

Review

Detecting Deceptive Behaviours through Facial Cues from Videos: A Systematic Review

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Abstract: Interest in detecting deceptive behaviours by various application fields, such as security systems, political debates, advanced intelligent user interfaces, etc., makes automatic deception detection an active research topic. This interest has stimulated the development of many deception-detection methods in the literature in recent years. This work systematically reviews the literature focused on facial cues of deception. The most relevant methods applied in the literature of the last decade have been surveyed and classified according to the main steps of the facial-deception-detection process (video pre-processing, facial feature extraction, and decision making). Moreover, datasets used for the evaluation and future research directions have also been analysed.

Keywords: deception detection; facial cues; dataset; feature extraction; decision-making algorithms

1. Introduction

Lying is a complex social activity by someone (i.e., the deceiver) aimed at causing a specific behaviour in another person (i.e., the deceived) by making their view of the situation more congruent with the view and behaviour of the deceived that usually occurs, according to the deceiver's knowledge [1]. Deception may destroy the relationship and hamper communication, leading to negative consequences [2]. Therefore, deception detection has been an investigated research topic for decades, and the development of tools and methods for detecting deceptive behaviours has become an urgent need for society. However, despite a rich corpus of deception research, detecting deceptive behaviours is still a very challenging task, mainly because human beings do not have good lie-detection abilities. A study by Bond and DePaulo [3] quantifies the human accuracy of discriminating between lies and truths at 54% on average, in other words just slightly above a random guess. This percentage is also confirmed by the Hartwig's [4] more recent study. In response to the necessity to improve this accuracy rate, researchers have long been trying to decode human behaviour in an attempt to discover deceptive cues. In this study, what we consider "deceptive" is human behaviour in which the deceiver intentionally acts to make the deceived believe in something the deceiver considers false [5]. This is a conscious and deliberated act, opposed to the unconscious (non-deceptive) behaviour in which a person provides false information believed to be true.

To discover deceptive cues, different methods have been proposed by scientists from different disciplines, ranging from psychologists and physiologists to technologists. For instance, methods based on the psycho-physiological detection of deception that uses mainly psychological tests and physiological monitoring have been applied [6,7]. A positive contribution is also given by technologists that developed methods for deceptive detection based on technological tools. This study focuses on the technological field, in which a considerable number of methods for detecting verbal (explicit) and non-verbal (implicit) cues of deception have been developed [8]. Explicit cues are categorised according to their nature (i.e., visual, verbal, or paralinguistic) [9], while implicit cues involve facial expressions, body movements/posture, eye contact, and hand movements [10].



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Detecting deceptive behaviours from explicit cues makes deception harder because explicit cues are easier to manipulate through carefully chosen language and wording, while implicit cues, even if also subject to manipulation, are more spontaneous and challenging to control consciously [11]. On the other hand, the interpretation of implicit cues tends to be more subjective and context-dependent, requiring a deeper understanding of individual differences and cultural norms, while explicit cues are typically more straightforward and easier to analyse in isolation. Finally, detection deception using implicit cues requires collecting data through video recordings or specialised sensors to capture non-verbal behaviours, which is more challenging compared to collecting text data for explicit cues.

Considering the above-mentioned differences, the solutions provided in the literature for detecting deceptive behaviours have different characteristics if relying on explicit or implicit cues. The systematic literature review provided in this paper deals with implicit cues and, in particular, focuses on a specific type of implicit cues, i.e., facial cues. Specifically, the most relevant deception-detection systems focusing on facial cues have been described and classified considering the methods used in the main steps of the facial-deception-detection process (i.e., video pre-processing, facial feature extraction, and decision making). The choice to focus on facial cues is justified by the results of several existing studies [12,13] arguing that facial cues have an important role in detecting deceptive behaviours due to their involuntary aspects. As stated by Darwin in his “inhibition hypothesis” [13], some actions of the facial muscles are the hardest to be inhibited due to the difficulty to control them voluntarily.

The main contributions of this review are as follows:

1. to collect and systematise the scientific knowledge related to automated face deception detection from videos;
2. to summarise (i) the methods used for video pre-processing, (ii) the facial extracted features, (iii) the decision-making algorithms, and (iv) the datasets used for the evaluation;
3. to point out future research directions that emerged from the analysis of the existing studies.

The paper is structured as follows. Section 2 introduces the related work. Section 3 illustrates the methodology followed for the systematic literature review, while in Section 4, the results are discussed. Section 5 describes how the surveyed studies answered the review questions defined in the paper. Section 6 summarises future research directions that emerged from the literature review. Finally, Section 7 concludes the paper.

2. Related Work

Automated deception detection from videos is a challenging task that can find applications in many real-world scenarios, including airport security screening, job interviews, court trials, and personal credit risk assessment [14].

Various surveys of automated deception-detection methods from videos have been developed in the literature, classifying the methods according to different dimensions. In particular, recent surveys (see Table 1) have provided a very broad overview of deception-detection methods considering monomodal and multimodal features. The survey developed by Constâncio et al. [15] provides a systematic literature review of deception detection based on machine-learning methods, underlying the techniques and approaches applied, the difficulties, the kind of data, and the performance levels achieved. In this survey, verbal and non-verbal cues, such as facial expressions, gestures, and prosodic and linguistic features, have been considered. The 81 surveyed papers are classified according to the type of extracted features (emotional, psychological, and facial) and the kinds of machine-learning algorithms. Analogously, the survey in [16] gives an overview of automated deception detection through machine-intelligence-based techniques by providing a critical analysis of the existing tools and available datasets. The authors focused on deception detection through text, speech, and video data analysis by classifying the 100 surveyed papers according to both the research domain (i.e., psychological, professional, and computational)

and the type of extracted features (verbal, non-verbal, and multimodal). A further survey focused on monomodal features (speech cues) is proposed by Herchonvicz and de Santiago [17], in which deep-learning-based techniques, available datasets, and metrics extracted from the surveyed papers are discussed.

Table 1. Comparative analysis of surveys.

Reference	Cues	Techniques	Datasets	Steps of the Deception Detection Process (Figure 1)
Constâncio et al., 2023 [15]	Verbal and non-verbal cues	Machine-learning methods	Not surveyed	Step 2 and Step 3
Alaskar et al., 2023 [16]	Verbal and non-verbal cues	Machine-intelligence-based techniques	Surveyed	Step 2 and Step 3
Herchonvicz and de Santiago, 2021 [17]	Verbal cues	Deep-learning-based techniques	Surveyed	Step 2 and Step 3
Our survey	Non-verbal cues	Machine-learning methods	Surveyed	Step 1, Step 2, and Step 3

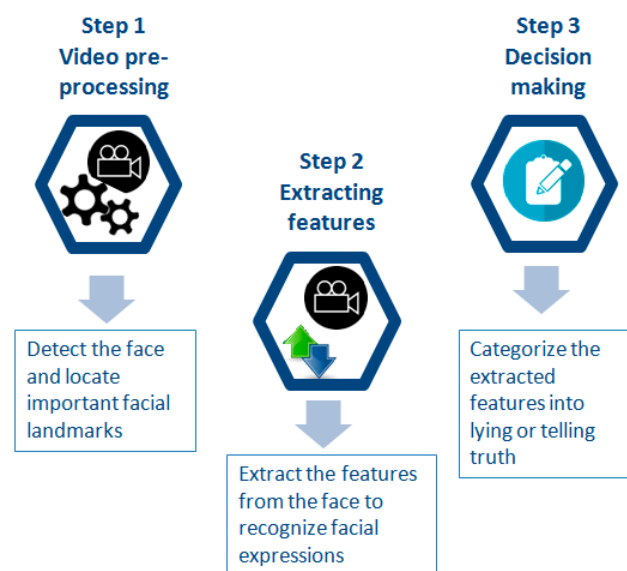


Figure 1. The workflow of the deception detection process from videos followed in the review.

Different from existing surveys, this work focuses on deception detection methods specifically based on facial cues and proposes a classification of these methods based on the main steps of the facial deception detection process (video pre-processing, facial feature extraction, and decision making), as proposed by Thannoon et al. [18]. On the contrary, the existing surveys considered only the second and third steps of this process.

A general workflow of the followed deception detection process that used video datasets is provided in Figure 1.

During the video pre-processing step, the video is analysed by a face detector, which bounds the box containing the face, and by a facial-landmark-tracking tool, which locates and tracks the facial landmarks. In the facial-feature-extraction step, the extraction of a set of facial features for recognizing the facial cues meaningful to deception is carried out. Finally, the classification of the extracted features into truthful or deceptive behaviour is performed in the decision-making step. According to these steps, the studies included in the review are analysed to extract (i) the methods used for video pre-processing, (ii) the facial extracted features, (iii) the decision-making algorithms, and (iv) the datasets used for the evaluation.

3. Materials and Methods

This section illustrates the methodology for systematically searching and analysing the existing literature on automated face deception detection from videos. The followed methodology was the systematic literature review (SLR) described in the PRISMA recommendations [19] composed of the following steps: (1) identifying the review focus; (2) specifying the review question(s); (3) identifying studies to include in the review; (4) data extraction and study quality appraisal; (5) synthesizing the findings; and (6) reporting the results.

The review focus consists of the collection and systematization of the scientific knowledge related to automated deception detection from videos focusing on facial signals. Specifically, we aim to study the methods for video pre-processing, the facial extracted features, the decision-making algorithms, and the available datasets.

As required by the second step of the SLR process, the following review questions (RQ) were defined:

RQ 1: Which methods for video pre-processing are used?;

RQ 2: Which facial features for automated deception detection are extracted?;

RQ 3: Which decision-making algorithms for automated deception detection are used?;

RQ 4: Which datasets for automated deception detection are used?

In the third step of the SLR process, the identification of the studies to include in the review was carried out following the four phases of the PRISMA recommendations [19], as shown in Figure 2.

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and registers only

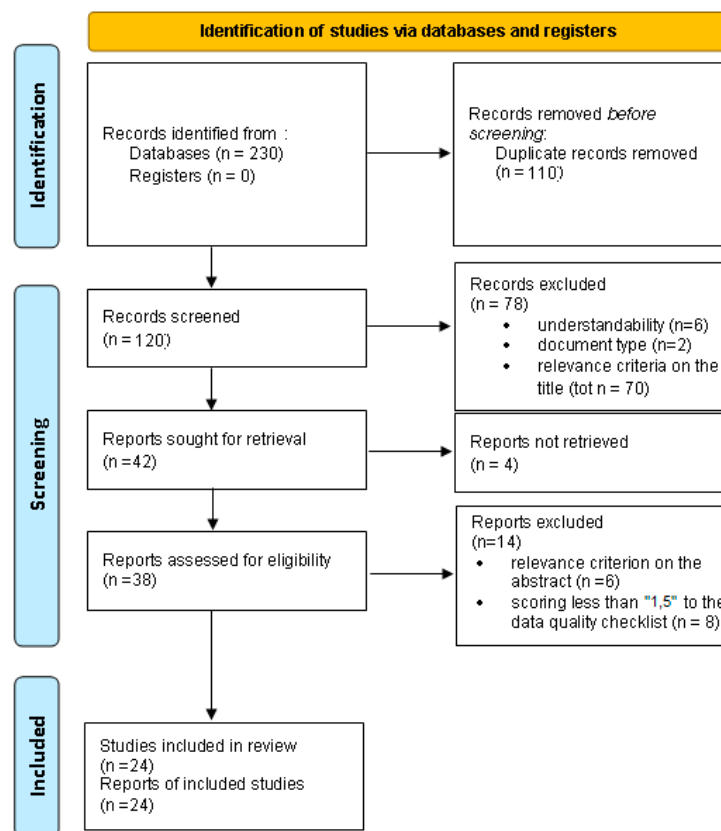


Figure 2. The PRISMA flow diagram, adapted from [20]. For more information, visit: <http://www.prisma-statement.org/> (accessed on 9 August 2023).

For the identification of an initial set of scientific works, two indexed scientific databases (Web of Science (WoS) and Scopus) containing formally published literature (e.g., journal articles, books, and conference papers) were used. Specifically, WoS and Scopus were used due to their proven usefulness in conducting bibliometric analyses of the existing literature in various research domains to establish trends [21]. Grey literature has not been included in the systematic review because there is no gold standard method for searching grey literature, nor is there a defined methodology for the same, which makes it all the more difficult [22].

The search strings defined to search the scientific papers on the databases are as follows: (“deception detection” OR “lie detection” OR “deceptive behaviour*” OR “lie behaviour*” OR “detect* deception” AND “video*” AND “facial expression*”). Note that this study does not disambiguate among the different forms of deception (e.g., bluff, mystification, propaganda, etc.) because it aims to find studies focused on deceptive behaviours in general without restricting the search to specific forms of deception.

During the screening phase, the obtained results were filtered according to the inclusion and exclusion criteria shown in Table 2.

Table 2. Exclusion and inclusion criteria formulated for the study.

Phase	Exclusion Criteria	Inclusion Criteria
Screening phase	e1. Understandability criterion: <ul style="list-style-type: none"> - articles that are written not in English. 	i1. Relevance criterion on the title: <ul style="list-style-type: none"> - studies relevant to the review focus, i.e., describing automated deception detection from videos focusing on facial expressions; - studies answering the defined review questions: (i) the methods for video pre-processing, (ii) the facial extracted features, (iii) the decision-making algorithms, or (iv) the available datasets.
	e2. Duplication criterion: <ul style="list-style-type: none"> - same articles retrieved from two different databases; - articles having the same title and authors retrieved from the same database but published in different sources. 	i2. Temporal criterion: <ul style="list-style-type: none"> - studies published in the period 2013–2023. i3. Document type criterion: <ul style="list-style-type: none"> - studies belonging to the following document types: article, review, book chapter, conference/proceedings paper.
Eligibility phase	e3. Availability criterion: <ul style="list-style-type: none"> - studies that are not accessible in full text. 	i4. Relevance criterion on the abstract: <ul style="list-style-type: none"> - studies relevant to the review focus, i.e., describing automated deception detection from videos focusing on facial expressions; - studies answering the review questions: (i) the methods for video pre-processing, (ii) the facial extracted features, (iii) the decision-making algorithms, or (iv) the available datasets.

The full text of the eligible studies was analysed by two reviewers using a quality evaluation checklist composed of four questions and related scores (see Table 3). The “disagreed” studies were evaluated by a moderator who provided the final scores.

Table 3. Quality evaluation checklist and scores.

Quality Assessment Questions		Scores
QA1	Does the study describe the methods for video pre-processing?	1—yes, the methods for video pre-processing are described in detail. 0.5—partially, the methods for video pre-processing are summarised without providing details on the different steps. 0—no, the methods for video pre-processing are only cited, without providing a description.
QA2	Does the study describe the facial extracted features?	1—yes, the facial extracted features are described in detail. 0.5—partially, the facial extracted features are summarised without providing a detailed description. 0—no, the facial extracted features are not described.
QA3	Does the study describe the decision-making algorithm?	1—yes, the decision-making algorithm is fully described. 0.5—partially, the decision-making algorithm is summarised without providing a detailed description. 0—no, the decision-making algorithm is not described.
QA4	Does the study use some datasets for the evaluation of the method?	1—yes, one or more datasets are used. 0—no, datasets are not used.

Studies that obtained a score < 1.5 were excluded from the qualitative analysis, while studies that scored 1.5 or more were included in the review.

Finally, analysis of the full texts of the included studies was performed, extracting the following information (if any):

- Pre-processing techniques of facial cues;
- Facial features, facial action coding system, and action units;
- Facial deception classification approaches;
- Evaluation datasets

In the following sections, the findings resulting from the application of the SLR process are described.

4. Results of the SLR

As depicted in Figure 2, during the identification phase (performed in May 2023), a total of 230 articles were retrieved using the two search engines: 203 from Scopus and 27 from WoS.

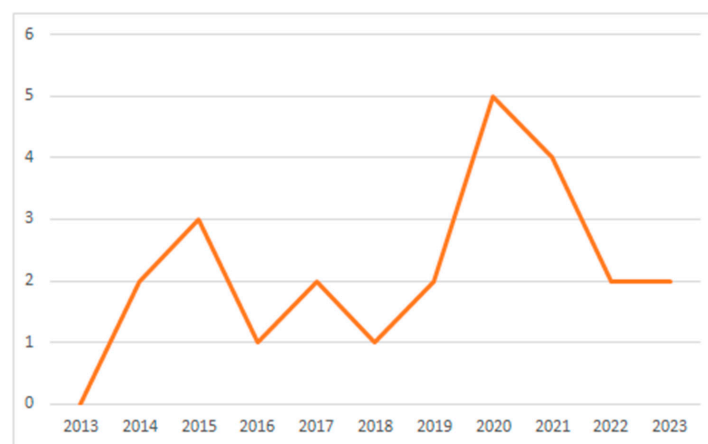
As required by the duplication criterion, removing duplicate records resulted in 120 studies. By applying the understandability criterion, 6 studies that were not written in English were excluded, and therefore, a total of 114 articles were screened for the inclusion criteria. Moreover, the studies that did not satisfy the document type criterion (2 articles) and those that did not contain in the titles the terms used for the search (70 studies) were removed, and therefore, a total of 42 studies resulted at the end of the screening phase.

Four studies that were not accessible in full text (availability criterion) and six studies that were considered not relevant for the focus of the review (relevance criterion) were removed. The relevance criterion to the abstract was also applied, and therefore, a total of 32 articles were retained for a full evaluation of eligibility, evaluated by two reviewers according to the quality evaluation checklist shown in Table 3. Seven studies with a score less than 1.5 were excluded, while the remaining twenty-four studies were included in the qualitative synthesis. Table 4 provides an overview of the selected studies.

Table 4. Studies selected for the analysis.

Reference	Authors	Year	Document Type
[23]	Chebbi and Jebara	2020	Conference paper
[24]	Abbas and Al-Ani	2023	Article
[25]	Shen et al.	2021	Article
[26]	Gadea et al.	2015	Article
[27]	Monaro et al.	2022	Article
[28]	Su and Levine	2016	Article
[14]	Ding et al.	2019	Conference Paper
[29]	Abd et al.	2021	Article
[30]	Su and Levine	2014	Conference Paper
[31]	Ngo et al.	2021	Conference Paper
[32]	Mathur and Matarić	2020	Conference paper
[33]	Yu et al.	2014	Article
[34]	Zhang et al.	2020	Conference Paper
[35]	Belavadi et al.	2020	Conference paper
[36]	Feinland et al.	2022	Conference Paper
[37]	Sen	2017	Conference paper
[38]	Yildirim et al.	2023	Article
[39]	Mathur and Matarić	2021	Conference Paper
[40]	Pérez-Rosas et al.	2015	Conference paper
[41]	Venkates et al.	2020	Conference paper
[18]	Thannoon et al.	2019	Conference paper
[42]	Demyanov et al.	2015	Conference paper
[43]	Pentland et al.	2017	Article
[44]	Carissimi et al.	2018	Conference paper

The selected studies were published mainly in conference proceedings (15 studies; 62.5%), followed by journals (9 studies; 37.5%). Figure 3 shows the temporal distribution of the selected studies, underlying the growing interest of the scientific community in the facial-deception-detection topic, which reached a peak in 2020.

**Figure 3.** Temporal distribution of the surveyed studies.

5. Discussion

In this section, an analysis of the answers to the four review questions (introduced in Section 3) extracted from the 24 surveyed studies is carried out. Specifically, to deal with RQ1, we analyse the methods for video pre-processing. Addressing RQ2, the facial features are classified. Concerning RQ3, the decision-making algorithms used for automated deception detection are analysed. Finally, as part of RQ4, the used datasets are analysed.

5.1. RQ1: Which Methods for Video Pre-Processing Are Used?

Pre-processing consists of those operations that prepare data for subsequent analysis in an attempt to compensate for systematic errors. The videos are subjected to several corrections, such as geometric, radiometric, and atmospheric, although all these corrections might not be necessarily applied in all cases. These errors are systematic and can be removed before they reach the user. According to the nature of the information to be extracted from the videos, the most relevant pre-processing techniques are chosen.

Facial region detection, landmark localisation, and tracking are necessary for pre-processing when capturing videos in unconstrained recording conditions. This step has the aim of localizing and extracting the face region from the background and identifying the locations of the facial key landmark points. These points have been defined as “either the dominant points describing the unique location of a facial component (e.g., eye corner) or an interpolated point connecting those dominant points around the facial components and facial contour” [44]. Regardless of the application domain, face detection and landmark tracking from input video streams are preliminary steps necessary to process any kind of information extractable from the face.

Over the past few decades, several face-detection and landmark-tracking algorithms have been developed [33,43,45,46], as well as academic or commercial software that performs joint face detection and landmark localization [47–54].

The vast majority of these methods and tools are based on 2D image processing. The main drawback of 2D face-detection and landmark-tracking methods is that their performances depend strictly on the following four factors: the pose of the head that can generate self-occlusions and deformations; occlusions caused by masks, sunglasses, or other faces; illumination variations caused by internal camera control and skin reflectance properties; time delay caused by face changes over time. However, these methods have the advantages of being generally easier and less expensive in terms of computational load compared to 3D face-detection methods. This last class of methods uses a 3D dataset that contains both face and head shapes as range data or polygonal meshes [55]. The 3D methods allow the fundamental limitations of 2D methods to be overcome since they are insensitive to pose and illumination variations.

A widely accepted classification of face-detection techniques [56] distinguishes them into two categories: feature-based and image-based approaches. On the one hand, feature-based techniques make explicit use of face knowledge by extracting local or global features (e.g., eyes, nose, mouth) and use this knowledge to classify between facial and non-facial regions. The active shape model (ASM) [38] and the Viola–Jones method [33] are two of the most applied and successful feature-based methods so far. On the other hand, image-based approaches learn to recognise a face pattern from examples following a training step for classifying examples into face and non-face prototype classes. The only image-based approach, applied by the surveyed studies, is the Constrained Local Neural Field (CLNF) [46].

There is also academic and commercial software that performs joint face-detection and landmark localization, such as OpenFace [47], FaceSDK [49], IntraFace [48], ‘dlib’ library [50], OpenCV [51], PittPatt SDK [52], InsightFace [53], and FAN [54].

A total of 18 papers among those surveyed (24) use the face-detection and landmark-tracking methods represented in Table 5.

From the table, we can observe that during the video pre-processing step, mainly 2D methods are used (17 studies; 94%), while only two works apply 3D methods. Moreover,

the majority of the studies (14 studies; 78%) apply academic and commercial software that allows joint face-detection and landmark localization tasks to be performed. OpenFace [45] is the open-source tool most applied by surveyed facial-deception-detection works (7 studies; 39%). The remaining three surveyed works use specific face-detection and face-tracking algorithms, mainly belonging to the feature-based category. The most applied algorithms are the Viola–Jones face detector [33] and the Constrained Local Neural Field (CLNF) [46] used for face detection and face tracking, respectively.

5.2. RQ2: Which Facial Features for Automated Deception Detection Are Extracted?

The feature-extraction process consists of transforming raw data into a set of features to be used as reliable indicators for detecting deceptive behaviours.

A multitude of facial cues has been correlated with deception in the literature, including lip pressing, eye blinking, facial rigidity, smiling, and head movement. A total of 22 papers among those surveyed (24 studies) extracted the following 10 facial features, represented in Table 6 with the respective number: (I) facial expression; (II) facial rigidity; (III) head pose; (IV) eye blink; (V) eyebrow motion; (VI) wrinkle occurrence; (VII) mouth motion; (VIII) gaze motion (IX); lip movement (X).

More than half of the studies (15 studies; 68%) rely on the Facial Action Coding System (FACS), an anatomically based system for representing all visually discernible facial movements proposed by Ekman et al. [42]. The FACS provides a list of action units (AUs) that are the individual components of muscle movement extracted from facial expressions. Ekman et al. [57] provided a list of AUs that are the most difficult to produce deliberately and the hardest to inhibit. Therefore, the majority of the analysed studies detect the movements of these AUs as potential indicators for distinguishing liars from truth-tellers in high-stakes situations.

A total of 18 studies (82%) rely on extracting facial expression features for detecting deceptive behaviours. Facial expressions, particularly micro-expressions (i.e., facial expressions of emotion that are expressed for 0.5 s or less), are often considered strong indicators of deception. Six basic facial expressions of emotion are defined in the literature: disgust, anger, enjoyment, fear, sadness (or distress), and surprise. In particular, the surveyed studies have detected deceptive behaviours by analysing the presence of both extreme facial movements, which can indicate high-intensity emotions that are not really being experienced, and facial rigidity (i.e., little or no facial movements) that deceivers could purposefully inhibit to appear truthful. Moreover, half of the studies (11) rely on head pose, followed by gaze (9 studies; 41%).

5.3. RQ3: Which Decision-Making Algorithms for Automated Deception Detection Are Used?

During the decision-making step, the extracted features are used to train a classification approach to automatically distinguish between deceptive and truthful videos.

Specifically, 20 studies among the surveyed ones apply a deception classification approach, as represented in Table 7. Most of them (19 studies; 95%) use supervised learning techniques that require labelled training data (i.e., a set of feature vectors with their corresponding labels (deceptive vs. truthful)). The most applied supervised technique is the support vector machine (SVM), which is applied in seven studies (35%), followed by six studies (30%) applying Random Forest, five studies applying neural networks (25%), and four studies (20%) applying K-nearest neighbourhood. Various types of regression models have been experimented by surveyed papers on facial deception detection, including multinomial logistic and multivariate regression. Only one study relies on unsupervised methods that do not need manually annotated facial attributes to train the model. Specifically, it applies hidden Markov models [42].

Table 5. Algorithms and software tools applied for face detection and landmark tracking by surveyed papers.

Reference	2D	3D	Which Face-Detection Technique?			Which Face Tracking Technique?		
			Algorithm		Software Tool	Algorithm		Software Tool
			Feature-Based	Image-Based		Feature-Based	Image-Based	
Abbas and Al-Ani, 2023 [24]	X	X	Viola–Jones face detector [33]				Constrained Local Neural Field (CLNF) [46]	
Shen et al., 2021 [25] Monaro et al., 2022 [27] Mathur and Matarić, 2020 [32] Belavadi et al., 2020 [35] Sen, 2017 [37] Mathur and Matarić, 2021 [39] Carissimi et al., 2018 [44]	X				OpenFace [47]			OpenFace [47]
Su and Levine, 2016 [28] Su and Levine, 2014 [30]	X				PittPatt SDK [52]			PittPatt SDK [52]
Abd et al., 2021 [29] Thannoon et al., 2019 [18]	X		Viola–Jones face detector [33]				Constrained Local Neural Field (CLNF) [46]	
Ngo et al., 2021 [31]	X				‘dlib’ library [50]			FAN [54]
Yu et al., 2014 [33]		X	Active Shape Model (ASM) tracker [43]				Active Shape Model (ASM) tracker [43]	
Zhang et al., 2020 [34]	X				‘dlib’ library [50]			‘dlib’ library [50]
Pérez-Rosas et al., 2015 [40]	X				InsightFace [53]			InsightFace [53]
Demyanov et al., 2015 [42]	X				OpenCV lib [51]			FaceSDK [49]
Pentland et al., 2017 [43]	X				IntraFace [48]			IntraFace [48]

To evaluate the deception classification approaches shown in Table 7, different metrics have been proposed in the reviewed literature, as listed below:

- Area under the curve (AUC): it measures the probability that the model ranks a random positive example more highly than a random negative example;
- Accuracy (ACC): it measures the probability of correspondence between a positive decision and true condition (i.e., the proportion of correct classification decisions);
- Precision: it is defined as the number of true positives divided by the number of true positives plus the number of true negatives;
- Recall: it is defined as the number of true positives divided by the number of true positives plus the number of false negatives;
- F1 score: It is a weighted average of precision and recall.

Table 8 provides a summary of the extracted metrics. Not all the surveyed studies are included in the table because only some of them evaluated their methods. Note that this table does not provide a comparative analysis because the studies rely on different databases to validate the approaches.

Table 8. Performance measures obtained by deception classification approaches applied by surveyed papers.

Reference	AUC (%)	ACC (%)	Precision (%)	Recall (%)	F1 Score (%)
Chebbi and Jebara, 2020 [23]	-	94	88	100	94
Abbas and Al-Ani, 2023 [24]	94.21	88.46	-	-	-
Shen et al., 2021 [25]	-	-	-	-	-
Monaro et al., 2022 [27]	78	-	-	-	-
Su and Levine, 2016 [28]	-	76.92	-	72.41	-
Ding et al., 2019 [14]	96.71	93.16	-	-	-
Abd et al., 2021 [29]	-	89.64	-	-	-
Su and Levine, 2014 [30]	-	76.92	-	-	-
Ngo et al., 2021 [31]	-	68	66	72	-
Mathur and Matarić, 2020 [32]	91	84	-	-	84
Yu et al., 2014 [33]	-	66.8	66.8	65.1	-
Zhang et al., 2020 [34]	73	63.6	-	-	-
Belavadi et al., 2020 [35]	-	48.15	-	-	-
Yildirim et al., 2023 [38]	-	74.17	-	-	-
Mathur and Matarić, 2021 [39]	75	74	-	-	73
Pérez-Rosas et al., 2015 [40]	-	82.14	-	-	-
Venkates et al., 2020 [41]	-	100	-	-	-
Thannoon et al., 2019 [18]	-	90	-	-	-
Demyanov et al., 2015 [42]	61	-	-	-	-
Carissimi et al., 2018 [44]	-	99	-	-	-

5.4. RQ4: Which Datasets for Automated Deception Detection Are Used?

An important step for a systematic evaluation of the performance of the deception-detection method is the preparation and use of well-defined evaluation datasets [58].

Table 9 summarises the datasets used by the selected studies and their main characteristics, i.e., the size, the source used to acquire the data, and the availability. The most popular dataset (seven studies; 33%) is the real-life trial dataset [59], which is available upon request. This dataset consists of 121 videos (average length of 28.0 s) collected from public court trials, including 61 deceptive and 60 truthful trial clips. The remaining studies

(14 studies; 67%) developed their own dataset to evaluate the deception-detection method mainly by recording videos from game/TV shows (5 studies; 24%), followed by the use of spontaneous (4 studies; 19%) or controlled (4 studies; 19%) interviews, and by the use of storytelling (2 studies; 10%) or the download of videos from YouTube (2 studies; 10%). The larger dataset is Abd et al.'s database [18] containing 888 video clips from 102 participants. Considering the availability, the majority of the studies collected datasets without making them available (11 studies; 52%), while 7 studies (33%) made datasets available on request. Only three studies (14%) published the collected dataset.

Table 9. Datasets used by the selected studies.

Reference	Dataset	Availability	Size	Source
Chebbi and Jebara, 2020 [23]	Real-life trial	Available upon request	121 videos (61 deceptive and 60 truthful)	"The Innocence Project" website
Abbas and Al-Ani, 2023 [24]	Abd et al.'s database	Not available	888 video clips from 102 participants	Spontaneous interview
Shen et al., 2021 [25]	Shen et al.'s database	Available on request	32 video clips of 16 individuals	The game show "the Moment of Truth."
Gadea et al., 2015 [26]	Deceit-detection test	Not available	12 video-recordings	Storytelling of life moments
Monaro et al., 2022 [27]	Monaro et al.'s dataset	Not available	62 videos of Italian volunteer participants	Spontaneous interview
Su and Levine, 2016 [28]	Su and Levin's dataset	Not available	324 video clips	YouTube
Ding et al., 2019 [14]	Real-life trial	Available upon request	121 videos (61 deceptive and 60 truthful).	"The Innocence Project" website
Abd et al., 2021 [29]	Abd et al.'s database	Not available	888 video clips from 102 participants	Spontaneous interview
Su and Levine, 2014 [30]	Su and Levin's dataset	Not available	324 video clips	YouTube
Ngo et al., 2021 [31]	Low-stakes deceit (LSD) dataset	Not available	624 recordings of 312 participants	Interviewees under a controlled environment
	Real-life trial	Available upon request	121 videos (61 deceptive and 60 truthful).	"The Innocence Project" website
Mathur and Matarić, 2020 [32]	Real-life trial	Available upon request	121 videos (61 deceptive and 60 truthful).	"The Innocence Project" website
Yu et al., 2014 [33]	Yu et al.'s dataset	Not available	242 videotaped interviews of 121 interviewer–interviewee pairs	Spontaneous interview
Zhang et al., 2020 [34]	Box of Lies corpus	Publicly available	68 recorded clips (39 truths and 29 lies)	"Box of Lies" game
Belavadi et al., 2020 [35]	Real-life trial	Available upon request	121 videos (61 deceptive and 60 truthful).	"The Innocence Project" website
	Opinion dataset	Not available	Not available	Storytelling of movies
	Crime dataset	Not available	Not available	Interviewees under a controlled environment

Table 9. *Cont.*

Reference	Dataset	Availability	Size	Source
Feinland et al., 2022 [36]	Poker Bluff Detection Dataset	Not available	65 recordings of bluff events (15 unique faces with 2320 face images)	Poker game
Pérez-Rosas et al., 2015 [40]	Perez-Rosas et al.'s dataset	Publicly available	118 deceptive and truthful video clips	TV shows
Venkates et al., 2020 [41]	Real-life Trial	Available upon request	121 videos (61 deceptive and 60 truthful).	"The Innocence Project" website
Thannoon et al., 2019 [18]		Not available	400 video clips (50% lie response, 50% truth response)	Interviewees under a controlled environment
Demyanov et al., 2015 [42]	Mafia game database	Publicly available	(60 deceptive and 210 truthful players)	Mafia TV show
Pentland et al., 2017 [43]	Pentland et al.'s dataset	Not available	95 videos of interviews	Interviewees under a controlled environment
Carissimi et al., 2018 [44]	Real-life Trial	Available upon request	121 videos (61 deceptive and 60 truthful)	"The Innocence Project" website

6. Future Research Directions

The development of facial-deceptive-detection methods brings many opportunities for future research. Table 10 summarises the future research directions extracted from the surveyed studies and opportunely classifies them according to the aim of the future research. Note that only the studies that provided a future work discussion have been included in the table (14 studies; 58%).

Table 10. Future research directions envisaged by the selected studies.

Reference	Future Research Directions	Aim of the Future Research
Chebbi and Jebara, 2020 [23]	- Reducing the complexity for real-time use through other approaches for combining speech and video modalities.	- Complexity reduction
Shen et al., 2021 [25]	- Extending the number of participants in the current dataset for the generalization of the results.	- Dataset extension
Gadea et al., 2015 [26]	- Performing experiments with larger gender-matched samples to check if women are better lie detectors than men; increasing the number of videos in the dataset.	- Larger gender/race-matched samples - Dataset extension
Monaro et al., 2022 [27]	- Analysis of the personality and morality of the subjects to understand how they react in a high-stakes setting. - Improving the explainability of the machine-learning models to obtain reliable hints on which specific features are useful for detecting deception. - Using a multimodal approach to include the audio features and the text transcripts in the machine-learning analysis. - Exploring transfer learning techniques for exploiting other lie-detection datasets.	- Further psychological analysis - Explainability of the algorithm - Multimodal approach - Transferability

Table 10. Cont.

Reference	Future Research Directions	Aim of the Future Research
Su and Levine, 2016 [28]	<ul style="list-style-type: none"> - Integrating verbal, non-verbal, and facial cues for higher accuracy. - Extending the size of the database 	<ul style="list-style-type: none"> - Multimodal approach - Dataset extension
Mathur and Matarić, 2020 [32]	<ul style="list-style-type: none"> - Developing affect-aware systems for automatically detecting deception and other social behaviours, particularly those occurring in unconstrained situations in the wild. 	<ul style="list-style-type: none"> - Development of further methods
Yu et al., 2014 [33]	<ul style="list-style-type: none"> - Generalization to the greater sample population and to other scenarios. - Incorporating 3D deformable models. 	<ul style="list-style-type: none"> - Larger samples - Transferability - 3D deformable models
Zhang et al., 2020 [34]	<ul style="list-style-type: none"> - Evaluating the models on real-world multimodal deception data. - Exploring more complex classifiers to model conversational context and time-dependent features. 	<ul style="list-style-type: none"> - Model validation - Development of further methods
Feinland et al., 2022 [36]	<ul style="list-style-type: none"> - Extending the dataset with equal representation by gender and race and with a large number of videos. 	<ul style="list-style-type: none"> - Dataset extension - Larger gender/race-matched samples
Sen, 2017 [37]	<ul style="list-style-type: none"> - Utilizing an individual's expression during specific baseline mental states. 	<ul style="list-style-type: none"> - Further psychological analysis
Yildirim et al., 2023 [38]	<ul style="list-style-type: none"> - Developing a fully autonomous deception detection system by combining other modalities, such as vocal and text. - Increasing video features using hand gestures, head movements, and body posture. - Reducing the complexity for real-time deception detection. 	<ul style="list-style-type: none"> - Multimodal approach - Increasing the features - Complexity reduction
Pérez-Rosas et al., 2015 [40]	<ul style="list-style-type: none"> - Using automatic facial and gesture identification and automated speech transcription for real-time deception detection. 	<ul style="list-style-type: none"> - Multimodal approach
Demyanov et al., 2015 [42]	<ul style="list-style-type: none"> - Developing more accurate methods of action unit detection. - Extraction of more meaningful features. - Using a multimodal approach combining all types of features. - Using less expensive features or more powerful hardware for real-time use. - Increasing the number of videos on the database. 	<ul style="list-style-type: none"> - Development of further methods - Increasing the features - Multimodal approach - Complexity reduction - Dataset extension
Carissimi et al., 2018 [44]	<ul style="list-style-type: none"> - Exploring ways to automatically learn the best views combination for the classification task for reducing the complexity. 	<ul style="list-style-type: none"> - Complexity reduction

The majority of the surveyed studies underline the need to extend the current dataset for the generalization of the results (five studies; 36%) and use of a multimodal approach (five studies; 36%) that combines different types of features (speech, video, text, hand gestures, head movements, etc.). In more detail, evaluating the accuracy of the detection algorithms over a larger database yields a generalization of results, as well as an increase

in the performance of the algorithms, while the integration of several modalities yields higher accuracy.

Relevance is also given to the complexity reduction (four studies; 29%) by exploring innovative ways of combining and classifying the features for real-time deception detection.

Furthermore, a look at the development of further methods and the use of larger samples (three studies; 21% each) is also suggested by the surveyed studies. In more detail, the need to develop more accurate methods of action unit detection, more complex classifiers to model conversational context and time-dependent features, and affect-aware systems resulted from the analysis. On considering the use of larger samples, particular attention is given to an equal representation by gender and race and generalization to other scenarios.

Finally, it is also important to mention the future research directions looking for further psychological analysis, transferability, and increase in the extracted features (two studies; 14% each), as well as the explainability of the algorithms, model validation, and use of 3D deformable models (one study; 7% each).

7. Conclusions

This study provided a systematic literature analysis on facial deception detection in videos. The main contribution was a discussion of the methods applied in the literature of the last decade classified according to the main steps of the facial-deception-detection process (video pre-processing, facial feature extraction, and decision making). Moreover, datasets used for the evaluation and future research directions have also been analysed.

The initial search on WoS and Scopus databases returned 230 studies, of which 38 studies were retained after the application of the inclusion and exclusion criteria defined in the methodology. Finally, 24 studies were included in the qualitative synthesis according to the scores obtained in the quality evaluation checklist. The analysis revealed that in the last ten years, the interest of the scientific community in the topic of facial deception detection began growing in 2014 and reached a peak in 2020.

Considering the methods for video pre-processing, we observed that the majority of the surveyed studies use academic and commercial software for face detection and landmark tracking. Moreover, the most applied and successful feature-based methods are the active shape model [43] and the Viola–Jones method [33], while the Constrained Local Neural Field (CLNF) [46] is the only used image-based approach.

Concerning the extracted facial features, the Facial Action Coding System (FACS) is the most used system to represent all visually discernible facial movements, applied by 68% of the studies. Moreover, 82% of the studies rely on extracting facial expression features, followed by head pose (50% of the studies) and gaze motion (41%).

Concerning the decision-making algorithms, 95% of the studies use supervised learning techniques, mainly the support vector machine (SVM) (35% of the studies), followed by random forest (30%), neural networks (25%), and K-nearest neighbourhood (20%).

Furthermore, the real-life trial dataset [59] is the most popular dataset used for the evaluation of the performance of the decision-making algorithms (33% of the studies), while the remaining studies (67%) developed their own dataset mainly by recording videos from game/TV shows (24%), using spontaneous (19%) or controlled (19%) interviews, and using storytelling (10%).

Finally, the surveyed studies highlight the following future research directions: (i) extension of the current datasets for evaluating the detection algorithms; (ii) use of a multimodal approach that combines different types of features (facial, speech, video, text, hand gestures, etc.); (iii) reduction in the complexity of the detection process for real-time use; (iv) use of larger samples for an equal representation by gender and race; and (v) development of further more accurate and affect-aware methods.

The study has some limitations mainly related to the focus on facial cues from videos. Future studies could also include analysis of explicit cues (verbal communication) from

face-to-face interactions. Indeed, multimodal analysis that combines both verbal and non-verbal cues is the most valuable approach for detecting deception [15].

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