami University Deception Detection Database	Bag-Of-Life Dataset
LSTM	84%	74%	63%
gcForest	95%	91%	88%

In this study, we used FaceReader to detect changes in facial skin color and thereby determine heart rate variability. Using FaceReader, we processed a large number of videos in batches and automatically generated charts through label classification. However, FaceReader required an authorized dongle for activation. In addition, complete (frontal) facial expression frameworks without hat or mask obstruction were required during the recognition process. Therefore, we selected five videos with complete facial expressions of people telling the truth and lies each for comparison and analyzed them against the heart rate and confession probability results. In other words, we compared the heart rate results obtained when FaceReader was activated versus when it was deactivated. The comparison results for truth and lie videos are presented in Figures 6 and 7, respectively.

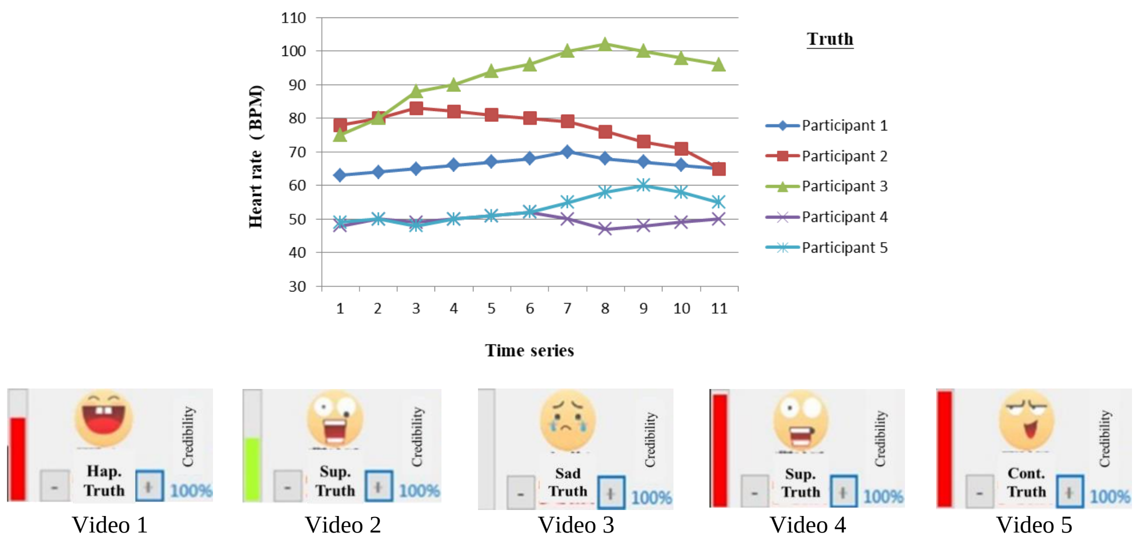

Figure 6. Comparison results for participants telling the truth

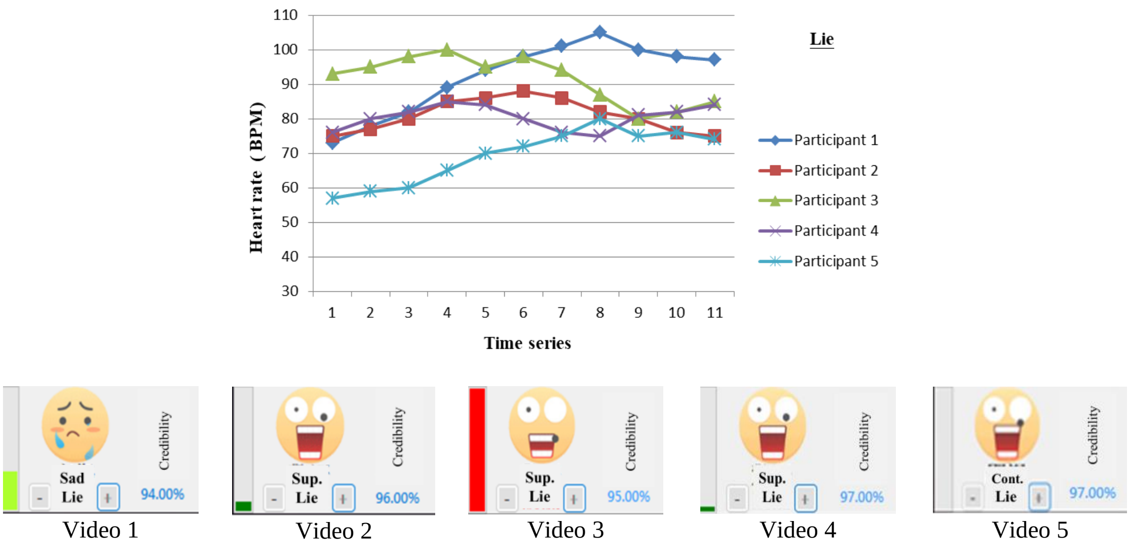

Figure 7. Comparison results for participants telling lies

The top portion of the chart depicts heart rate variability, whereas the bottom portion presents the recognition results of the system. The leftmost side of the chart represents the intensity of emotions, whereas the rightmost side represents the initial credibility level, set at 100%. Credibility changed with truthful and deceptive responses. It decreased when the interrogatee told a lie and increased when they told the truth. According to the comparison charts, the heart rate observed with truth responses ranged between 50 and 80 beats per minute (BPM), whereas that observed with lie responses ranged between 70 and 100 BPM. At some points, the heart rate ranges overlapped, but no distinct peaks were observed. In terms of heart rate changes associated with truth responses, Participant 3 exhibited a relatively elevated heart rate due to a sad emotional response. According to these detection results, no substantial heart rate changes were noted in the five videos. Furthermore, the elevated heart rates caused by participants' emotional responses hindered the determination of whether they were telling the truth or lies depending only on their heart rate.

4. CONCLUSION

In this study, we upgraded existing hardware and employed AI to develop a system that can provide interrogators with objective references to uncover the truth in interrogations. Given its ability to rapidly process big data, our system can aid in expediting investigations, thereby realizing the essence of judicial fairness. Our experimental results indicated that gcForest is more suitable than LSTM for small sample sizes. However, our datasets primarily contained short laboratory videos. In addition, other factors, such as the number of test samples and whether the participant was wearing makeup, may have influenced the training and recognition results. Therefore, further training with additional videos is required to increase the feature extraction accuracy of the proposed system.

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