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A review on multimodal approaches for deception detection: State-of-the-art, challenges, and future directions

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ABSTRACT

Deception detection (DD) presents a critical challenge across high-stakes domains such as security, finance, and education, necessitating accurate, non-invasive, and portable solutions. Traditional unimodal DD systems, which often rely solely on facial expressions or basic physiological signals, exhibit inherent limitations in both accuracy and complexity. To overcome these shortcomings, multimodal approaches have become the state of the art, integrating diverse data streams, including facial cues, vocal characteristics, body language, and advanced physiological metrics, to capture deeper insights into deceptive behaviour. This literature review systematically analyses contemporary multimodal DD methodologies. First, we provide an overview of current models for deception detection, focusing on methods that use computers to analyse multiple types of information. It explains how combining behavioural, physiological, and contextual evidence improves accuracy. Drawing from many studies, it outlines common trends in emotional cues, research methods, and evaluation approaches. Overall, the abstract identifies both the benefits and limitations of today's strategies for detecting deception with diverse data sources.

Keywords: ***Deception detection, multimodal approach, artificial intelligence, deep learning, machine learning, facial expression***

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INTRODUCTION

Deception refers to intentionally persuading someone to accept a false statement (or a sequence of claims) as accurate. Psychologically, a person engages in deceptive behaviour. To determine whether a person is telling the truth, individuals typically pay attention to what their interlocutors say and their physical appearance, notably their face. However, it is often difficult for humans to detect when someone is lying. Some people often use deception for a variety of reasons. From a psychological viewpoint, deceptions can be divided into low-stakes (face-saving) and high-stakes malicious deception (Hu, 2019). Spotting prospective liars in real time is becoming increasingly important as this trend worsens. In the long history of humanity, the detection of deception has been a significant social challenge.

Crime rate is increasing (Tonry, 2023); thus, improving deception detection (DD) techniques may help exponentially lower the crime rate and serve as a model for other nations. Investigative techniques designed to identify deception and lies have been in existence throughout human history, essentially since people began lying to each other. DD is crucial for promoting truthfulness and improving decision making in various settings, ultimately contributing to a more transparent, trustworthy, and fair society. Enhancing DD techniques can enable law enforcement agencies to effectively identify and apprehend criminals, creating a safer environment for citizens.

In contrast to unimodal systems that depend exclusively on facial or physiological data, multimodal systems integrate many cues to enhance detection accuracy and flexibility across different contexts and populations. This work comprehensively evaluates the present status of multimodal DD, examining its theoretical underpinnings, technological progress, methodological strategies, and practical implementations. We begin by discussing the psychological underpinnings of deception and the rationale for a multimodal approach. Following this, we examine the various technologies and techniques employed in multimodal DD, evaluating their efficacy and challenges. We also consider ethical concerns and the potential implications of these technologies in real-world scenarios.

The following are the main three contributions of our work:

- We delve deeply into DD, exploring the design and development of current methodologies, highlighting the pivotal role these techniques play in identifying deceitful behaviour.
- Our review extensively examines different approaches for pinpointing and recognizing deceptive individuals. It includes an analysis of our data collected.
- We present an overview of existing datasets utilized in this domain alongside a comparative analysis of various models.

The structure of the paper is organized as follows: Section 2 explains the technique utilized in this study. Section 3 discusses several techniques employed in the discipline, including multimodal, machine learning (ML), deep learning (DL), and facial expression analysis. Section 4 delivers the overall discussion. Section 5 concludes the paper.

REVIEW METHODOLOGY

The research methodologies and procedures are outlined in this section to assist readers comprehend how data was gathered and examined as well as acts as an outline for the analysis.

Review plan

This research used a conventional systematic literature review (SLR) methodology to rigorously analyse published scholarly articles on the subject at hand. An SLR is a methodical and systematic technique extensively employed for literature reviews. Our research employed a three-phase systematic literature review methodology:

- Phase-I: Perform an initial search utilizing pertinent keywords and databases to ascertain the sufficiency of available material for conducting a systematic literature review. Initially, we explored the five foremost internet databases for pertinent studies and identified 437 studies for the SLR. After this step, duplicate articles were eliminated, leaving 240 for screening.
- Phase-II: Upon the completion of Phase-I, we meticulously examined the article titles, abstracts, and keywords and eliminated extraneous publications from the preliminary study list. Subsequently, we removed the list.
- Phase-III: A total of 129 articles were selected for this SLR.

The screening phase is crucial to a literature review, involving evaluating and analysing chosen articles based on predetermined inclusion and exclusion criteria. Figure 1 illustrates the sequential process for the screening phase. The selection criteria step is essential, particularly for systematic reviews or meta-analyses. It entails establishing comprehensive criteria to guide the selection of studies. The final distribution of selected papers collected from various academic databases is shown in Figure 2.

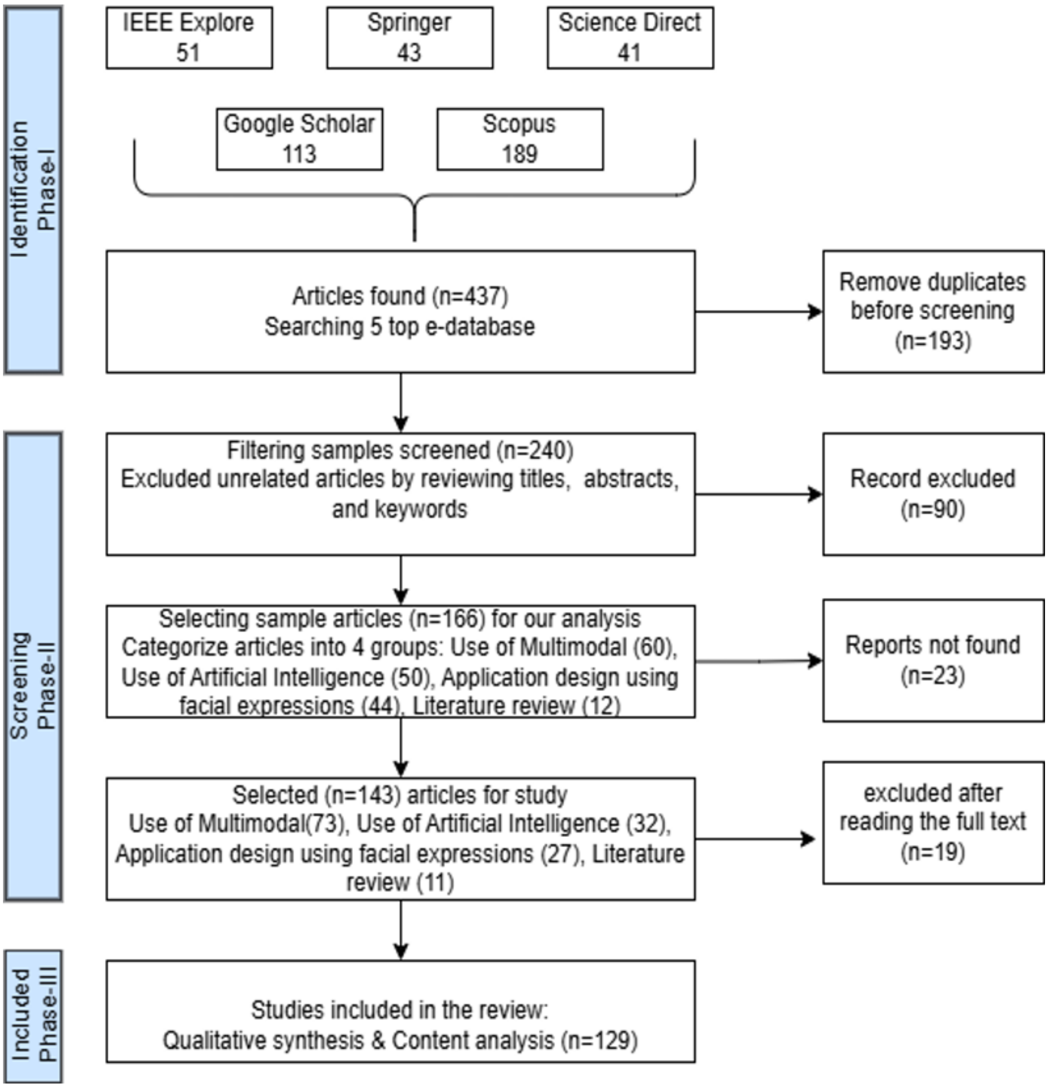

Figure 1. Review methodology for sample collection, pre-processing, and comprehensive analysis

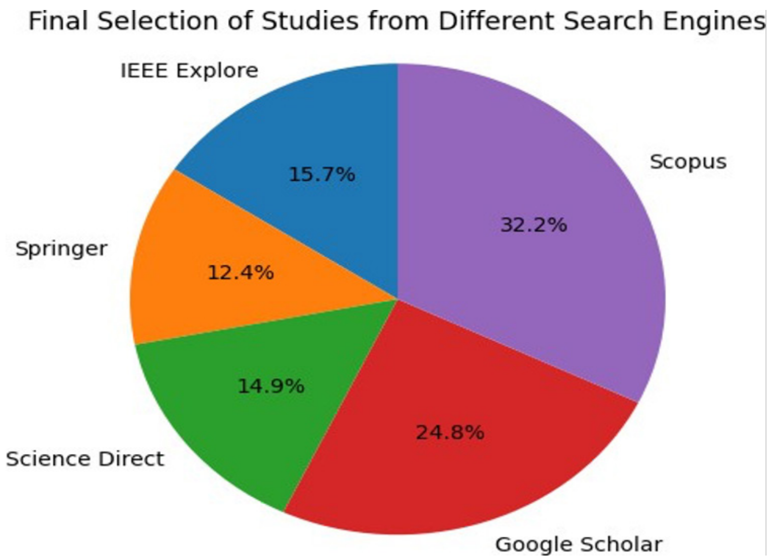

Figure 2. Searching strategies, selection criteria, and number of studies reviewed

Research questions

SLR's main goal is to provide answers to the following three research questions, such as:

- RQ1: What are the key advancements in DD methodologies over the past decade?
- RQ2: How have transformer-based models influenced DD in real-world applications?
- RQ3: What are the limitations of current DD systems in legal, forensic, and online contexts?

We incorporate RQ1 to comprehend the need to find essential markers and modalities in multimodal DD methods, acknowledging its vital contribution to enhancing results in areas such as national security, finance, and business. RQ2 examines the difficulties and efficacy of parameter tuning and feature selection in these methodologies, taking into consideration factors such as context, the characteristics of deception, and the dynamics between the deceiver and the detector. RQ3 seeks to evaluate the efficacy and constraints of contemporary multimodal systems, emphasizing existing deficiencies and establishing an outline for future research directions to address these issues.

Research protocol

A research protocol is an extensive plan that delineates the approach, processes, and objectives of the study. It serves as a framework that ensures consistency and lucidity throughout the study process. The procedures of our study protocol are described as follows:

- Execution of database queries and searches: Execute methodical searches across electronic databases with established queries.
- Classification of documents: Sort papers according to publication year, language, and relevancy parameters.
- Export outcomes: Store acquired data and encompasses metadata including title, year, abstract, keywords, and publisher details.
- Preliminary evaluation: Conduct schematic screening by examining titles, abstracts, and keywords to exclude irrelevant research.
- Comprehensive text retrieval: Obtain and extract the full text of designated articles for comprehensive analysis.
- Conclusive article selection: Perform a comprehensive evaluation of full-text papers to ascertain relevance, excluding any research that fails to match the established criteria.
- Data extraction and structuring: Derive essential information from chosen articles. Generate a summary table that includes pertinent details and preserves the corresponding metadata.
- Data examination: Conduct statistical studies on the retrieved data. Create visual representations, including charts and graphs, to substantiate findings.

DECEPTION DETECTION: STATE-OF-THE-ART

DD techniques have progressed from traditional methods to advanced ML and DL approaches, which are called multimodal techniques. Different types of approaches are used in DD, such as psychological and behavioural, data-driven, as well as contextual and computational, as shown in Figure 3.

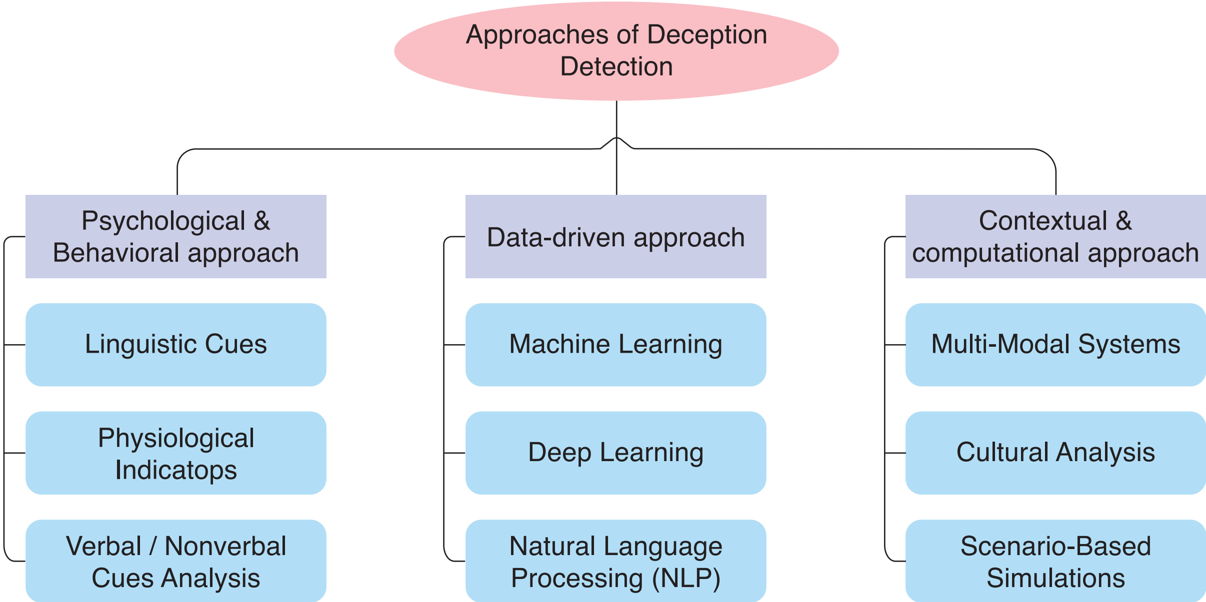

Figure 3. Different approaches of DD

Psychological and behavioural approaches

Deception is behaviour in which a person intentionally misleads another person while keeping their true intent a secret. It involves hiding the truth from others while displaying facial expressions and physical gestures. DD involves identifying when someone is lying or not being truthful. It involves various techniques, including analysing verbal and nonverbal cues, physiological responses, and behaviour patterns. However, it is not always possible to accurately determine if someone is lying.

Linguistic cues

Deception is a complicated psychological and behavioural issue that affects individuals' linguistic usage. The research found that when individuals deceive, they change their speech patterns due to the cognitive effort needed to sustain deception, maintain their emotions, and control the dissemination of information (Vrij et al., 2008). The cognitive load theory and interpersonal deception theory elucidate that deception heightens cognitive burden, frequently resulting in discernible verbal indicators. These may encompass extended pauses, increased hesitations, diminished self-references (notably a reduced usage of "I"), and variations in emotional tone (Hancock et al., 2007).

Linguistic signals were retrieved from the papers and classified according to their taxonomy and operational definitions. We merged phrases that referred to the same fundamental concept to eliminate repetition. Metrics include type-token ratio, unique words, lexical diversity, and distinct words that collectively assess vocabulary variance and are, therefore, categorized under a singular construct. This standardization guarantees uniformity in analysis and interpretation. In addition, the way deceptive information is spread, such as through Clickbait headlines, intentionally creates an information gap that lures readers to engage, yet often delivers misleading or insufficient content, thereby spreading misinformation and exhibiting clear deceptive behaviour in online news practices (Lim & Wilson, 2024).

Physiological indicator

Deception can be identified by linguistic patterns and involuntary physiological responses linked to cognitive and emotional processes. Psychological frameworks, including the arousal theory and cognitive load theory, suggest that lying causes physiological alterations due to increased stress, anxiety, and the augmented mental effort required to fabricate information. It can be detected psychologically by probing for details, asking unexpected questions, and exerting cognitive strain on the subject. Despite progress, the diversity in cerebral activity among individuals raises concerns about the generality and ethical implications of these procedures (Poulou, 2021). A systematic review (Yusoff et al., 2025) found that TikTok has an overall negative impact on youth mental health, highlighting risks such as addictive use, the spread of mental illness behaviours, and decreased self-esteem.

Although some contend that the technique might reduce psychological inhibitions, research suggests that information obtained under these circumstances may be unreliable, susceptible to suggestion, and unusable in court due to issues of voluntariness and human rights abuses (Goormans et al., 2024). The legal standing of these psychophysiological methods has been widely debated in Indian courts. Cases have highlighted their role in influencing verdicts, yet judicial bodies have often questioned their scientific diligence and ethical implications (Sahni & Langan, 2021).

Verbal / Nonverbal cues analysis

Deception is a cognitively demanding process that affects both verbal communication (spoken and written language) and nonverbal behaviour (facial expressions, gestures, and posture, and vocal tone). Using the FER dataset, Zahara et al. (2020) developed a custom-trained DL model to analyse these micro-expressions. Based on convolutional neural networks (CNNs), the model successfully classifies various facial expressions. This study contributes to the field and showcases the promising potential of automated systems in detecting deception through nonverbal cues, particularly micro-expressions. A significant limitation of this study is potential overfitting due to the small dataset size, which questions the model's effectiveness in more varied real-world situations.

Data-driven approach

A data-driven approach leverages ML, DL, and NLP techniques to enhance deception and misinformation detection. ML models utilize statistical patterns in text data to classify deceptive content, while DL methods, particularly neural networks, enable automatic feature extraction and deeper contextual understanding. NLP techniques further refine this process by analysing linguistic structures, semantic relationships, and contextual dependencies, making them essential for DD, misinformation, and fake news.

Machine learning

Facial expressions play a crucial role in DD, as they can offer insights into the emotional state of the interrogated individual. Research has shown that certain facial expressions, such as micro-expressions (brief, involuntary facial expressions that occur in response to an emotional stimulus), can indicate deception (Goh et al., 2020; Zloteanu, 2020). These micro-expressions can be challenging to detect, as they occur very quickly and are often subtle (Goh et al., 2020; Takalkar et al., 2018). The primary objective of the Facial Action

Coding System (FACS) is to describe all facial movements using Action Units, each of which corresponds to the movement of one or more facial muscles (Martinez et al., 2017; Polikovsky et al., 2013).

Their developed system is independent, operates with database data in an unconstrained environment, and avoids direct physical touch with the human body. Later, they proposed a systematic review method for detecting depression from facial signals, and the existing signal processing and feature extraction framework for earlier investigations in this area compared the methods used in various studies and discussed the best technologies (Nasser et al., 2020).

Table 1. List of existing traditional approaches

Author	Methods	Proposed Technique	Dataset
Azaria et al. (2015)	Feature selection and SVM	Proposed a framework for examining DD through a text-based videogame that facilitates group conversation	Gaming data (320 subjects)
Volkova & Bell (2017)	LSTM	Proposed a method to analyse autonomous deleted account	Twitter data
Ceballos et al. (2021)	SVM, NB, RF, LR, and DT	Introduced an approach for DD that is automated	Buzzfeed and PolitiFact (540 and 540 subjects)
Kleinberg & Verschuere (2021)	Feature extraction	Investigated how computer automated decision making can be integrated with human judgment, such as fraudulent intentions	
Mathur & Matarić (2021)	SVM	Proposed distinctive testing of the discriminative capacity of facial affect for automated decision-making including interpretable characteristics based on visual signals	Video data (108 videos)
Mambreyan et al. (2022)	Classification	Proposed an approach for DD experimental	Real-life trial dataset (121 data points)
Yang et al. (2020)	SVM, DT, and KNN	Used ETF features from videos for DD	Video data (121 video clips)
Qureshi et al. (2022)	RF, SVM, DT, and KNN	Presented a multidimensional model capable of detecting diverse forms of deception	PolitiFact and GossipCop
Srivastava & Dubey (2018)	SVM	Developed a model that identifies deception by analysing speech and physical features	Physiological and speech features (50 subjects)
Crockett et al. (2020)	SVM	Used physical features for DD	Image vector data (86,584 vectors)
Pak & Zhou (2015)	SVM	Executed an experiment that exhibits the efficacy of fundamental variables in DD	Mafia game data
Labibah et al. (2018)	DT	Developed a DD system integrating optical movements	Eye-tracking data

Deep learning

Belavadi et al. (2020) explored DD using a multi-view learning (MVL) model, which processes different feature groups separately. The study utilized three datasets with varying degrees of deception, including courtroom trial videos, opinion narratives, and crime scenarios. A significant limitation identified is the challenge of generalizing the MVL model across different deception scenarios, indicating that models trained on specific types of deception may need to be more effective in detecting deception under different conditions or contexts.

The research collectively explored different models and datasets for identifying deceit, utilizing techniques such as AffWildNet, OpenFace, OpenSmile, and MVL in various scenarios, including courtroom footage, YouTube court trial excerpts, and entertainment segments like the Box of Lies. The graphic displays the number of works per model from 2020 to 2023. The CNN model is the most widely used, with more instances than others, followed by the SVM model, which has 19 cases. The least favoured models are the hidden Markov model (HMM) and RF, which have two applications. LSTM and RNN are both widely used models, each with 16 applications. The models' popularity may stem from their optimal suitability for various jobs. CNNs are renowned for their exceptional performance in tasks related to image classification, whereas RNNs are commonly employed for tasks that involve sequential input, such as natural language processing (NLP).

DD is a complex and multi-disciplinary field that involves identifying false or misleading information. Many techniques have been developed and applied to detect deception. The most widely used methods include polygraph tests, eye-tracking, speech analysis, biometric detection, and emotional response analysis. Polygraph tests, also known as deception detector tests, have been used for decades to detect deception. These tests measure physiological responses, such as heart rate and sweat gland activity, in response to questions. The theory behind these tests is that people will experience higher physiological arousal when they lie. However, the accuracy of polygraph tests has been the subject of much debate, and many experts question their reliability as it has been shown that a polygraph can be deceived by a trained individual quite easily (Bhamare et al., 2020; Lv et al., 2024; Peng et al., 2021).

Natural language processing

Several studies have explored NLP-based DD, emphasizing the importance of contextual information in classification. Fornaciari et al. (2021) demonstrated that incorporating preceding linguistic context enhances DD, particularly when the context comes from the same speaker rather than an interlocutor. Their study employed deep neural models, including BERT, to capture semantic information, with attention mechanisms improving performance by identifying deception cues from BERT's representations. In the broader scope of misinformation detection, Su et al. (2020) provided a comprehensive review of detection methods, analysing feature representations, evaluation metrics, and reference datasets. They highlighted the strengths and weaknesses of content-based analysis and predictive modelling while emphasizing emerging hybrid approaches that integrate multi-modal representation, multi-source data, and multi-facet inference to tackle the evolving nature of misinformation.

Similarly, Saquete et al. (2020) used a PRISMA-compliant approach to examine various computational methodologies, available resources, and competitions, ultimately outlining future research directions in the field. Kozik et al. (2023) conducted a meta-analysis and bench- marking study, comparing models based on precision, F1-score, recall, and balanced accuracy across multiple benchmark datasets to assess the effectiveness of fake news detection models. Using a 5×2 cross-validation methodology, their research evaluated state-of-the-art NLP-driven approaches, providing valuable insights for researchers, practitioners, and policymakers combating fake news. In the context of cross-domain DD, Panda and Levitan (2022) examined the generalizability of DD models across five different domains. Their empirical study revealed significant performance gaps when models are applied to unseen domains. To address this challenge, they proposed distance metrics to quantify domain differences and analyse their impact on DD.

Contextual and computational approaches

A contextual and computational approach integrates multimodal analysis and cultural factors to improve deception and misinformation detection. Multimodal techniques combine textual, visual, and acoustic cues to capture diverse deception indicators beyond textual content alone. Additionally, cultural analysis is crucial, as deception patterns vary across languages, social norms, and communication styles.

Multimodal system

The ability of multimodal approaches to integrate various types of input data has been receiving significant attention in the field of DD in recent years. To improve detection effectiveness, several models that combine text, audio, and video data have been presented. Some systems utilize classical ML methods such as SVM, MLP, and AdaBoost to process contact-based modalities like EEG alongside non-contact modalities such as video and audio. Others employ DL models, including ensemble fusion of CNNs and LSTMs, to analyse complex cues such as gestures, micro-expressions, and speech characteristics in real-time settings. Several multimodal approaches are shown in Table 2 that focus specifically on high-stakes scenarios like courtroom trial recordings, employing architectures like Bidirectional LSTM and ResNet50 to detect deception from facial movements and speech. Emerging techniques also integrate underexplored modalities, including gaze tracking and thermal imaging, to extract subtle physiological cues.

Rill-Garc´ıa (2019) investigated the effectiveness of various high-level features extracted from videos for DD. The study explored features across visual, auditory, and textual modalities using real-life court trials and a novel Mexican dataset. A significant limitation is the potential overfitting of ML models due to the complex nature of the features and the diversity of the datasets, which could affect the generalizability of the findings. This research underscores the challenges in multimodal DD and the need for careful model training and validation. Krishnamurthy et al. (2018) introduced a multimodal DD model that utilizes features from textual, audio, visual, and micro-expression modalities. It employs a simple multi-layer perceptron architecture and tests its performance on a dataset containing 121 video clips from actual courtroom trials.

A limitation of this study is the small dataset size, which consists of only 121 videos. This limitation raises concerns about the potential overfitting of the model and its performance in diverse, real-world scenarios. Carissimi (2019) presented a unique approach to DD using an MVL model. This model processes different feature groups (views) separately to leverage their unique statistical properties, improving classification accuracy. The dataset included 121 video recordings from real-life court trials, encompassing a variety of nonverbal cues like facial expressions and hand movements. A notable limitation of this study is its reliance on a single, albeit diverse, dataset, which might not fully represent the complexity and variability of deceptive behaviour in different contexts.

Table 2. List of existing multimodal approaches

Name	Methods	Proposed Technique	Dataset
Mohan & Seal (2021)	SVM, MLP, and AdaBoost	Proposed a multimodal DD approach by using contact and non-contact-based modalities	Bag-of-Lies
Uskaikar et al. (2024)	Ensemble Fusion MLP-CNN	Proposed a multimodal DL system for DD that integrates audio characteristics and micro-expressions	Trial hearing recordings
Tran-Le et al. (2021)	Ensemble Fusion	Proposed a real-time algorithm for detecting lies during conversations by analysing facial expressions and movements through computer vision and signal processing techniques	Real-time dataset
Bhamare et al. (2020)	Audio ensemble	Introduced a DL model that integrates micro-expressions and audio features to DD effectively	Real-time dataset
Sehrawat et al. (2023)	LSTM, Bidirectional LSTM, and ResNet50	Proposed a DD system that classifies deceptive behaviour in real- world contexts, specifically focusing on trial data from actual court proceedings	Bag-of-Lies and Miami University DD dataset
Gupta et al. (2022)	Multimodal Fusion	Introduced a new multimodal dataset designed for DD, incorporating traditional modalities (video, audio) along with underexplored modalities (EEG and gaze data)	EEG and gaze dataset
Kang et al. (2024)	Siamese Transformer for Temporal Analysis	Proposed a DD model that combines global and local facial features using attention mechanisms to address the limitations of current visual-based DD methods	Real-time dataset
Sen (2020)	Multimodal approach	Proposed a multimodal DD system to evaluate visual, linguistic modalities, and acoustic to detect deception in statements made by witnesses	Public court trials
Abouelenien	Physiological, Linguistic, thermal features techniques	Proposed approach across different sectors of domains and identified key features for DD	149 multimodal recordings

Cultural analysis

DD is a complex and multi-disciplinary field that involves the identification of false or misleading information. Many techniques have been developed and applied to detect deception (Sartori et al., 2018; Mishra et al., 2022). The most widely used methods include polygraph tests, eye-tracking, speech analysis, biometric detection, and emotional response analysis (Celniak et al., 2023; Cantoni et al., 2018). These tests measure physiological responses, such as heart rate and sweat gland activity, in response to questions. The theory behind these tests is that people will experience higher physiological arousal when they lie.

However, the accuracy of polygraph tests has been the subject of much debate, and many experts question their reliability as a polygraph can be deceived by a trained individual quite easily (Bhamare et al., 2020). For example, ML algorithms can be trained on significant speech and text data datasets to identify patterns indicative of deception. A person's behaviour can be revealed through quick, unconscious facial movements known as facial micro-expressions. Analysing these expressions makes it possible to detect deception in real time. On the other hand, deep neural networks analyse and model complex patterns in data.

DISCUSSION

DD aims to deepen the understanding of how different signals such as text, video and audio, work together to improve the reliability of identifying deceptive behaviour. Our contribution provides an in-depth examination of how these modalities complement one another, outlining the theoretical foundations and practical methods used across existing research. By showing how cues from the body, voice, and face interact, we highlight why multimodal systems often achieve higher accuracy than single-modality approaches such as polygraphs, which are prone to stress-related false positives.

Facial cues are particularly prominent in DD studies, appearing in nearly 40% of the reviewed work, as micro-expressions, gaze shifts, and subtle head movements often reveal emotions a person tries to hide. When combined with vocal and physiological information, facial data consistently boosts system performance. However, challenges remain in understanding which visual features most influence outcomes, especially when models like SVMs or neural networks offer limited transparency. Recent efforts involving LSTMs, attention mechanisms, and interpretable decision-tree strategies show promise for improving explicability and clarifying the specific facial patterns that contribute to more accurate multimodal detection.

CONCLUSION

This literature review thoroughly examined the use of multimodal techniques in DD. Multimodal techniques, which synthesises data from diverse modalities, including facial expressions, speech patterns, textual clues, and physiological signs, represents the future of DD by addressing the shortcomings of single modal systems. In practical, high-stakes situations, dependence on a single modality frequently results in inferior outcomes, especially since most current systems are trained on limited, controlled datasets that do not accurately represent the complexity and variety of real-world environments.

The paper emphasises the importance of varying the modalities used in DD systems to enhance accuracy and guarantee reliability, irrespective of the quality or quantity of data available for analysis. It highlights the advancements in developing multimodal datasets and applying sophisticated fusion algorithms for DD while emphasising ongoing problems. Future research should prioritize building models that are strong, adaptable, and widely applicable. Advancing ways to combine different types of data, making methods more understandable, and ensuring fairness in data selection should be central goals. Exploring new approaches, including recent network designs, is also important. Ethical issues, protecting privacy, and making systems that adjust in real time deserve a thorough investigation. This review aims to guide researchers and professionals in developing trustworthy and effective multimodal DD systems.

AVAILABILITY OF DATA MATERIAL

This manuscript has no associated data.

AUTHOR CONTRIBUTIONS

All authors actively contributed to the conception and design of the research. Md Kowsar Hossain Sakib, Shanjita Akter Prome, and Md Rafiqul Islam played key roles in preparing materials, conducting analysis, and demonstrating strong teamwork and dedication. Md Kowsar Hossain Sakib wrote the initial draft of the manuscript, integrated the core findings, and structured the study's narrative. Neethiahnanthan Ari Ragavan, Goh Wei Wei, David Asirvatham, and Bharati Rathore engaged in thorough discussions to refine the content, enhance clarity, and approved the final version of the manuscript.

ETHICS APPROVAL

This study involved human subjects and was conducted by ethical standards. Taylor's University, Malaysia's Human Ethics Committee (HEC) reviewed and approved the study protocol. The ethics approval reference number is HEC 2023/021.

CLINICAL TRIAL NUMBER

Not Applicable.

FUNDING

Not Applicable.

CONSENT FOR PUBLICATION

All authors have reviewed the manuscript and consented to its publication.

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DECLARATION FOR COMPETING INTEREST

We declare that we do not have any conflict of interest, and this manuscript has no associated data.

References

Azaria, A., Richardson, A., & Kraus, S. (2015, February). An agent for deception detection in discussion-based environments. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing* (pp. 218–227). Association of Computing Machinery.

Belavadi, V., Zhou, Y., Bakdash, J. Z., Kantarcioglu, M., Krawczyk, D. C., Nguyen, L., Rakic, J., & Thuriasingham, B. (2020, October). MultiModal deception detection: Accuracy, applicability and generalizability. In *2020 Second IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA)* (pp. 99–106). IEEE.

Bhamare, A. R., Katharguppe, S., & Nancy, J. S. (2020, November). Deep neural networks for lie detection with attention on bio-signals. In *2020 7th international conference on soft computing & machine intelligence (ISCMI)* (pp. 143–147). IEEE.

Cantoni, V., Musci, M., Nugrahaningsih, N., & Porta, M. (2018). Gaze-based biometrics: An introduction to forensic applications. *Pattern Recognition Letters, 113*, 54–57.

Carissimi, N. (2019). *Investigating social interactions using multi-modal nonverbal features* [Unpublished dissertation].

Ceballos Delgado, A. A., Glisson, W., Shashidhar, N., Mcdonald, J., Grispos, G., & Benton, R. (2021). Deception detection using machine learning. *Proceedings of the 54th Hawaii International Conference on System Sciences. Hawaii International Conference on System Sciences* (pp. 7122–7131). https://doi.org/10.24251/hicss.2021.857.

Celniak, W., Słapczyńska, D., Pająk, A., Przybyło, J., & Augustyniak, P. (2023). Intelligent eye-tracker-based methods for detection of deception: A survey. *Electronics, 12*(22), 4627.

Crockett, K., O'Shea, J., & Khan, W. (2020, July). Automated deception detection of males and females from non-verbal facial micro-gestures. In *2020 International Joint Conference on Neural Networks (IJCNN)* (pp. 1–7). IEEE.

Fornaciari, T., Bianchi, F., Poesio, M., & Hovy, D. (2021). BERTective: Language models and contextual information for deception detection. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume* (pp. 2699–2708). Association for Computational Linguistics.

Goh, K. M., Ng, C. H., Lim, L. L., & Sheikh, U. U. (2020). Micro-expression recognition: an updated review of current trends, challenges and solutions. *The Visual Computer, 36*, 445–468.

Goormans, I., Mergaerts, L., & Vandeviver, C. (2024). SCANning for truth. Scholars' and practitioners' perceptions on the use (fulness) of Scientific Content Analysis in detecting deception during police interviews. *Psychology, Crime & Law, 30*(9), 971–993.

Gupta, M. V., Vaikole, S., Oza, A. D., Patel, A., Burduhos-Nergis, D. P., & Burduhos-Nergis, D. D. (2022). Audio-visual stress classification using cascaded RNN-LSTM Networks. *Bioengineering, 9*(10), 510. https://doi.org/10.3390/bioengineering9100510

Hancock, J. T., Curry, L. E., Goorha, S., & Woodworth, M. (2007). On lying and being lied to: A linguistic analysis of deception in computer-mediated communication. *Discourse Processes, 45*(1), 1–23.

Hu, S. (2019, July). Detecting concealed information in text and speech. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* (pp. 402–412). Association for Computational Linguistics.

Kang, J., Qu, W., Cui, S., & Feng, X. (2024, May). Deception detection algorithm based on global and local feature fusion with multi-head attention. In *2024 3rd International Conference on Image Processing and Media Computing (ICIPMC)* (pp. 162–168). IEEE.

Kleinberg, B., & Verschuere, B. (2021). How humans impair automated deception detection performance. *Acta Psychologica, 213*, 103250.

Kozik, R., Pawlicka, A., Pawlicki, M., Choraś, M., Mazurczyk, W., & Cabaj, K. (2023). A meta-analysis of state-of-the-art automated fake news detection methods. *IEEE Transactions on Computational Social Systems, 11*(4), 5219–5229. doi: 10.1109/TCSS.2023.3296627.

Krishnamurthy, G., Majumder, N., Poria, S., & Cambria, E. (2018, March). A deep learning approach for multimodal deception detection. In *International Conference on Computational Linguistics and Intelligent Text Processing* (pp. 87–96). Springer Nature Switzerland.

Labibah, Z., Nasrun, M., & Setianingsih, C. (2018, November). Lie detector with the analysis of the change of diameter pupil and the eye movement use method Gabor wavelet transform and decision tree. In *2018 IEEE International Conference on Internet of Things and Intelligence System (IOTAIS)* (pp. 214–220). IEEE.

Lim, S. S., & Wilson, S. (2024). Unravelling clickbait news as viral journalism in Malaysia: Its phenomeon and impacts. *SEARCH Journal of Media and Communication Research, 16*(1), 33–47.

Lv, P., Li, S., & Yin, X. (2024). Optimal deceptive strategy synthesis for autonomous systems under asymmetric information. *IEEE Transactions on Intelligent Vehicles, 9*(10), 6108–6121. doi: 10.1109/TIV.2024.3362585

Mambreyan, A., Punskaya, E., & Gunes, H. (2022, August). Dataset bias in deception detection. In *2022 26th International Conference on Pattern Recognition (ICPR)* (pp. 1083–1089). IEEE.

Martinez, B., Valstar, M. F., Jiang, B., & Pantic, M. (2017). Automatic analysis of facial actions: A survey. *IEEE transactions on affective computing, 10*(3), 325–347.

Mathur, L., & Matarić, M. J. (2021, June). Unsupervised audio-visual subspace alignment for high-stakes deception detection. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP*) (pp. 2255–2259). IEEE.

Mishra, K. N., Mishra, V. P., Saket, S., & Mishra, S. P. (2022). Hybrid approach for deception tracing in smart cities using LR and n-fold intelligent machine learning techniques. *International Journal of Management Practice, 15*(4), 460–487.

Mohan, K., & Seal, A. (2021). Deception detection on "Bag-of-Lies": Integration of multi-modal data using machine learning algorithms. In *Proceedings of International Conference on Machine Intelligence and Data Science Applications: MIDAS 2020* (pp. 445–456). Springer Singapore.

Nasser, G., Morrison, B. W., Bayl-Smith, P., Taib, R., Gayed, M., & Wiggins, M. W. (2020). The role of cue utilization and cognitive load in the recognition of phishing emails. *Frontiers in Big Data, 3*, 546860.

Pak, J., & Zhou, L. (2015, May). A comparison of features for automatic deception detection in synchronous computer-mediated communication. In *2015 IEEE International Conference on Intelligence and Security Informatics (ISI*) (pp. 141–143). IEEE.

Panda, S., & Levitan, S. (2022). Deception detection within and across domains: identifying and understanding the performance gap. *ACM Journal of Data and Information Quality, 15*(1), 7.

Peng, Q., Jiao, Y., Zhang, J., Liu, T., & Zhou, S. (2021). It's hard for children to accept a teacher's lies: Implications of authority on children's evaluation of lies. *Cognitive Development, 60*, 101093.

Polikovsky, S., Kameda, Y., & Ohta, Y. (2013). Facial micro-expression detection in hi-speed video based on facial action coding system (FACS). *IEICE transactions on information and systems, 96*(1), 81–92.

Poulou, C. G. (2021). Lie detection in the brain-Moral, social, legal and religious challenges. *Bioethica, 7*(1), 72–85.

Qureshi, K. A., Malick, R. A. S., Sabih, M., & Cherifi, H. (2022). Deception detection on social media: A source-based perspective. *Knowledge-Based Systems, 256*, 109649.

Rajoub, B. A., & Zwiggelaar, R. (2014). Thermal facial analysis for deception detection. *IEEE transactions on information forensics and security, 9*(6), 1015–1023.

Rill-García, R., Jair Escalante, H., Villasenor-Pineda, L., & Reyes-Meza, V. (2019). High-level features for multimodal deception detection in videos. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshop*s (pp. 1565–1573). doi: 10.1109/CVPRW.2019.00198.

Sahni, S. P., & Langan, L. (2021). Psychological approaches to detection of deceit. In S. P. Sahni, & P. Bhadra (eds), *Criminal psychology and the criminal justice system in India and beyond* (pp. 173–184). Springer.

Saquete, E., Tomás, D., Moreda, P., Martínez-Barco, P., & Palomar, M. (2020). Fighting post-truth using natural language processing: A review and open challenges. *Expert Systems with Applications, 141*, 112943.

Sartori, G., Zangrossi, A., & Monaro, M. (2018). Deception detection with behavioral methods: the autobiographical implicit association test, concealed information test–reaction time, mouse dynamics, and keystroke dynamics. In J. P. Rosenfeld (ed), *Detecting concealed information and deception* (pp. 215–241). Academic Press.

Sehrawat, P. K., Kumar, R., Kumar, N., & Vishwakarma, D. K. (2023, March). Deception detection using a multimodal stacked BI-LSTM model. In *2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA)* (pp. 318–326). IEEE.

Şen, M. U. (2020). *Multi-modal deception detection from videos* (Doctoral dissertation).

Srivastava, N., & Dubey, S. (2018, March). Deception detection using artificial neural network and support vector machine. In *2018 Second international conference on electronics, communication and aerospace technology (ICECA)* (pp. 1205–1208). IEEE.

Su, Q., Wan, M., Liu, X., & Huang, C. R. (2020). Motivations, methods and metrics of misinformation detection: an NLP perspective. *Natural Language Processing Research, 1*(1), 1–13.

Takalkar, M., Xu, M., Wu, Q., & Chaczko, Z. (2018). A survey: Facial micro-expression recognition. *Multimedia Tools and Applications, 77*(15), 19301–19325.

Tonry, M. (Ed). (2023). *Crime and justice: Prisons and prisoners* (Vol. 51). University of Chicago Press.

Tran-Le, M. T., Doan, A. T., & Dang, T. T. (2021, December). Lie detection by facial expressions in real time. In *2021 International Conference on Decision Aid Sciences and Application (DASA)* (pp. 787–791). IEEE.

Uskaikar, O., Sonavane, A., Randive, M., & Dabre, K. (2024, June). Multi-modal deception detection using deep learning. In *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)* (pp. 1–7). IEEE.

Volkova, S., & Bell, E. (2017, May). Identifying effective signals to predict deleted and suspended accounts on twitter across languages. In *Proceedings of the International AAAI Conference on Web and Social Media, 11*(1), 290–298.

Vrij, A., Fisher, R., Mann, S., & Leal, S. (2008). A cognitive load approach to lie detection. *Journal of Investigative Psychology and Offender Profiling, 5*(1–2), 39–43.

Xia, F., Wang, H., & Huang, J. (2007, September). Deception detection via blob motion pattern analysis. In *International Conference on Affective Computing and Intelligent Interaction* (pp. 727–728). Springer Berlin Heidelberg.

Yang, J. T., Liu, G. M., & Huang, S. C. H. (2020, October). Emotion transformation feature: Novel feature for deception detection in videos. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 1726–1730). IEEE.

Yusoff, S. H., Rahman, S. H. A., Sabran, R., Hassan, F., Hussin, R., & Baharin, N. H. S. (2025). Cultivating consciousness: Unveiling TikTok's detrimental effects on youth mindset and behaviour. *SEARCH Journal of Media and Communication Research, 17*(4), 87–101. doi: 10.58946/search-Special Issue.ICIMaC2024.P6

Zahara, L., Musa, P., Wibowo, E. P., Karim, I., & Musa, S. B. (2020, November). The facial emotion recognition (FER-2013) dataset for prediction system of micro-expressions face using the convolutional neural network (CNN) algorithm based Raspberry Pi. In *2020 Fifth International Conference on Informatics and Computing (ICIC)* (pp. 1–9). IEEE.

Zloteanu, M. (2020). Reconsidering facial expressions and deception detection. *Handbook of facial expression of emotion* (Vol 3) (pp. 238–284).

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