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Review

Neural Network Applications in Polygraph Scoring—A Scoping Review

Dana Rad [1,2,*], Nicolae Paraschiv [1,*] and Csaba Kiss [3,*]

1 Doctoral School of Systems Engineering, Petroleum-Gas University of Ploiești, 100680 Ploiești, Romania
2 Center of Research Development and Innovation in Psychology, Faculty of Educational Sciences Psychology and Social Work, Aurel Vlaicu University of Arad, 310032 Arad, Romania
3 Faculty of Psychology and Educational Sciences, Hyperion University of Bucharest, 030615 Bucharest, Romania
* Correspondence: dana@xhouse.ro (D.R.); nparaschiv@upg-ploiesti.ro (N.P.); kiss.csaba@expertpoligraf.ro (C.K.)

Abstract: Polygraph tests have been used for many years as a means of detecting deception, but their accuracy has been the subject of much debate. In recent years, researchers have explored the use of neural networks in polygraph scoring to improve the accuracy of deception detection. The purpose of this scoping review is to offer a comprehensive overview of the existing research on the subject of neural network applications in scoring polygraph tests. A total of 57 relevant papers were identified and analyzed for this review. The papers were examined for their research focus, methodology, results, and conclusions. The scoping review found that neural networks have shown promise in improving the accuracy of polygraph tests, with some studies reporting significant improvements over traditional methods. However, further research is needed to validate these findings and to determine the most effective ways of integrating neural networks into polygraph testing. The scoping review concludes with a discussion of the current state of the field and suggestions for future research directions.

Keywords: polygraph testing; intelligent scoring; neural networks

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1. Introduction

The polygraph is a device that measures physiological responses to assess an individual's truthfulness or deception. It works by measuring various bodily changes, including changes in blood pressure, heart rate, respiration rate, and skin conductivity, in response to questions posed to the individual. These physiological responses are believed to be indicative of the individual's psychological and emotional state, which can be further analyzed to determine the truthfulness of their responses [1,2].

Researchers [3] conducted a study to gather opinions of scientists through mail surveys. The majority of respondents stated that polygraph lie detection is not founded on robust theory, that high validity claims for these methods are unsubstantiated, and that the test may be overcome by simple countermeasures that can be easily learned, and the results of polygraph tests should not be allowed as evidence in court. In addition, recently, the current state of polygraph techniques in detecting deception was analyzed by synthesizing various studies on techniques such as the Control, or Comparison, Question Test (CQT) and the Guilty Knowledge Test (GKT) [4]. The impact of polygraph evidence on jury decision making was also investigated. The results indicated that the GKT was more effective and theoretically sound compared to the CQT.

The polygraph has been used extensively in a variety of settings, including criminal investigations, pre-employment screening, and national security applications. Despite its widespread use, the reliability of the polygraph as a lie detector has been the subject of much debate [1].

The Comparison Question Test (CQT) is widely recognized as one of the most commonly employed techniques in forensic polygraph examination [5]. To ensure the comprehensive inclusion of relevant research, the study applied inclusive inclusion criteria, resulting in the meticulous coding of data and potential moderator variables from an extensive pool of 138 datasets. The meta-analysis conducted in this study yielded a substantial effect size of d = 0.69 (95% confidence interval: [0.66, 0.79]). This effect size signifies a significant and robust relationship between the variables under investigation, thereby highlighting the effectiveness of the Comparison Question Test in its intended forensic applications. Notably, the research uncovered compelling moderator effects that exert a substantial influence on the outcomes of polygraph examinations, particularly in the context of the Comparison Question Test. Among these moderator effects, a salient finding was the existence of a positive linear relationship between the level of motivation of the individuals undergoing polygraph testing and the resulting outcome measures. This suggests that an individual's motivation plays a pivotal role in the accuracy and reliability of the CQT results, emphasizing the need for tailored approaches to polygraph testing based on the examinee's motivation level. In addition to the effect size and moderator effects, the study also conducted an Information Gain analysis to discern the relative accuracy of the Comparison Question Test (CQT) compared to other methods, such as interpersonal deception detection. The results of this analysis unequivocally demonstrated that the CQT outperformed interpersonal deception detection methods in terms of accuracy, further substantiating its efficacy as a widely utilized forensic polygraph examination technique [5]. In summary, this study's findings underscore the substantial utility and reliability of the Comparison Question Test (CQT) within the realm of forensic polygraph examination. With a robust effect size, identified moderator effects, and superior accuracy compared to alternative methods, the CQT remains a cornerstone in the arsenal of tools for assessing truthfulness and deception in forensic contexts.

One major limitation of the polygraph test is the potential for false positives and false negatives, which can lead to incorrect accusations and damage to an individual's reputation [6–10]. The accuracy of the test can be influenced by a variety of factors, including the skill of the examiner, type of questions asked, and the respondent's physiological response to stress [11–14]. When people receive deceptive communication, they have to reject information they initially believed and infer the speaker's true intentions, at the same time that they seldom receive feedback on their inferences.

Despite its limitations, the polygraph test remains a widely used tool for assessing truthfulness and deception, and ongoing research seeks to improve its accuracy and reliability. Recent advancements in machine learning and artificial intelligence have led to the development of new methods for analyzing polygraph data and improving the accuracy of lie detection [15,16].

To address these issues, researchers have explored the use of advanced statistical and machine learning techniques to improve the accuracy of polygraph scoring. One approach is the use of neural networks, which are computational models inspired by the structure and function of the human brain. Neural networks have shown promise in a variety of fields, including image recognition, natural language processing, and predictive modeling. They are particularly well-suited for applications that involve complex datasets of physiological signals or speech patterns, which are commonly used in polygraph testing.

This scoping review aims to offer a comprehensive overview of the published literature on the topic of neural network applications in scoring polygraph tests. Specifically, we aim to answer the following questions:

- What are the main research topics in the literature on neural network applications in scoring polygraph tests?
- What are the most common methodologies used to integrate neural networks into polygraph scoring?
- What are the reported outcomes of these studies, and how do they compare to traditional polygraph scoring methods?

- What are the current challenges in the field, and what are the most promising areas for future research?

To answer these questions, we conducted a comprehensive search of databases (PubMed, Scopus, PsycInfo, and IEEE Xplore) using a combination of relevant keywords and Boolean operators. We searched the reference lists of identified articles to ensure completeness. Our search yielded a total of 57 articles, which were analyzed systematically.

The novelty of this research lies in its scoping approach to analyzing the literature on the application of neural networks in scoring polygraph tests. This review aims to offer a detailed overview of the current state of the field, including the most common methodologies used, reported outcomes, and current challenges. By addressing these questions, this research seeks to contribute to the development of more effective polygraph scoring methods by incorporating the latest advances in artificial intelligence and neural networks.

The structure of the upcoming sections is as follows. The subsequent section describes the techniques employed to select and analyze the articles for this review. Then, we present the results of our analysis, including an overview of the research topics, methodologies, and outcomes reported in the literature. Next, we discuss the implications of our findings for the field of polygraph testing and highlight areas for future research. Finally, we provide a conclusion and summary of our review.

2. Materials and Methods

The methodology employed for this scoping review adhered to established guidelines and principles as described by [17,18]. Our search strategy aimed to comprehensively identify the relevant literature pertaining to neural network applications in polygraph scoring. Electronic databases, including PubMed, Scopus, PsycInfo, and IEEE Xplore, were systematically searched in March 2023. To maximize the scope of our search, we employed a predefined set of keywords and Boolean operators, including (“neural network” OR “deep learning” OR “artificial neural network” OR “machine learning”) AND (“polygraph” OR “lie detector”). Additionally, the reference lists of identified articles were reviewed to ensure the inclusion of all relevant sources.

The inclusion criteria for this scoping review were established following the principles outlined by [19]:

- Relevance: Articles that investigated neural network applications in polygraph scoring or lie detection.
- Empirical Research: Articles that reported empirical results from primary research studies.
- Publication Source: Articles published in peer-reviewed journals or conference proceedings.

A team of three independent reviewers conducted an initial screening of titles and abstracts to identify articles meeting the inclusion criteria. Duplicate articles were systematically removed. Subsequently, the full text of potentially eligible articles was assessed for final inclusion.

Data extraction was performed independently by the three reviewers using a standardized data extraction form. Extracted data included the following elements:

- Author(s): Names of the author(s) and the year of publication.
- Research Focus: Main topic or research area of the study.
- Methodology: Description of the study’s design and research methodology.
- Sample Size and Characteristics: Information regarding the study’s sample size and the characteristics of the participants.
- Neural Network Details: Details regarding the neural network architecture, parameters, and configuration.
- Features and Data: Information on the features and data used in the research.
- Evaluation Metrics: Metrics employed for the evaluation of neural network performance.
- Results: Reported findings and outcomes.

- Limitations and Future Directions: Identified limitations of the study and suggestions for future research.

In accordance with the scoping review methodology, a formal quality assessment using tools such as QUADAS-2 was not employed. Instead, we critically evaluated the methodological rigor of each included study, considering the quality of research design, data sources, and potential biases.

Data from the included studies were synthesized to provide an overview of the research topics, methodologies, and outcomes reported in the literature. The synthesis process aimed to identify patterns, gaps, and areas of focus in the existing literature.

The reporting of this scoping review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines [19].

Our search yielded a total of 618 articles from the three databases, and an additional 8 articles were identified through reference list searches. During this phase, a set of predefined inclusion and exclusion criteria was meticulously applied to assess the eligibility of each article for further consideration. The establishment of these criteria aimed to maintain objectivity and consistency in the article selection process. Inclusion criteria were designed to identify articles that demonstrated relevance to the core themes of our scoping review, encompassing aspects such as research focus, the application of neural network methodologies, and pertinence to deception detection. Conversely, exclusion criteria were applied to articles that diverged significantly from these thematic domains or exhibited inadequacies, such as insufficient information or inaccessibility.

Following the title and abstract screening, we identified a subset of 71 articles that either clearly met our predefined inclusion criteria or necessitated an in-depth full-text examination for final determination. This subset proceeded to the second stage of our article selection process, wherein comprehensive full-text reviews were conducted. These reviews were executed to definitively ascertain the compatibility of the articles with our research objectives. Articles that, upon meticulous full-text scrutiny, failed to satisfy the inclusion criteria were subsequently excluded from our final corpus of selected articles. It is paramount to emphasize that the criteria employed for article inclusion and exclusion were not solely grounded in subjective judgments but were, in fact, meticulously formulated a priori to uphold methodological rigor and impartiality throughout the article selection process. Any ambiguities or disparities in article selection were systematically addressed through discussions and consensus among the authors, ensuring that the inclusion of articles in our scoping review was driven by stringent adherence to predetermined thematic relevance and methodological alignment.

The criteria for article inclusion and exclusion were designed to ensure methodological rigor and relevance to the scope of this review. To shed light on these criteria, we briefly outline some of the primary factors that guided our selection process:

- Relevance to Neural Network Applications: Articles were considered for inclusion if they pertained to the application of neural networks in polygraph scoring. This criterion aimed to ensure that the selected studies directly addressed the intersection of neural networks and polygraph testing.
- Publication Date: We focused on studies published up to the present date to capture the most recent advancements in the field. The "present" referred to the time of the review's initiation and should not be confused with a specific date within the manuscript.
- Research Methodology: We assessed the methodological quality of each study, looking for rigorous experimental designs, appropriate data collection procedures, and transparent reporting. Articles failing to meet methodological standards were excluded.
- Availability of Full Text: To maintain the integrity of the review, we prioritized articles with full-text availability. This criterion ensured that reviewers had access to complete information.

- Language: Articles written in languages other than English were excluded due to limitations in translation resources.
- Relevance to the Research Questions: Articles that did not directly address the research questions of this review, such as those focusing on unrelated topics or different applications of neural networks, were excluded.

Articles that initially appeared relevant based on title and abstract were subjected to a more thorough assessment, which sometimes revealed that they did not meet the predefined criteria upon closer inspection. Finally, we excluded 14 articles that failed to meet the inclusion criteria, culminating in a final sample of 57 articles.

3. Results

The research focus of the selected articles varied widely, with some studies focusing on improving the accuracy of polygraph tests, while others explored the use of neural networks for analyzing different types of physiological signals, such as electroencephalogram (EEG) and heart rate variability (HRV). Most studies used either feedforward neural networks (FFNN) or convolutional neural networks (CNN), and a variety of features and data were used as inputs to the networks, including physiological signals, speech patterns, and text data. The most commonly reported evaluation metrics were sensitivity, specificity, and accuracy.

In an extensive survey of the existing body of research, Ref. [20] offers a comprehensive summary of studies focusing on deception detection. This encompassing review spans various methodologies and diligently assesses their efficacy in discerning deception. Moreover, Smith and colleagues critically explore an array of factors that can exert influence over the precision of deception detection.

In a separate investigative study, Ref. [21] meticulously examines the strategies employed by both guilty and innocent suspects during police interrogations. Their inquiry extends to an investigation into the potential impact of these strategies on the overall accuracy of deception detection. Notably, the authors advocate for the pivotal role of training law enforcement officers in recognizing and effectively responding to these strategies, ultimately enhancing their proficiency in detecting deception.

Turning to an empirical analysis, Ref. [22] conducts a comprehensive meta-analysis focused on assessing the effectiveness of utilizing reaction times to response probes as a method for detecting deception. Their findings reveal a moderate level of accuracy associated with this approach. However, it is underscored that further research is indispensable to refine and optimize its effectiveness.

Expanding upon this theme, researchers [23,24] have delved into the innovative realm of utilizing response times as an alternative avenue for detecting deception. Their approach involves the manipulation of cognitive load to investigate its effects on response times as potential indicators of deception. The results of their research indicate that response times possess the potential to be used as a tool for detecting deception, albeit with a moderate level of accuracy.

Shifting focus toward technological advancements, Ref. [25] made notable strides in the development of neural network algorithms specifically tailored for scoring polygraph examinations. Their work demonstrates promising outcomes, suggesting the viability of neural networks in this context. In a parallel study, Ref. [26] introduces an adaptive neural network designed for scoring polygraph data, showcasing its superior performance when compared to traditional scoring methods in experimental settings. Conversely, in a contrasting perspective, Ref. [27] presents findings that, while neural networks exhibit promise, their performance does not significantly surpass that of conventional polygraph scoring methods. This study underscores the importance of the continued exploration and validation of emerging technologies in this domain.

In tandem, a thought-provoking paper [28] delves into the conceptual and methodological intricacies associated with the utilization of behavioral, autonomic, and neural measures in the realm of deception detection. The authors aptly argue that despite substantial progress, these measures remain subject to inherent limitations and challenges. Furthermore, they emphasize the importance of maintaining a sense of cautious interpretation of results and advocate for a thorough consideration of the underlying theoretical and methodological complexities. This paper serves to underscore the broader implications of their findings for the development of more accurate and reliable measures in the field of deception detection. In summation, it offers invaluable insights into the intricate landscape of deception detection, underscoring the imperative for ongoing research and development in this field.

In paper [29], an innovative study in automated deception detection is presented, leveraging computer vision and machine learning techniques. The research team devised a system that harnesses facial micro-expression analysis in conjunction with machine learning algorithms to autonomously identify deception within video recordings. Their system's performance was rigorously evaluated using a dataset featuring participants simulating a mock crime, revealing commendable accuracy in detecting deception. This paper further delves into the promising applications of this technology across various domains, encompassing law enforcement, security protocols, and human–computer interaction.

In the quest for automated deception prediction, Ref. [30] undertook a meticulous comparison of four commonly employed classification methods, assessing their efficacy in predicting deception. Their findings underscored the inherent potential of all four methods when it comes to deciphering cues indicative of deception. Notably, neural networks emerged as consistent high performers, demonstrating reliability across diverse testing conditions. The study additionally underscored the pivotal role of judiciously selecting relevant input variables and mitigating noise to enhance the classification methods' performance.

The robustness and utility of the Guilty Knowledge Test (GKT), frequently applied in polygraph examinations, have been extensively scrutinized. Researchers [31] conducted a meta-analytic review to shed light on the validity of the GKT in detecting information that a guilty individual would possess but an innocent individual would lack. Their comprehensive analysis yielded robust support for the GKT's effectiveness in this critical context.

Exploring a distinct dimension of deception detection, Ref. [32] delved into the realm of identifying deceptive opinion spam. Their study introduced a neural network model specifically designed to learn document-level representations. Leveraging a convolutional neural network (CNN), the model skillfully captured sentence representations within documents. These representations were subsequently integrated using a gated recurrent neural network equipped with an attention mechanism, effectively encapsulating discourse information and generating a comprehensive document vector.

In an ambitious endeavor, researchers [33] embarked on a mission to investigate the nuanced challenge of detecting deception levels within stimulus videos. Their methodology involved the capture of physiological signals from individuals as they engaged with video stimuli. The ensuing dataset was subjected to rigorous analysis using advanced machine learning and deep learning models. Addressing inherent challenges such as imbalanced class distribution and limited training data, the researchers adopted data augmentation techniques. Notably, when focusing on Electrodermal Activity (EDA) as a pivotal physiological indicator during training, their findings revealed that deep learning models, particularly ResNet and VAE-LSTM, exhibited the capacity to predict the degree of untruth with a commendable F1-measure, reaching up to 0.83. This pioneering research underscores the potential of physiological cues from spectators as robust predictors of deceitfulness in deceptive claims.

In a contemporary discourse, Ref. [34] meticulously examines the potential ramifications of artificial intelligence (AI) on lie detection and credibility assessment. Their analysis raises pertinent concerns surrounding the use of opaque "black box" processes and the emergence of new physiological markers, casting a shadow on matters of justice, mental privacy, and potential biases. The adoption of autonomous lie detection systems as a replacement for human agents within workplace integrity assessments is contemplated, offering a potential paradigm shift in organizational policies and practices. However, the authors judiciously caution against the dystopian specter of automated analysis and judgment of one's honesty, entwined with personal profiling, which raises unsettling questions regarding an individual's ability to represent themselves autonomously.

In parallel, several scholarly contributions within the literature discuss the theoretical underpinnings and practical aspects of polygraph examinations [35–41], further enriching the multifaceted landscape of research in the domain of deception detection.

In the realm of decision making and deception-related research, various studies have explored complementary themes. These include investigations into cognitive heuristics and feedback within dynamic decision-making environments [42], as well as the pivotal role of expertise and decision support tools for interviewers engaged in criminal investigations [43]. Furthermore, researchers have undertaken the development of a concise iteration of the Multidimensional Personality Questionnaire aimed at measuring personality traits associated with psychopathy [44], and they have delved into the intricate intersection of neuroscience and its application in legal decision-making processes [45].

Delving into the practical domain of deception detection, Ref. [46] presents a meticulous examination of data and text mining techniques deployed in real-world scenarios. This study employs an amalgamation of machine learning algorithms, including artificial neural networks, to analyze text-based data culled from authentic cases of deception spanning various contexts such as insurance fraud and military intelligence. Through a systematic comparison of multiple algorithms, the research reveals that a fusion of support vector machines and decision trees yields the highest accuracy for detecting deception. This insight leads to the conclusion that data and text mining techniques can indeed serve as potent tools for deception detection in real-world settings, encouraging further exploration of their applicability in diverse domains.

Another groundbreaking study introduces the utilization of BERT (Bidirectional Encoder Representations from Transformers) to advance the field of lie detection by discerning disparities between truthful and deceptive responses [47]. The proposed approach undergoes rigorous evaluation on a dataset comprising real-life human lies and truths, yielding promising results. This research underscores the potential of employing advanced machine learning techniques such as BERT in the development of more precise and dependable deception detection systems.

Researchers [48] have offered a comprehensive review of contemporary machine learning methodologies in the realm of deception detection, encompassing both verbal and non-verbal features. This paper provides a comprehensive overview of diverse feature extraction techniques, recognition rates, and computational timeframes within the context of machine learning methods. Furthermore, it presents an array of datasets employed in deception detection research. The study encapsulates key findings from prior research endeavors, discussing critical challenges intrinsic to deception detection techniques.

In a novel avenue of research, Ref. [49] suggests the utilization of machine learning to automate the functions of a polygraph examiner, employing neural network architectures from the scikit-learn library. Specifically, this approach advocates the use of the Voting Classification architecture and a transformer to enhance the efficiency of polygraph testing, align features, and diminish instances of erroneous conclusions regarding the subject's responses. This enhancement leverages indicators or channels such as electrodermal resistance (galvanic skin response), blood vessel capacity (plethysmogram), and respiratory rhythms.

The conventional bag-of-words model has served as the cornerstone for representing text characteristics in the extensive corpus of research on opinion spam detection [50]. However, recent studies have begun to embrace neural-network-based methodologies for this purpose. Deep learning, renowned for its prowess in natural language processing tasks, has made notable strides, with convolutional neural networks (CNNs) emerging as a standout performer [51]. This study advocates the utilization of features extracted from the pretrained GloVe, Global Vectors for Word Representation, model to bolster opinion spam detection. To enhance performance, word and character level characteristics are harnessed from the text and amalgamated with a feature set generated by the model's convolutional layers, surpassing state-of-the-art techniques.

In a pioneering venture, another research endeavor [52] outlines a deep learning strategy deploying a convolutional neural network (CNN) to autonomously discern sincerity from EEG data. The model accepts 14-channel EEG data as input, classifying statements as either truthful or deceptive. Impressively, this approach exhibits an accuracy rate of up to 84.44%. It merits recognition for its non-invasive nature, computational efficiency, resilience, and low temporal complexity, rendering it suitable for real-time applications.

In the realm of automated deception detection, various studies have undertaken extensive investigations, seeking innovative approaches to enhance accuracy and broaden the scope of applicability. Reference [53], for instance, conducts a comprehensive comparison of nine distinct recurrent deep learning models grounded in facial landmark recognition, a crucial aspect of lie detection. This investigation leverages a recently curated synthetic database and evaluates the models based on key metrics, including accuracy and AUC. Additionally, the study introduces two supplementary metrics designed to gauge the validity of each prediction. Remarkably, the Stacked GRU neural model emerges as the frontrunner, boasting an impressive AUC of 0.9853 and the highest accuracy, standing at 93.69%, as demonstrated through a rigorous 5-fold cross-validation procedure. Furthermore, when juxtaposed with various machine and deep learning approaches, the Stacked GRU model consistently outperforms its counterparts, particularly excelling in the AUC metric. These findings offer a glimpse into the potential future landscape of fraud detection, hinting at the possibility of computer- or smart-device-driven solutions.

In a similarly pioneering endeavor, Ref. [54] introduces a distinctive deep-learning-driven multimodal fusion framework tailored for automated deception detection. What sets this study apart is its amalgamation of auditory cues with visual and textual signals, marking a noteworthy departure from conventional approaches. The proposed methodology, grounded in deep convolutional neural networks (CNNs), showcases exceptional prowess, surpassing the accuracy levels reported in the previous literature by a substantial margin. Specifically, the model achieves a prediction accuracy of up to 96%, in stark contrast to the previous benchmark of 82%. This remarkable advancement underscores the potential for more robust and multifaceted deception detection systems.

Exploring the domain of brain–computer interface (BCI) signals as a conduit for lie detection, Ref. [55] presents an intriguing investigation. In this study, six participants engage in a lie detection task, responding to Boolean questions while their EEG, fNIRS, HRV, and GSR data are meticulously recorded. The EEG and fNIRS data collection involves the use of the g.Nautilus fNIRS-8 headset, while GSR data are captured with the g.GSRsensor 2, both products of g.tec. HRV data, on the other hand, are obtained through the Wellue Smart Pulse Oximeter for Adults and Infants, and the data are seamlessly integrated via Bluetooth using the ViHealth app on an iPhone X. The findings underscore the varying degrees of accuracy across models, spanning from 61.4% to 71.9%. Notably, a neural network model emerges as the top performer, achieving an accuracy rate of 71.9%. This particular model excels in predicting truths with a precision of 78.9% and falsehoods with an accuracy of 57.9%, shedding light on the potential of BCI signals for lie detection.

In a recent contribution to the field [56], the discourse delves into the significance of automatic deceit detection and its prospective applications within computational linguistics. The authors introduce a multimodal neural model designed to enhance the accuracy of deception detection in real-life videos. This innovative model harnesses data from various modalities, including video, audio, text, and micro-expressions, setting the stage for comprehensive deception assessment. On a dataset comprising genuine deception scenarios, the proposed model exhibits remarkable performance, achieving an accuracy rate of 96.14% and an ROC-AUC of 0.9799. These outcomes surpass the capabilities of existing deception detection algorithms and raise the prospect of employing this methodology to bolster fraud detection in real-world scenarios.

In the realm of polygraph scoring, the comparative performance of neural-network-based systems against human examiners has been a subject of substantial inquiry. Within this domain, an intriguing dichotomy emerges from the literature. A particular study [57] stands as a testament to the prowess of neural networks, as it demonstrates their ability to achieve a notably higher accuracy rate than human examiners. This outcome raises the prospect of computer-based systems surpassing human judgment in the intricate task of lie detection. However, this narrative is multifaceted, as evidenced by two distinct investigations [58,59] where human examiners exhibited superior lie-detection acumen compared to their neural network counterparts. These variations in outcomes underscore the intricate nature of lie detection, influenced by diverse factors and methodological nuances.

To harness the full potential of artificial neural networks (ANNs) in this context, a systematic approach to model development is imperative. The intricate process involves judiciously selecting optimal parameters, including network design, topology, data representation, training methodology, and termination criteria. However, the journey toward effective deployment extends beyond model creation and necessitates rigorous validation. Validation, a cornerstone in model development, relies on a well-defined ANN performance metric that scrutinizes the model's efficacy using data distinct from that employed during model construction. A seminal contribution in this domain, as presented in reference [60], is centered on the pivotal triad of performance metrics for pattern classification networks: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the correct classification rate. The paper sheds light on the not uncommon disparity encountered among these metrics, championing the applicability of error histogram analysis as a means to harmonize conflicting performance assessments. In the course of this endeavor, the paper introduces a neural network analog akin to the statistical concept of power, thereby unveiling its potential as a more encompassing metric for the comprehensive evaluation and projection of network quality.

The challenge posed by the task of detecting deception through an individual's cognitive responses is a formidable one. Brain–computer interfaces (BCIs) have emerged as a promising avenue for navigating this intricate landscape. They leverage visual stimuli and record cerebral responses to address this complex task. Central to this approach is the elicitation of the P300 response, a distinctive neural reaction triggered when an individual encounters a familiar stimulus amidst an array of unfamiliar ones. This neurological phenomenon forms the bedrock of lie detection.

To implement this paradigm effectively, data undergo meticulous preprocessing to eliminate noise. Feature extraction from electroencephalogram (EEG) data is achieved through the application of a short-time Fourier transform. A noteworthy feature selection technique, known as the binary bat technique, is harnessed to curate an optimal subset of features while effectively managing computational load [61]. Subsequently, the selected feature set is channeled into the extreme learning machine classifier, expertly trained on data sourced from both guilty and innocent individuals. The system's robustness and accuracy undergo rigorous evaluation through a 10-fold cross-validation regimen, culminating in an impressive accuracy rate of 88.3%. This technological innovation heralds a notable leap forward in the landscape of lie detection, outperforming contemporary algorithms and holding the promise of transformative applications.

However, as with any technology, the incorporation of neural networks in polygraph scoring is not without its limitations and ethical considerations. Some studies underscore that the accuracy of neural-network-based polygraph scoring may be susceptible to factors such as data quality and question complexity. These intrinsic limitations necessitate careful consideration and ongoing research efforts to refine the technology. Moreover, ethical concerns loom prominently in this discourse, with some studies raising valid apprehensions regarding the potential for false accusations and the encroachment upon privacy posed by the utilization of neural networks for lie detection. These ethical considerations underscore the importance of a judicious and balanced approach in deploying this technology within the domain of deception detection.

Among the 57 papers reviewed in our scoping literature review on neural networks' applications in polygraph scoring, three papers stood out for their original approach to addressing the challenge of accurately scoring polygraph tests.

Research conducted by [62] proposes a novel method for identifying fake news on social media by employing metaheuristic algorithms. The authors define false news identification as an optimization issue and propose to solve it using two metaheuristic algorithms, GWO and SSO. The suggested method is divided into three stages: data preprocessing, modifying GWO and SSO to build a novel FND model, and evaluating the model. The authors compare the outcomes of their technique to those of seven supervised artificial intelligence systems using three real-world datasets. The findings show that GWO surpasses SSO and the other algorithms in terms of performance, implying that GWO may be utilized to solve a variety of social media challenges.

Research performed by [63] presents an automatic system for detecting deception by analyzing non-verbal behavior captured during an interview conducted by an avatar. The system utilizes artificial neural networks to detect facial objects and extract non-verbal behavior, specifically micro-gestures, over short time periods. The system was evaluated using a set of empirical experiments based on a typical airport security scenario of packing a suitcase, where 30 participants were interviewed by a machine-based border guard avatar in either a truthful or deceptive scenario. Promising results were obtained using raw, unprocessed data on unoptimized classifier neural networks, indicating that a machine-based interviewing technique can capture non-verbal behavior, which enables an automatic system to detect deception.

Research conducted by [64] offers F-score_ELM, a unique machine learning approach for identifying lying and truth telling using EEG data gathered from 28 participants, both guilty and innocent. The probing answers of the subjects yielded a total of 31 features. Using a grid-searching training technique, the method integrated an extreme learning machine (ELM) with F-score, a feature selection method, to simultaneously maximize the number of hidden nodes of ELM and the feature subset. This method's performance was compared to two other classification models that used principal component analysis in conjunction with back-propagation networks and support vector machine classifiers. Several criteria were used in the evaluation, including training and testing duration, sensitivity, specificity, and network size. The findings showed that the suggested strategy was successful at reducing the number of hidden nodes, achieving the maximum classification accuracy, and requiring the least amount of training and testing time.

The insights gleaned from the comprehensive analysis of the papers presented in the results section of our scoping review are succinctly summarized in Table 1. This table encapsulates the main themes and key findings that emerged from our extensive exploration of the literature on neural network applications in polygraph scoring.

These themes collectively represent the diverse landscape of research at the intersection of neural networks and polygraph scoring, showcasing both the potential and challenges in this evolving field.

To facilitate a structured overview of the diverse research landscape in this domain, we categorized the selected studies into four main thematic categories. Table 2 provides a concise representation of these categories and the corresponding studies. The first category, "Deception Detection Methods and Techniques," encompasses studies that investigate various approaches to detecting deception, ranging from traditional methods such as polygraph testing to modern techniques employing machine learning and psychophysiological measures. The second category, "Machine Learning and Artificial Intelligence in Deception Detection," highlights research that explores the integration of advanced technologies, such as neural networks, for enhancing the accuracy of lie detection using diverse data sources. The third category, "Psychophysiological Measures and Traditional Methods," reviews studies focusing on the evaluation of traditional deception detection techniques and psychophysiological measures. Lastly, the fourth category, "Behavioral and Linguistic Analysis in Deception Detection," centers on research that delves into the behavioral and linguistic aspects of identifying deceptive behavior. This categorization aims to offer readers a systematic understanding of the different dimensions of neural network applications in polygraph scoring for deception detection.

Table 1. Main themes of the papers presented in the results section of the scoping review.

Themes	Key Points
Variability in Research Focus	-Wide range of research topics in polygraph testing and neural networks. -Some focus on improving polygraph accuracy, others explore neural networks for EEG and HRV.
Neural Network Architectures and Features	-Most used FFNN and CNN architectures. -Inputs included physiological signals, speech patterns, and text data.
Evaluation Metrics	-Common metrics: sensitivity, specificity, and accuracy to assess neural network performance.
Mixed Results	-Varied study results, with some showing improved accuracy, while others had small sample sizes and inconsistencies.
Limitations and Future Directions	-Identified limitations: need for larger-scale studies, standardized data collection, and exploration of new features. -Ethical concerns about privacy and false accusations.
Comparison with Human Examiners	-Mixed results in studies comparing neural-network-based scoring to human examiners.
Innovative Approaches	-Innovations include metaheuristic algorithms, avatar-based non-verbal behavior analysis, and feature selection with extreme learning machines.
Multimodal Approaches	-Exploration of combining various data sources such as audio, video, and text for improved deception detection.
Feature Selection	-Usage of feature selection methods such as F-score and principal component analysis for enhanced neural network efficiency.
Contextual Variables	-Highlighted importance of contextual variables, such as time of day and subject demographics, for better accuracy.

Table 2. Categorization of studies on neural network applications in polygraph scoring for deception detection.

Category	Studies
Deception Detection Methods and Techniques	[15,20,28,31,47]
Machine Learning and Artificial Intelligence	[16,25,26,29,50,51,53–56,58,61,63,65]
Psychophysiological Measures and Traditional Methods	[32,46,57,65–69]
Behavioral and Linguistic Analysis	[21–24,30,35–39,70,71]

This categorization offers a comprehensive view of the field, enabling researchers to explore the foundations, technological advancements, traditional practices, and linguistic nuances that shape the captivating realm of neural network applications in polygraph scoring for deception detection.

The reasons for including the 57 studies under one of the four categories reside in:

1. Deception Detection Methods and Techniques: This category encompasses studies that focus on the fundamental methods and techniques employed in the field of deception detection. These papers explore the traditional practices such as polygraph testing, which has been a cornerstone of lie detection for decades. They also investigate modern approaches that leverage psychophysiological measures and non-verbal cues to identify deceptive behavior.
2. Machine Learning and Artificial Intelligence in Deception Detection: With the advancement of technology, this category becomes crucial. It includes studies that delve into the application of machine learning and artificial intelligence (AI) techniques for deception detection. Machine learning and AI have introduced innovative ways to enhance the accuracy and efficiency of lie detection. These studies showcase how neural networks, deep learning, and data-driven approaches can analyze various

data sources, such as EEG signals, text, voice, and physiological responses, to identify deceptive patterns.

3. Psychophysiological Measures and Traditional Methods: Some studies are dedicated to examining the reliability and limitations of traditional deception detection methods and psychophysiological measures. By categorizing these papers together, researchers can gain insights into the ongoing debate surrounding methods such as the Guilty Knowledge Test (GKT) and polygraph testing. This category highlights the ongoing relevance of established techniques in the field.
4. Behavioral and Linguistic Analysis in Deception Detection: This category brings together studies that focus on behavioral and linguistic aspects of deception detection. These papers explore how verbal and non-verbal cues, speech analysis, and linguistic patterns can be utilized to detect deception. By categorizing these studies, researchers can appreciate the significance of language and behavior analysis in uncovering deceptive behavior, offering an alternative or complementary approach to traditional methods.

Incorporating these categories provides a structured framework for understanding the diverse range of research in the field of neural network applications in polygraph scoring for deception detection.

Accuracy Results

In terms of accuracy results, the papers identified in this systematic review demonstrate that neural networks have been used extensively in the development of automated polygraph scoring systems. Most of the studies used physiological signals such as skin conductance, blood pressure, and respiration to train and test neural networks. The majority of the studies reported that neural-network-based systems performed better than or were comparable to human examiners in terms of accuracy, reliability, and consistency. The studies also demonstrated the potential of neural-network-based systems to detect deception with high sensitivity and specificity, although some studies reported lower accuracy rates in real-life scenarios compared to laboratory settings.

The overall accuracy rate of neural networks used in the reviewed studies ranged from 60.5% to 100%, with a mean accuracy rate of 88.7%. For example, in [49], the accuracy of binary learning (strong and weak responses to a given question) was found to be: for the plethysmogram, 86.8% $\pm$ 3%, for the galvanic skin response, 95.3% $\pm$ 3%, and for respiratory rhythms, 72.7% $\pm$ 3%. In [55], the accuracies of the models ranged from 61.4% to 71.9%. The neural network with the 71.9% accuracy predicted 78.9% of the truths and 57.9% of the lies. Research [25] reported a 100% accuracy rate for deep neural networks detecting lies with the attention on bio-signals. The method proposed by [52] achieved up to 84.44% accuracy when identifying if a person was telling a truth or lie.

However, it is crucial to exercise caution when interpreting these figures, as the direct comparability of accuracy rates across studies is hampered by variations in study design, data collection methodologies, and choice of evaluation metrics. Furthermore, certain studies presented multiple accuracy rates corresponding to different scenarios or data subsets, contributing to the complexity of the reported accuracy landscape. While the majority of the reviewed papers did not explicitly report specific metrics (effect sizes, p-values, and other statistical measures to provide a clearer understanding of the reliability of polygraph systems), we concur that future research should place a stronger emphasis on quantifying the performance of neural-network-based polygraph scoring systems through robust statistical analysis. This will facilitate a more rigorous evaluation of the reliability and effectiveness of these systems and enable researchers to make more informed assessments of their utility.

4. Discussion

The scoping review has provided a comprehensive overview of the current state of research at the intersection of polygraph testing and neural networks. The selected articles cover a wide spectrum of topics, reflecting the diverse interests and applications within this field. In this discussion, we delve into the key findings, implications, and areas that warrant further investigation.

4.1. Variability in Research Focus

One prominent observation is the significant variability in research focus across the selected articles. While some studies concentrate on enhancing the accuracy of polygraph tests, others explore the potential of neural networks for analyzing various physiological signals, including EEG and HRV. This diversity reflects the evolving landscape of lie detection and underscores the interdisciplinary nature of this research. Future studies might benefit from fostering collaboration between experts in psychology, machine learning, and neuroscience to leverage these varied perspectives.

4.2. Neural Network Architectures and Features

The prevalence of neural network architectures, predominantly feedforward neural networks (FFNNs) and convolutional neural networks (CNNs), indicates the growing reliance on deep learning techniques in this field. These architectures have showcased their flexibility in handling diverse data types, such as physiological signals, speech patterns, and text data. This adaptability offers promise in creating comprehensive models that can leverage multiple information sources for more accurate deception detection. Nevertheless, it is essential to continue exploring novel network structures and feature engineering approaches to further enhance model performance.

4.3. Evaluation Metrics and Mixed Results

Sensitivity, specificity, and accuracy were the most frequently reported evaluation metrics for assessing the performance of neural network models. These metrics offer a standardized way to measure the success of these models in distinguishing between truthful and deceptive responses. However, the scoping review revealed mixed results across studies. While some reported substantial improvements in accuracy using neural networks compared to traditional polygraph methods, others faced challenges due to small sample sizes and inconsistent findings. This disparity highlights the complexity of the problem and underscores the need for more robust research methodologies and larger-scale studies to establish the true efficacy of neural-network-based lie detection.

4.4. Limitations and Ethical Concerns

Identified limitations in the reviewed literature encompass the necessity for larger-scale studies, the standardization of data collection protocols for physiological signals, and the exploration of new features and data sources. These limitations underline areas where further research and development are essential for advancing the field. Additionally, ethical concerns surrounding privacy, false accusations, and the broader societal implications of automated lie detection systems were repeatedly raised. Researchers and policymakers must address these ethical dilemmas to ensure the responsible and just deployment of neural-network-based deception detection technologies.

4.5. Comparison with Human Examiners

Some studies in the scoping review compared the performance of neural-network-based polygraph scoring with that of human examiners, yielding mixed results. While the potential for automated systems to outperform humans is tantalizing, the variations in outcomes underscore the need for continued collaboration between human experts and machine learning practitioners. Combining the strengths of both approaches could lead to more reliable and accurate lie detection methods.

4.6. Innovative Approaches and Multimodal Exploration

The scoping review identified several innovative approaches in the field, such as the utilization of metaheuristic algorithms, analysis of non-verbal behavior through avatars, and feature selection techniques to improve the efficiency of neural network models. Furthermore, some studies explored multimodal approaches, integrating data from various sources, such as audio, video, and text, to enhance deception detection accuracy. These innovative methods open exciting avenues for future research, offering novel ways to tackle the challenges in lie detection.

4.7. Contextual Variables

Finally, the inclusion of contextual variables, such as the time of day and subject demographics, emerged as a valuable strategy to enhance the accuracy of neural network models. Recognizing that deception detection is influenced by a myriad of situational factors, accounting for these variables could lead to more robust models that perform effectively in real-world scenarios.

4.8. Theoretical Implications

The scoping review conducted on the intersection of polygraph testing and neural networks not only reveals practical applications but also carries significant theoretical implications. These implications extend beyond the technological advancements and delve into the fundamental understanding of deception detection, human behavior, and cognitive processes. Here, we discuss these theoretical implications in depth, shedding light on the broader significance of this research area.

(1) Unraveling the Complexity of Deception: One of the core theoretical implications arising from this review pertains to the inherent complexity of deception. The mixed results observed in the performance of neural-network-based lie detection models highlight the intricate nature of distinguishing truth from deception. This complexity is rooted in the dynamic interplay of various cognitive, physiological, and behavioral factors that contribute to deceptive behavior. Understanding the limitations and challenges faced by neural networks in this context underscores the need for a more comprehensive theoretical framework that accounts for the multifaceted nature of deceit.

(2) Cognitive Processes and Deception: The use of neural networks in lie detection research draws attention to the underlying cognitive processes involved in deception. As researchers explore the potential of deep learning algorithms to detect subtle cues of deception, they indirectly contribute to our understanding of cognitive mechanisms such as memory encoding, retrieval, and emotional regulation. Theoretical insights into how these processes manifest in physiological signals, linguistic patterns, and non-verbal behavior are invaluable for advancing theories of deception within psychology and neuroscience.

(3) Ethical and Societal Implications: The ethical concerns raised in the scoping review underscore the broader societal implications of automated lie detection systems. These concerns extend far beyond technology and touch upon questions of privacy, individual rights, and the potential for false accusations. Theoretical discussions surrounding the ethical use of neural-network-based deception detection technologies contribute to the evolving field of ethics in artificial intelligence (AI) and machine learning. Theoretical frameworks that address these ethical dilemmas are essential for guiding policymakers and practitioners toward responsible and equitable deployment.

(4) Interdisciplinary Collaboration: The diversity of research focus areas within this field highlights the need for interdisciplinary collaboration. Theoretical implications emphasize that lie detection is no longer confined to the realms of psychology or technology but necessitates the integration of knowledge from various disciplines. Theoretical frameworks that facilitate cross-disciplinary dialogue and knowledge exchange are essential for fostering a holistic understanding of deception and advancing the field.

(5) Human–Machine Interaction: Neural-network-based lie detection also raises intriguing questions about the interaction between humans and AI systems. Theoretical

considerations extend to how individuals perceive and interact with automated lie detection technologies. This research domain provides insights into human trust, acceptance, and behavioral responses when confronted with AI-driven decisions. Theoretical models that elucidate these dynamics can inform the design and implementation of AI systems in various domains beyond lie detection.

(6) Contextual and Situational Factors: The inclusion of contextual variables in neural network models for deception detection emphasizes the role of situational factors in shaping deceptive behavior. Theoretical implications highlight the importance of context in understanding deception, suggesting that a comprehensive theory of deceit should account for variations in situational cues, motivations, and cultural influences. Theoretical frameworks that incorporate contextual elements offer a more nuanced perspective on deception dynamics.

(7) Cognitive Heuristics and Decision Making: The scoping review indirectly touches upon cognitive heuristics and decision-making processes involved in both human examiners and AI algorithms. Theoretical discussions can delve into how heuristics and biases influence human judgment in deception detection and how AI systems can be designed to mitigate or leverage these cognitive tendencies. Understanding the theoretical underpinnings of cognitive decision making is critical for advancing the reliability and validity of lie detection methods.

In conclusion, the theoretical implications of the intersection between polygraph testing and neural networks extend beyond the immediate applications of AI-driven deception detection. This research area contributes to our understanding of complex cognitive processes, ethical considerations, interdisciplinary collaboration, human–machine interaction, contextual influences, and cognitive decision making. By exploring these theoretical dimensions, researchers can pave the way for a more comprehensive and integrated framework for the study of deception. This, in turn, has the potential to impact not only the field of lie detection but also broader domains within psychology, neuroscience, ethics, and AI research.

5. Conclusions

Starting with the prolific research of [65–68] until recent studies of [69,71], the evolution of polygraph assessment has clearly improved in terms of reliability and validity.

This scoping review illuminated the multifaceted landscape of research at the intersection of polygraph testing and neural networks, shedding light on the diverse topics, methodologies, and findings that characterize this field. In this concluding section, we summarize the key takeaways and outline the implications for future research and applications.

One of the most striking findings of this review is the wide array of research focus areas within the domain of polygraph testing and neural networks. Researchers have explored a spectrum of topics, ranging from enhancing the accuracy of traditional polygraph tests to leveraging neural networks for the analysis of diverse physiological signals, such as EEG and HRV. This diversity highlights the dynamic nature of this field, as it continually evolves to address new challenges and opportunities.

The prevalence of neural network architectures, with feedforward neural networks (FFNNs) and convolutional neural networks (CNNs) as prominent examples, underscores the growing adoption of deep learning techniques in the pursuit of more accurate deception detection. These architectures have demonstrated their adaptability in handling various data types, encompassing physiological signals, speech patterns, and textual data. The versatility of neural networks offers promise in developing comprehensive models capable of integrating multiple data sources to improve the accuracy of lie detection.

Sensitivity, specificity, and accuracy emerged as the primary evaluation metrics used to gauge the performance of neural network models. While some studies reported significant enhancements in accuracy compared to traditional polygraph methods, others faced challenges due to small sample sizes and inconsistent findings. The variation in results underscores the complexity of the lie detection problem. Robust research methodologies and larger-scale studies are imperative to establish the true effectiveness of neural-network-based deception detection.

The review highlighted several limitations in the current literature, including the need for more extensive studies, standardized data collection protocols for physiological signals, and exploration of novel features and data sources. Addressing these limitations will be essential for advancing the field. Additionally, ethical concerns surrounding privacy, false accusations, and the broader societal implications of automated lie detection systems must be addressed responsibly to ensure the equitable and ethical deployment of neural-network-based deception detection technologies.

Comparative studies that pitted neural-network-based polygraph scoring against human examiners yielded mixed results. The potential for automated systems to surpass human performance is tantalizing. However, these variations underscore the importance of continued collaboration between human experts and machine learning practitioners. Combining the strengths of both approaches holds the promise of more reliable and accurate lie detection methods.

Several innovative approaches emerged from the reviewed literature, including the use of metaheuristic algorithms, analysis of non-verbal behavior through avatars, and feature selection techniques to enhance model efficiency. Furthermore, the exploration of multimodal approaches, which integrate data from various sources such as audio, video, and text, presents exciting possibilities for improving deception detection accuracy.

The inclusion of contextual variables, such as the time of day and subject demographics, was highlighted as a valuable strategy to enhance the accuracy of neural network models. Acknowledging that deception detection is influenced by situational factors opens the door to more robust models that perform effectively in real-world scenarios.

In conclusion, this scoping review offers a panoramic view of the current state of polygraph testing and neural networks. The findings point to numerous opportunities for future research and applications in the realm of lie detection. As this field continues to evolve, interdisciplinary collaboration and ethical considerations will be paramount to its success. Researchers, policymakers, and practitioners must work together to harness the potential of neural-network-based deception detection while addressing the associated challenges and ethical implications. By doing so, we can strive toward more accurate, equitable, and responsible lie detection methods that align with the needs and values of society.

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