

A SYSTEMATIC LITERATURE REVIEW OF FACE RECOGNITION BASED ATTENDANCE SYSTEM: METHODS, TRENDS, AND RESEARCH GAPS

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Review



ABSTRACT

This systematic literature review examines facial-recognition-based attendance systems published between 2020 and 2024. The review analyzes preprocessing techniques, face detection approaches, feature extraction methods, recognition strategies, evaluation metrics, and state-of-the-art implementations across educational and workplace environments. The findings show that traditional approaches such as Viola-Jones, Haar Cascade, LBP, and LBPH remain widely used due to their computational efficiency, while deep learning models, including CNN-based architectures, FaceNet, and MobileFaceNet, offer superior accuracy but require higher computational resources. Single-face recognition systems demonstrate high accuracy yet lack scalability for real classroom scenarios, whereas multi-face recognition systems improve efficiency but still rely heavily on conventional methods with limited robustness under pose and illumination variations. The study highlights ongoing challenges in scalability, environmental resilience, and evaluation consistency, providing insights for enhancing future facial-recognition-based attendance solutions.

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1. INTRODUCTION

Attendance recording for students is still largely done manually through attendance forms, or semi-manually using Radio Frequency Identification (RFID) technology, both of which are vulnerable to data manipulation (Surantha & Sugijakko, 2024). In fact, student attendance is an important factor that directly contributes to the success of the learning process (Sunaryono et al., 2021a). Students with high attendance rates tend to show better academic performance (Ha et al., 2024; Keppens, 2023). Even in the context of online

learning, active attendance has been shown to improve understanding and retention of concepts (Ha et al., 2024). Therefore, attendance recording mechanisms need to be designed in such a way that they are accurate, transparent, and free from manipulation, so that they can support objective and fair learning evaluation.

One innovation to ensure that student attendance is recorded validly and accurately is the application of facial recognition technology (Rao, 2022). This technology enables automatic identification of individuals through facial images captured by cameras, making the attendance process faster, more accurate, and

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minimizes human intervention (Khan et al., 2020a). Facial recognition-based systems are considered the most suitable replacement for manual attendance methods, which are inefficient and prone to data manipulation (Alhanaee et al., 2021; Surantha & Sugijakko, 2024).

In general, the face recognition-based attendance recording process begins with capturing facial images through a camera. Next, the algorithm detects faces and marks them using bounding boxes or square areas (Khan et al., 2020a). The next stage is matching the image with facial data stored in the database to identify individuals (Nguyen-Tat et al., 2024). Once identification is successful, the system automatically records attendance along with the time and date (Nguyen-Tat et al., 2024; Sunaryono et al., 2021a).

Research conducted by Sunaryono et al. (2021a), Surantha and Sugijakko (2024) shows that face recognition-based attendance systems can achieve an accuracy rate of over 95%. However, these studies still focus on single-face recognition, making them less than optimal when applied in real-world situations such as classrooms where many faces appear simultaneously in a single image.

To overcome these limitations, Khan et al. (2020a) applied a deep learning approach using the You Only Look Once version 3 (YOLOv3) algorithm to detect multiple faces simultaneously, then performed recognition using Microsoft Azure Face API. The implementation results showed good system performance under varying lighting conditions and room configurations. However, deep learning-based approaches have high computational complexity and are often considered difficult to interpret (black box models) (Bai et al., 2021; Sarker, 2021; Suyanto et al., 2022).

Another approach was taken by Bah and Ming (2020), who used a combination of Local Binary Pattern (LBP) and Haar-cascade classifier. This method has lower computational complexity than deep learning (Nguyen-Tat et al., 2024; Shah et al., 2023) and is capable of achieving up to 95% accuracy. However, LBP is sensitive to noise (Alkhatib & Hafiane, 2019; P. D. Chen et al., 2024), while Haar-cascade is only effective for frontal orientation images (Nguyen-Tat et al., 2024) and often fails to detect faces with oblique poses (Naser et al., 2025).

Furthermore, Ahsan et al. (2020) combined Local Binary Pattern Histogram (LBPH) with Bilateral Median Convolution to improve the system's robustness against lighting variations. The results of the study showed good performance in uncontrolled environmental conditions. However, this method remains weak against changes in facial pose (Ahsan et al., 2021; Chen et al., 2023).

These findings indicate that facial recognition technology for attendance systems has undergone rapid development through various approaches, both traditional and deep learning. However, each method has its own advantages and limitations that need to be studied in greater depth. Therefore, a systematic review is needed to map research trends, datasets used, dominant methods, and future research directions. In line with these needs, this study

aims to identify research trends, datasets used, proposed methods, and future research directions in facial recognition for attendance systems during the period 2020 to 2024.

2. METHODOLOGY

2.1 Review Method

This study adopted SLR in accordance with the guidelines of Kitchenham and Charters (2007). SLR aims to identify, assess, and interpret all research evidence to answer specific research questions. SLR was chosen because it has been widely used by previous researchers, namely: Hidayat et al. (2024), Mohana and Subashini (2024), and Sharma et al. (2024). This shows that SLR is suitable for use in literature reviews.

Figure 1 shows the SLR process with three main stages, namely: planning, implementation, and reporting. In the planning stage, three activities are carried out, namely: formulating research questions, developing a literature review protocol, and evaluating the literature review protocol. In the conducting stage, five activities are carried out, namely: searching for studies, selecting studies, extracting studies, assessing study quality, and summarizing data. In the reporting stage, the activity is to present a report on the results of the literature review.

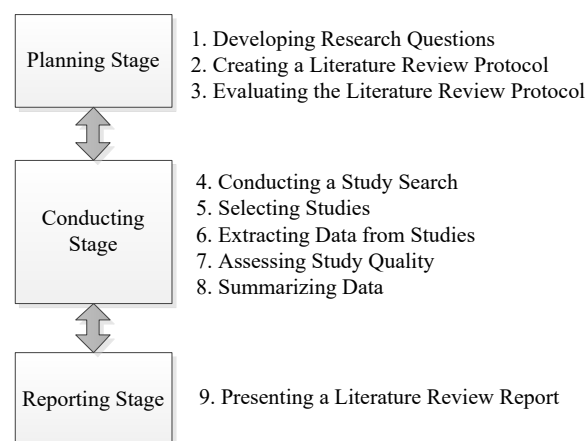


Figure 1. SLR process with 3 main stages and 9 sub-stages

The SLR process is not merely an activity of collecting references, but rather a systematic library-based experiment that aims to answer research questions objectively and reproducibly. Therefore, each stage in the figure is not only linear, but can also return to the previous process. For example, when finding inconsistencies in selected studies, researchers can return to the protocol or search stage.

2.2 Research Questions

Research questions are formulated at the outset before conducting a literature review. This is done to ensure that the literature review remains focused and to provide

boundaries for the study to be analyzed. In this study, the research questions were formulated based on Population, Intervention, Comparison, Outcomes, and Context (PICOC).

Table1. PICOC list

Criteria	Key Words
Population	School, university, workplace
Intervention	Face recognition, facial recognition, face detection, biometric identification
Comparison	-
Outcomes	Attendance system, attendance tracking, roll call, presence detection
Context	Research in academia and industry

Table1 shows a list of PICOC that formed the basis for developing research questions. Population describes the entities that are the focus of the literature review. The

methodological approach used in Population is reflected in Intervention. Comparison indicates the method used as a comparison. The desired results of Intervention are described in Outcomes. Finally, Context refers to the area in which the literature review was conducted.**Error!**

Reference source not found. shows a list of research questions (RQ) from the literature review used in this study. The results of RQ1 can be used as a basis for publishing research results, while the results of RQ2 can be used as a basis for conducting research collaborations. The results of RQ3-RQ8 can be used as a basis when selecting preprocessing methods, face detection, feature extraction, face recognition, evaluation in the main study, and identifying state-of-the-art methods to determine future research opportunities.

Table2.Literature review research questions list

Code	Research Question	Objective
RQ1	Which journals publish a lot of research on attendance systems that use facial recognition?	Identify journals that publish a lot of research on attendance systems that use facial recognition.
RQ2	Who are the influential researchers in research on attendance systems using facial recognition?	Identifying influential researchers in research on attendance systems using facial recognition.
RQ3	What preprocessing methods are widely used in research on attendance systems that use facial recognition?	Identifying preprocessing that is widely used in research on attendance systems that use facial recognition.
RQ4	What are the face detection methods that are widely used in research on attendance systems that use face recognition?	Identifying facial detection methods that are widely used in research on attendance systems that use facial recognition.
RQ5	What feature extraction methods are widely used in research on attendance systems that use facial recognition?	Identifying feature extraction methods that are widely used in research on attendance systems that use facial recognition.
RQ6	What facial recognition methods are widely used in research on attendance systems that use facial recognition?	Identifying facial recognition methods that are widely used in research on attendance systems that use facial recognition.
RQ7	What evaluation methods are frequently used in research on attendance systems that use facial recognition?	Identifying evaluation methods frequently used in research on attendance systems that use facial recognition.
RQ8	What are the state-of-the-art methods in research on attendance systems using facial recognition?	Identifying state-of-the-art methods in research on attendance systems using facial recognition

2.3 Creating a Literature Review Protocol

The review protocol was created to ensure that the SLR was conducted systematically. It began with establishing digital libraries as sources for searching for studies. Four digital libraries were selected, namely Scopus (scopus.com), ScienceDirect (sciencedirect.com), IEEE (ieeexplore-ieee-org), and ProQuest (proquest.com). This was followed by the development of inclusion and exclusion criteria, with Table3 showing the list of inclusion and exclusion criteria. These criteria were developed as guidelines for selecting studies. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow chart was used to clarify the study selection process. The extraction of key data refers to the SLR research questions.

The extraction results are summarized in an Excel table, which represents the answers to the literature review research questions. The quality of the studies is assessed

based on the clarity of the methods used and the ability of the study content to answer the literature review research questions. Meanwhile, data synthesis uses a narrative-descriptive method.

Table3. Inclusion and exclusion criteria

Criteria	Value
Inclusion	A study that discusses an attendance system that uses facial recognition
	Duplicate studies, the most complete and most recent were selected.
	Study with journal and proceedings versions, journal version was selected
Exclusion	Studies written in languages other than English
	Studies without strong validation

2.4 Research Questions

Once the systematic review protocol has been fully developed, the next step is to evaluate the protocol. The purpose of this evaluation is to ensure that all components of the protocol have been developed comprehensively, logically, and can be implemented without bias. Protocol evaluation is also important to minimize the risk of methodological errors and ensure that the SLR process can be carried out in a structured and consistent manner from start to finish. The evaluation is conducted through internal review by researchers.

2.5 Search Strategy

The search process began with selecting digital libraries. Four digital libraries were selected, including Scopus (scopus.com), ScienceDirect (sciencedirect.com), IEEE (ieeexplore.ieee.org), and ProQuest (proquest.com). Next, search keywords were compiled with reference to PICOC as a guideline, so that the search results could answer the questions in the literature review that had been

compiled. The search keywords were compiled by applying intervention and outcome to the population. The Boolean operator 'OR' was used to combine synonyms, while 'AND' was used to ensure that keywords in the intervention, outcome, and population criteria appeared in the search.

shows a list of search keywords. The list is tailored to each digital library without changing the original keywords so as not to increase the number of irrelevant results. On Scopus, searches are conducted by applying search keywords to advanced searches based on title, abstract, and keywords. On ScienceDirect, searches are conducted through advanced searches by applying search keywords to the quick search field. On IEEE and ProQuest, searches are conducted through advanced searches by applying search keywords to the search command field. The search limitations applied are: searches are limited to the years 2020 to 2024, research studies in the form of journals and proceedings, not review studies, and studies in English.

Table4. List of search keyword

Library	Search String
Scopus	TITLE-ABS-KEY(("face recognition" OR "facial recognition" OR "face detection" OR "biometric identification") AND ("attendance system" OR "attendance tracking" OR "roll call" OR "presence detection") AND ("school" OR "university" OR "workplace"))
ScienceDirect	("face recognition" OR "facial recognition" OR "biometric identification") AND ("attendance system" OR "attendance tracking" OR "roll call" OR "presence detection") AND ("school" OR "university")
IEEE	("face recognition" OR "facial recognition" OR "face detection" OR "biometric identification") AND ("attendance system" OR "attendance tracking" OR "roll call" OR "presence detection") AND ("school" OR "university" OR "workplace")
ProQuest	("face recognition" OR "facial recognition" OR "face detection" OR "biometric identification") AND ("attendance system" OR "attendance tracking" OR "roll call" OR "presence detection") AND ("school" OR "university" OR "workplace")

2.6 Study Selection

Study selection uses inclusion and exclusion criteria, which serve as guidelines for selecting and filtering studies relevant to the research topic. These criteria help ensure that only eligible studies are analyzed, thereby maintaining the quality and relevance of the literature review. The inclusion criteria contain the criteria for studies to be included, while the exclusion criteria contain the criteria for studies to be excluded or discarded.

Figure2 shows the study selection flowchart created using the PRISMA 2020 (2021) flowchart. This flowchart consists of three stages: 1) Study identification stage, from 4 databases, namely Scopus, ScienceDirect, IEEE, and ProQuest, 548 studies were obtained, 21

studies were removed due to duplication, leaving 513 studies. 2) Study screening stage: 513 studies were screened based on their titles and abstracts. 399 studies were excluded because 349 studies were outside the scope of the research topic, 49 were review studies, and 1 was withdrawn by the author, resulting in 114 studies to be downloaded. Of the 114 studies, 7 studies could not be downloaded because they did not have access, resulting in 107 studies ready to be screened based on study content. Based on the screening of study content, 7 studies were excluded because the explanation of the research methods was not comprehensive, leaving 100 studies. 3) Study inclusion stage: 100 studies were included and extracted for reporting in the literature review.

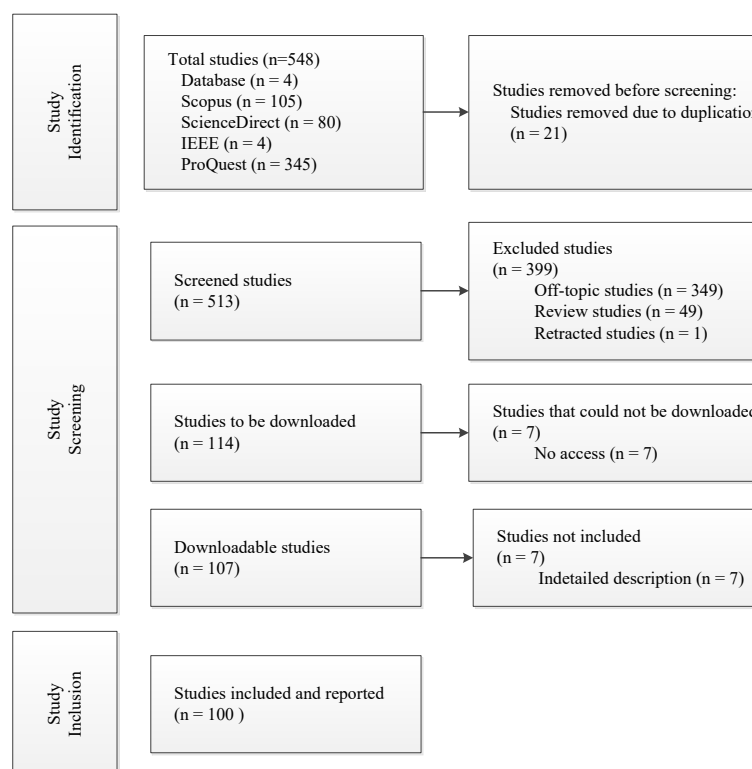


Figure2. Study selection flowchart

2.7 Data Extraction

Data extraction in SLR aims to collect important information from each selected study. Data extraction is carried out in a structured and transparent manner to produce accurate data that can be analyzed consistently. The results of data extraction should be able to answer the research questions of the literature review. The following are the elements that will be extracted from the study: study identity (title, author, year, journal/conference name, number of citations), preprocessing methods, face detection methods, feature extraction methods, face recognition methods, evaluation methods, datasets used, and evaluation results.

2.8 Study Quality Assessment and Data Synthesis

The assessment of study quality aims to ensure that the studies included in the literature review have adequate methodological validity and are capable of answering the research questions of the literature review. The list of study quality assessment criteria is presented in Table 5. Six main criteria are used, namely clarity of research objectives, completeness of methodology description, validation of experiments or methods, suitability of methods to research questions, clear presentation of results, and availability of data.

These six criteria are important foundations for ensuring that the studies selected in the literature review have adequate methodological validity, are transparent, and are capable of answering the research questions.

Table 5. List of study quality assessment criteria

No	Criteria	Motivation
1.	Clarity of research objectives	Are the research objectives clearly stated?
2.	Complete description of the methodology	Are the research methods, including datasets and experimental procedures, described in detail?
3.	Experimental validation	Are the research results validated with external datasets?
4.	Suitability of the method to the research question	Are the methods used relevant to answer the research question?
5.	Clear presentation of results	Does the study present research results with clear evaluation metrics?
6.	Data availability	Is the data or dataset used available?

Each study is assigned a rating category: 1) Good category, if it meets all or almost all criteria. 2) Fair category, if it meets most criteria, but there are still shortcomings. 3) Poor category, if it meets few criteria and has many shortcomings.

3. RESEARCH RESULT

3.1 Significant Journal Publications (RQ1)

Figure3 shows a graph of the selected studies. From 2020 to 2021, there was an increase in the number of publications, from 17 to 23 studies. There was then a

decline in 2022 and 2023, with 18 and 15 studies, respectively. In 2024, there was a significant increase to 27 studies.

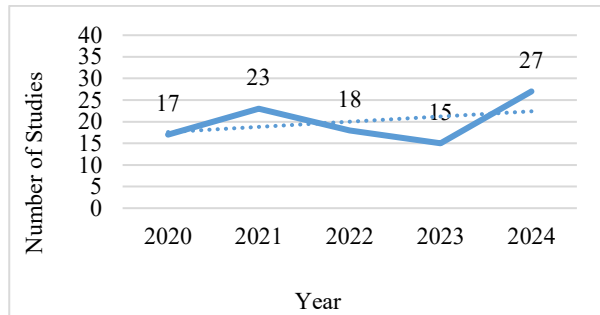


Figure3.Distribution of selected studies

2.1 This pattern suggests that research on facial recognition based attendance systems remains an

active and growing area of interest. **Error! Reference source not found.** shows a graph of selected primary studies based on Scopus quartiles, while

Table6 shows total of selected primary studies.

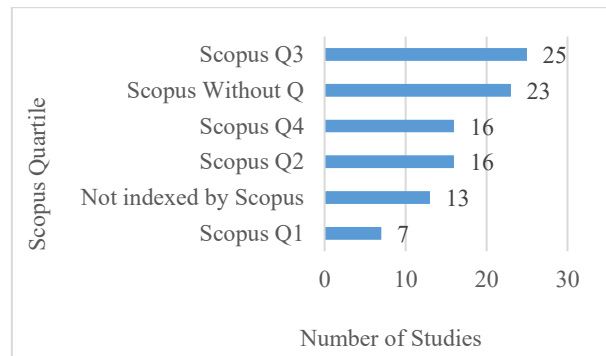


Figure4.Selected studies based on Scopus quartiles

Table6. List of selected primary studies

Year	Studies	Total of Studies
2020	(Alghamdi et al., 2020; Bah & Ming, 2020; Bhavana et al., 2020; Gnanaprakash et al., 2020; Hamami et al., 2020; Khan et al., 2020b; Long, 2020; Merugu et al., 2020; Muttaqin et al., 2020; Nagendra, 2020; Nordin & Fauzi, 2020; Puthea et al., 2020; M. V. G. Rao et al., 2020; Sabeenian et al., 2020; Son et al., 2020; Statistics et al., 2020; Zhu et al., 2020)	17
2021	(Aishwarya et al., 2021; Ali Al-Mallah et al., 2021; Andiani & Soewito, 2021; Bekzod & Daeik, 2021; Bhavani et al., 2021; Chandra et al., 2021; Dini et al., 2021; Girish et al., 2021; Hariharan et al., 2021; Kavimuhil et al., 2021; Kodhai et al., 2021; Mustam et al., 2021; Nguyen et al., 2021; Pant et al., 2021; Parveen et al., 2021; Pranoto & Kusumawardani, 2021; Rajamanogaran et al., 2021; Saraswat et al., 2021; Suhaimin et al., 2021; Sunaryono et al., 2021b; Tamilkodi, 2021; Technology & Utara, 2021; Wati et al., 2021)	23
2022	(Ahmed et al., 2022; Annubaha et al., 2022; Azizi et al., 2022; Bhosale et al., 2022; Hamed & Fatnassi, 2022; Ismail et al., 2022; Lin & Huang, 2022; W. Liu & Pan, 2022; Mcp et al., 2022; Mohammed & Alothman, 2022; Nadhan et al., 2022; Parhi et al., 2022; Rastogi et al., 2022; Shi & Tang, 2022; Uçar & Özdemir, 2022; Wang et al., 2022; Zhang et al., 2022; Zhao et al., 2022)	18
2023	(Alniemi & Mahmood, 2023; X. Chen, 2023; Dang, 2023; Hosen et al., 2023; Kamil et al., 2023; Lateef & Kamil, 2023; M. Liu & Pang, 2023; Rahmad et al., 2023; Raj Kumar et al., 2023; Rohini et al., 2022; Satria et al., 2023; Shabaneh et al., 2023; Tran & Ly, 2023; Warman & Kusuma, 2023; Widjaja et al., 2023)	15
2024	(Abdiwi, 2024; Ali et al., 2024; Azzahra et al., 2024; Beri et al., 2024; Boe et al., 2024; Dayananda et al., 2024; Ekwealor et al., 2024; Ennajar & Bouarifi, 2024; Gaur et al., 2024; Hussain Hassan et al., 2024; Jadhav et al., 2024; Juliandy et al., 2024; Lateef & Kamil, 2024; Makigod et al., 2024; Manimekalai et al., 2024; Nagagopiraju et al., 2024; Nguyen-Tat et al., 2024; Nikam et al., 2024; Onaifo, 2024; Parbat et al., 2024; Sayyad et al., 2024; Siew et al., 2024; Sugijakko et al., 2024; Surantha & Sugijakko, 2024; Susanto et al., 2024; Talele et al., 2024; Thanoon, 2024)	27

Scopus Q3 dominates, followed by Scopus without quartiles, with 25 and 23 studies, respectively. Scopus Q4 and Q2 each have 16 studies, followed by non-Scopus indexed studies and Scopus Q1, with 13 and 7 studies, respectively. Based on Figure5, Scopus-indexed studies dominate over non-Scopus-indexed studies, 87% versus 13%. This indicates that Scopus continues to be the preferred platform for disseminating research in this field due to its credibility and visibility.

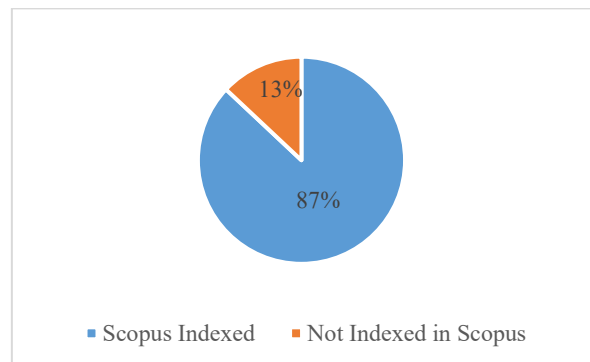


Figure5. Comparison of primary studies indexed and not indexed by Scopus

Figure6 shows a graph of the number of studies based on the country of publication of the journal. The United Kingdom leads with 19 studies, followed by the United States and Indonesia, which each contributed 17 studies. Next, India, Turkey, and the Netherlands are in the next order with 13, 12, and 8 studies, respectively. Japan, Malaysia, and Switzerland each contributed 4 studies, while Singapore published 3 studies. The data shows that the United Kingdom, the United States, and Indonesia are the most active journal publishers in publishing research on face recognition-based attendance systems. In addition, the relatively even distribution of studies between Asian and European countries shows that the development of face recognition-based attendance systems is a global topic that has attracted the attention of researchers.

Table 7 shows a list of journals with the most studies. The distribution of studies in the table shows that research on face recognition-based attendance systems is more widely published in Scopus journals without quartiles and journals that are not indexed by Scopus. Publications

in Scopus Q1 and Q2 journals are still few. This reflects that there is still a great opportunity to improve the quality of research in order to penetrate international journals with higher quartiles on this topic.

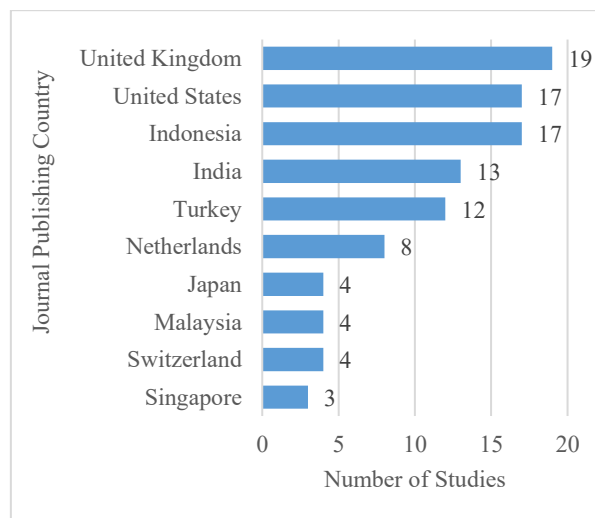


Figure6. Countries with the most journal publishers

Table 7. Journal with the most studies

No	Journal Name	Quartile	Number of Studies
1	Journal of Physics: Conference Series	Scopus Without Q	10
2	Turkish Journal of Computer and Mathematics Education	Scopus Without Q	9
3	International Research Journal of Innovations in Engineering and Technology	Not Indexed in Scopus	6
4	Wireless Personal Communications	Scopus Q2	2
5	International Journal of Interactive Mobile Technologies	Scopus Q3	2
6	Bulletin of Electrical Engineering and Informatics	Scopus Q3	2
7	Journal of Advances in Information Technology	Scopus Q3	2
8	International Journal on Informatics Visualization	Scopus Q3	2
9	Multimedia Tools and Applications	Scopus Q2	2
10	Indonesian Journal of Electrical Engineering and Computer Science	Scopus Q4	2
11	International Journal of Intelligent Systems and Applications in Engineering	Scopus Without Q	2
12	Multimedia Tools and Applications	Scopus Q1	2
13	SN Computer Science	Scopus Q2	2

3.2 Influential Researchers (RQ2)

Figure7 shows a graph of the most influential researchers measured by the number of citations. Sunaryono et al. received the most citations with 164 citations, followed by Khan et al. and Dang with 71 and 42 citations, respectively. The next places are occupied by Zhao et al., Nguyen-Tat et al., and Uçar and Özdemir, with 36, 27, and 25 citations, respectively. The next places are occupied by Nadhan et al., Wati et al., Surantha and Sugijakko, and Bah and Ming, with 23, 21, 18, and 16 citations, respectively.

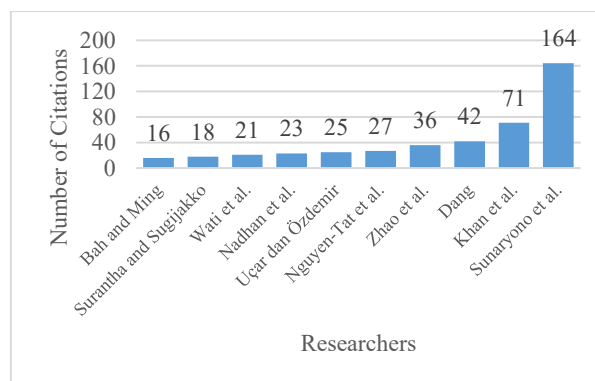


Figure7. The most influential researchers

Table8 shows a list of the most influential studies based on the number of citations. Based on this table, it can be

seen that publications published in high quartile journals (Q1–Q3) tend to receive more citations.

Table8.The most influential studies

No	Research Title	Researcher	Quartile	Number of Citations
1	An android based course attendance system using face recognition	Sunaryono et al. (2021a)	Scopus Q1	164
2	Real Time Automatic Attendance System for Face Recognition Using Face API and OpenCV	Khan et al. (2020a)	Scopus Q2	71
3	Smart Attendance System based on Improved Facial Recognition	Dang (2023)	Scopus Q3	42
4	College Smart Classroom Attendance Management System Based on Internet of Things	Zhao et al. (2022)	Scopus Q1	36
5	Automating attendance management in human resources: A design science approach using computer vision and facial recognition	Nguyen-Tat et al. (2024)	Scopus Q1	27
6	Recognizing Students and Detecting Student Engagement with Real-Time Image Processing	Uçar dan Özdemir (2022)	Scopus Q2	25
7	Smart Attendance Monitoring Technology for Industry 4.0	Nadhan et al. (2022)	Scopus Q2	23
8	Security of facial biometric authentication for attendance system	Wati et al. (2021)	Scopus Q2	21
9	Lightweight face recognition-based portable attendance system with liveness detection	Surantha and Sugijakko (2024)	Scopus Q1	18
10	An improved face recognition algorithm and its application in attendance management system	Bah and Ming (2020)	Scopus Q1	16

3.3 Pre-processing Methods (RQ3)

Pre-processing plays a crucial role in facial recognition workflows by ensuring that the input image is standardized and of sufficient quality for the subsequent feature extraction and classification stages. Proper pre-processing helps minimize variations in lighting, scale, pose, and noise, thereby improving the robustness of recognition systems. The most frequently used pre-processing techniques are described below.

- **Image cropping**, both traditional and deep learning approaches, the detected facial region is cropped from the original image to isolate it from the background. This step focuses the feature extraction process on the most relevant facial components, primarily the eyes, nose, and mouth, while removing redundant background information.
- **Image resizing**, image resizing is commonly applied to achieve consistent input dimensions across datasets. Traditional algorithms typically use smaller resolutions (e.g., 96×96 pixels) to reduce computational cost, whereas deep learning models adopt larger inputs (e.g., 160×160 pixels) to preserve spatial detail and improve feature representation.
- **Grayscale conversion**, traditional methods rely on texture and gradient information rather than color. Converting images to grayscale simplifies computation and reduces dimensionality. In contrast, deep learning models can exploit color cues to enhance recognition accuracy, making grayscale conversion optional or unnecessary.

- **Histogram equalization**, histogram equalization enhances image contrast, particularly under uneven lighting conditions. It is frequently used in traditional algorithms to make facial features more distinguishable. Deep learning approaches, however, can learn illumination-invariant representations directly from raw images, reducing the need for explicit equalization.
- **Noise reduction filter**, both traditional and deep learning methods employ noise-reduction filters to suppress random artifacts that can obscure key facial details. Reducing noise enhances the quality of feature extraction and contributes to more stable recognition performance. Common filters include Gaussian, bilateral, or median filters, depending on the dataset's characteristics.
- **Face alignment**, face alignment ensures that facial landmarks (such as eyes, nose, and mouth) occupy consistent spatial locations across samples. Traditional approaches depend heavily on alignment to handle pose variation, while in deep learning, alignment improves training stability and accuracy by reducing intra-class variance and emphasizing discriminative features.

Pre-processing remains an essential foundation for reliable face recognition. Traditional approaches depend heavily on explicit image normalization techniques, whereas deep learning methods rely increasingly on data-driven representations that implicitly learn robustness to lighting, noise, and pose variations.

3.4 Face Detection Methods (RQ4)

Figure 8 presents the distribution of face detection method categories used across the reviewed studies. The traditional category dominates with 62 studies, followed by deep learning with 26 studies, machine learning with 9 studies, and 3 hybrid studies that combine both traditional and deep learning approaches.

Figure 9 illustrates the specific face detection methods most frequently applied. The Haar Cascade Classifier remains the most widely used, reported in 43 studies, followed by the Viola Jones algorithm in 15 studies, Multi-task Cascaded Convolutional Networks (MTCNN) in 9 studies, Histogram of Oriented Gradients (HOG) + Support Vector Machine (SVM) in 8 studies, Single Shot Multibox Detector (SSD) in 3 studies, and YOLOv3 in 2 studies.

These findings suggest that, despite the superior accuracy and robustness of deep learning and machine learning-based face detection methods, traditional approaches such as Haar Cascade Classifier and Viola-Jones remain the dominant choices in academic and applied research. Their popularity can be attributed to computational efficiency, simplicity of implementation, and compatibility with low cost or embedded hardware, particularly in classroom and attendance-monitoring scenarios where real-time performance is essential.

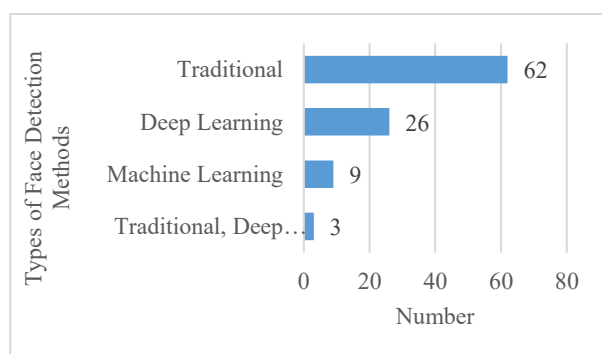


Figure 8.Categories of face detection methods

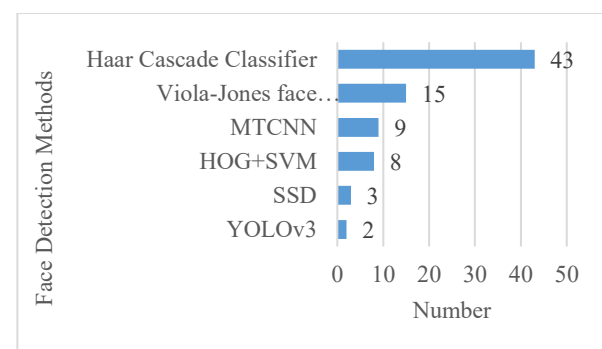


Figure 9. Commonly used face detection methods

In contrast, deep learning based detectors such as MTCNN, SSD, and YOLOv3 have been adopted more selectively, often in studies emphasizing accuracy under complex conditions such as occlusion, pose variation, or illumination changes. The limited use of these methods

reflects the computational demands and hardware constraints in many institutional settings.

Interestingly, several hybrid approaches that integrate traditional feature extraction with deep learning based classification have emerged, reflecting an ongoing transition period in face detection research. These efforts highlight an evolving trend toward balancing accuracy, interpretability, and efficiency within practical deployment contexts.

3.5 Feature Extraction Methods (RQ5)

Figure10 shows the distribution of feature extraction method categories applied in the reviewed studies. Both traditional and deep learning approaches dominate, each employed in 45 studies. Machine learning based feature extraction appeared in 6 studies, while 4 studies implemented hybrid approaches combining traditional and deep learning techniques.

Figure11 presents the specific feature extraction methods most frequently used. The Local Binary Pattern Histogram (LBPH) and Convolutional Neural Network (CNN) methods are the most common, appearing in 17 studies each. FaceNet was utilized in 12 studies, followed by Histogram of Oriented Gradients (HOG) in 9 studies, Eigenface in 4 studies, Local Binary Pattern (LBP) in 3 studies, and ResNet in 2 studies.

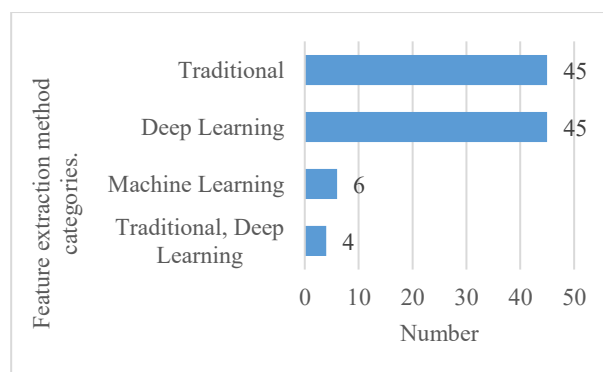


Figure10.Feature extraction method categories

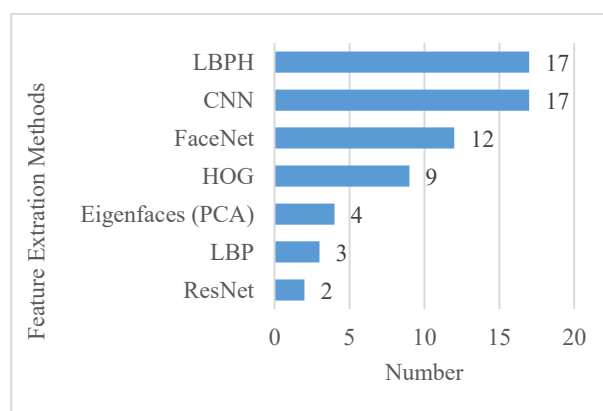


Figure11.Feature extraction method categories

This results indicate that although deep learning based approaches such as CNN and FaceNet have become increasingly popular for feature extraction, traditional

methods particularly LBPH and HOG remain highly relevant. Their continued use can be attributed to their computational simplicity, lower hardware requirements, and robustness under limited data conditions, making them suitable for real-time applications such as classroom attendance monitoring.

Conversely, deep learning based methods demonstrate superior performance in terms of accuracy and adaptability when trained on large and diverse datasets. CNN-based architectures, including FaceNet and ResNet, have the ability to learn high-level abstract facial representations, enabling better discrimination under variations in pose, illumination, and expression.

Overall, these findings highlight a transitional landscape in feature extraction research, where traditional and deep learning techniques coexist. The choice of method depends largely on application context, available computational resources, and dataset size. This balance suggests that while deep learning continues to advance the field, traditional approaches still offer practical advantages in constrained environments.

3.6 Facial Recognition Method (RQ6)

Figure 12 presents the distribution of facial recognition method categories identified in the reviewed studies. The distance based matching category is the most widely used, appearing in 53 studies. The deep learning based recognition category is represented in 23 studies, while machine learning classifier based approaches were used in 20 studies. In addition, two studies employed both distance-based and deep learning-based approaches, and one study combined machine learning classifiers with deep learning. One study did not fall into any recognition category because it focused solely on face detection.

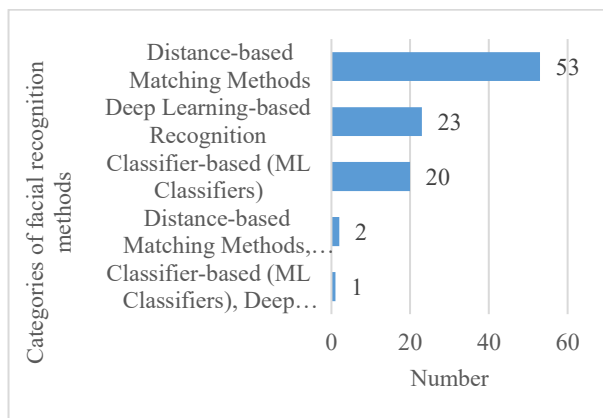


Figure 12.Categories of facial recognition method

Figure 13 shows the specific facial recognition methods most frequently applied. The distance-based matching approach dominates with 53 studies, followed by Support Vector Machine (SVM) in 13 studies and Convolutional Neural Networks (CNN) in 11 studies. Meanwhile, LBPH Face Recognizer, k-Nearest Neighbors (KNN), and FaceNet each appear in three studies.

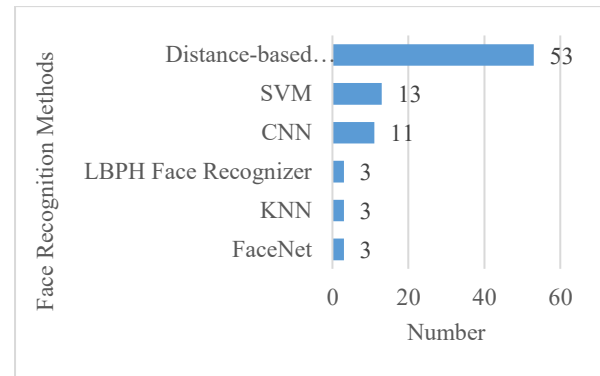


Figure 13. Commonly used facial recognition methods

This results show that although deep learning based facial recognition methods (CNN, FaceNet) have gained significant traction, traditional distance-based matching approaches remain the most widely adopted. Their persistent relevance can be attributed to their simplicity, low computational requirements, and suitability for real-time or resource constrained environments such as classroom attendance systems. Machine learning classifier based methods, such as SVM and KNN, also maintain a notable presence due to their interpretability and relatively low training cost, especially when working with smaller datasets. Overall, these findings indicate that facial recognition research continues to occupy a hybrid landscape, where both traditional and modern approaches coexist. The choice of method largely depends on application context, accuracy requirements, dataset scale, and hardware constraints, rather than on technological novelty alone.

3.7 Evaluation Methods (RQ7)

Figure14 illustrates the distribution of evaluation metrics used across the reviewed studies. Accuracy emerges as the most dominant metric, reported in 81 studies, indicating its position as the primary measure for assessing facial recognition system performance. Other evaluation metrics appear far less frequently, with precision, recall, and recognition rate used in 12, 11, and 7 studies, respectively. In addition, the F1-score, confusion matrix, and processing time were each reported in four studies.

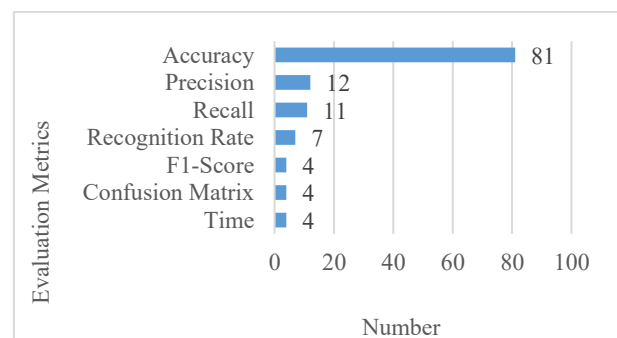


Figure14.Commonly used evaluation methods

The overwhelming reliance on accuracy suggests that many studies prioritize a simple and intuitive

performance measure. However, this trend may also indicate that class imbalance, error distribution, and computational efficiency are less frequently examined, despite their importance in real-world applications. The limited use of precision, recall, and F1-score shows that only a small number of studies adopted more nuanced evaluation approaches capable of capturing false positives or false negatives. The scarcity of time-related metrics also suggests that real-time constraints, although relevant for attendance systems, are not consistently evaluated.

3.8 State-of-The-Art Methods (RQ8)

Sunaryono et al. (2021a) developed an Android-based student attendance system integrating QR-code scanning for presence confirmation and facial recognition for identity authentication. This system was designed to address the low efficiency and accuracy of prior attendance methods. The workflow operates under a single-face recognition paradigm, as each student performs attendance individually using a mobile phone camera. After scanning the QR-code, the phone camera captures the student's face and sends the image to the server, where it is cropped to 224×224 pixels, converted to grayscale, and resized to 96×96 pixels. Face detection is carried out using the Viola–Jones algorithm, followed by feature extraction via PCA and LDA, producing a one-dimensional feature vector (9216×1). Recognition is performed using LR, LDA, and KNN. The results show that LR yielded the highest accuracy (97.48%), whereas KNN demonstrated the fastest training time. However, the study has limitations: a small test scale, no evaluation under large-classroom scenarios, and the absence of comprehensive evaluation metrics such as precision, recall, or F1-score.

Khan et al. (2020a) proposed a real-time classroom attendance system using multi-face recognition. The system employs YOLOv3 for multi-face detection and Microsoft Azure Face API for recognition. Classroom cameras capture images at the beginning and end of each session. Detected faces are cropped, processed, recognized, and subsequently recorded in the attendance database. Their system achieved 100% accuracy across test scenarios involving 2 to 12 students, with zero false recognitions. Nonetheless, several limitations exist, including reliance on cloud services, the absence of time-related performance metrics, and limited explanation of preprocessing stages, which may hinder reproducibility. Dang (2023) introduced a real-time multi-face attendance system integrating SSD-MobileNetV2 for face detection, FaceNet for feature extraction, and KNN and SVM for classification. SSD detects all faces within a frame, which are then cropped and resized to 160×160 pixels before FaceNet generates embeddings. SSD-MobileNetV2 achieved a high detection speed (20–23 FPS), significantly outperforming RetinaFace and MTCNN (4–5 FPS). However, SSD struggles with small-face detection and uneven lighting. FaceNet requires large training datasets and careful fine-tuning. Additionally, SVM depends heavily on parameter

optimization, while KNN suffers from computational inefficiency on large datasets and is sensitive to outliers. Zhao et al. (2022) developed an IoT-based attendance system integrating RFID and multi-face recognition. RFID provides automated seat-position verification, while identity authentication is performed through facial recognition. Haar Cascade is used for face detection, followed by grayscale conversion, histogram equalization, and LBPH-based feature extraction. Identity matching is conducted using the Chi-Square metric. The dual-verification approach improves accuracy and mitigates cheating behaviors such as proxy attendance. However, Haar Cascade and LBPH remain limited by their sensitivity to pose variations, lighting inconsistencies, and image noise. The Chi-Square metric also struggles in complex visual conditions as it only compares local histogram distributions without considering global structure.

Nguyen-Tat et al. (2024) designed an employee attendance system based on Design Science Research Methodology (DSRM). Haar Cascade is used for face detection, LBPH for feature extraction, and Euclidean Distance for identity matching. Images captured via Raspberry Pi undergo grayscale conversion, histogram equalization, and median filtering before feature extraction. The system achieved 93% recognition accuracy and real-time operation at 30 FPS on Jetson Nano. Nevertheless, limitations remain: Haar Cascade performs best only on frontal faces, LBPH lacks robustness against noise and irregular lighting, and Euclidean Distance struggles to differentiate highly similar facial representations.

Uçar and Özdemir (2022) developed the Student Engagement Classification Software (SECS), a system capable of recognizing student attendance and simultaneously estimating engagement levels in real time. It operates under a multi-face recognition framework, detecting and labeling multiple students within a single video frame. Face detection is performed using HOG+SVM, followed by cropping, alignment, grayscale conversion, and resizing. LBP is used for feature extraction. Facial recognition is carried out using the Chi-Square distance metric, while engagement classification uses head-pose estimation (PnP generating yaw, pitch, and roll features) and eye openness ratio (EAR), classified using SVM. The system achieved 98.95% accuracy for face recognition and 72.4% accuracy for engagement classification. Despite these promising results, HOG, LBP, and SVM are limited when dealing with pose variation and uneven lighting, and SVM requires careful parameter tuning.

Nadhan et al. (2022) proposed a real-time, contactless employee attendance system using Viola Jones for detection, LBPH for feature extraction, and SVM for classification. After detection, facial images are cropped, converted to grayscale, resized, and recognized using SVM. The system is lightweight, cost-effective, and performs well in controlled environments, but Viola Jones and LBPH exhibit sensitivity to pose and lighting

variations, while SVM performance heavily depends on parameter selection.

Wati et al. (2021) built a multi-face attendance system using Viola–Jones for detection, Gabor Wavelet for feature extraction, and Pearson correlation for template matching, combined with Best First Search for work-time verification. The system achieved high performance in group recognition (88% accuracy, 97% precision) and moderate performance in individual recognition (75% accuracy, 88% precision). However, Gabor Wavelet produces high-dimensional features requiring substantial computation, Viola Jones is limited to frontal faces, and Pearson correlation is highly sensitive to noise, expression changes, and positional shifts, making the system less reliable under dynamic real-world conditions.

Surantha and Sugijakko (2024) developed a student attendance system incorporating liveness detection using MobileNetV2 and feature extraction using MobileFaceNet. Viola Jones is used for detection, and cosine similarity is used for identity matching. The goal is to mitigate spoofing attacks, including the use of photographs or videos to fake presence. Liveness detection achieved 96% accuracy and a 97% F1-score, yet the system still inherits limitations from Viola–Jones, which struggles with non-frontal faces. Cosine similarity may also misclassify identities when embedding vectors are extremely similar, reducing robustness in complex scenarios.

Bah and Ming (2020) designed a multi-face attendance system using Haar Cascade, LBP Cascade, and LBPH for feature extraction, with identity matching based on Chi-Square distance. The system achieved a high recognition accuracy of 99%, operated in real time, and offered a fully contactless mechanism suitable for workplace and educational environments. Despite this strong performance, the approach is constrained by the inherent limitations of Haar Cascade and LBP, including vulnerability to lighting variations, pose changes, and image noise. Chi-Square distance, which compares histogram distributions without structural context, can further hinder performance in visually complex conditions.

Based on the state-of-the-art methods described above, it can be concluded that the studies by Sunaryono et al. (2021a), Nguyen-Tat et al. (2024), Nadhan et al. (2022), and Surantha and Sugijakko (2024) still adopt a single-face recognition approach. Although these methods achieve high accuracy, they are not efficient for classroom environments with large numbers of students, since the identification process must be repeated for each individual and therefore requires more processing time.

In contrast, multi-face recognition approaches have been implemented in several studies, including those by Bah and Ming (2020), Wati et al. (2021), Zhao et al. (2022), Uçar and Özdemir (2022), and Dang (2023). By detecting multiple faces simultaneously within a single frame, these systems demonstrate higher operational efficiency and are better aligned with real-world classroom scenarios. However, multi-face approaches in current

literature generally rely on conventional detection, feature extraction, and classification techniques, each of which presents specific limitations.

First, detection methods such as Viola Jones and Haar Cascade operate optimally only for frontal-face images and experience significant performance degradation under pose variations and uneven illumination. Second, feature extraction techniques also present challenges. Methods such as LBP and LBPH are sensitive to noise and pose variations and capture only limited local texture information. Gabor Wavelets, while more expressive, produce high-dimensional feature vectors and require substantial computational resources. Meanwhile, deep-learning-based approaches such as FaceNet depend on large training datasets and require careful fine-tuning that is highly sensitive to local data distribution. Third, classification and matching methods introduce additional constraints. Distance-based metrics such as Chi-Square compare histogram distributions without considering global facial structure, reducing accuracy under complex visual conditions. KNN is sensitive to outliers, which may negatively affect classification boundaries, while SVM demands precise parameter tuning to achieve optimal performance.

The reviewed studies demonstrate a clear distinction between single-face and multi-face recognition approaches in the development of attendance systems. Single-face recognition methods, such as those proposed by Sunaryono et al. (2021a), Nguyen-Tat et al. (2024), Nadhan et al. (2022), and Surantha and Sugijakko (2024) show consistently high accuracy and stable performance under controlled conditions. These systems typically rely on classical pipelines using Viola Jones for detection, PCA/LDA or LBPH for feature extraction, and lightweight classifiers such as LR, SVM, or distance-based matching. While effective on a per-individual basis, these approaches inherently lack scalability due to their sequential identification workflow, making them unsuitable for classroom environments where many individuals must be authenticated simultaneously.

In contrast, multi-face recognition systems such as those by Bah and Ming (2020), Wati et al. (2021), Zhao et al. (2022), Uçar and Özdemir (2022), and Dang (2023) illustrate a shift toward more efficient attendance automation capable of processing multiple faces in real time. These studies incorporate more advanced detection models such as YOLOv3, SSD-MobileNetV2, or cascaded classifiers to localize faces within crowded scenes. However, despite improvements in detection efficiency, many of these systems continue to employ conventional feature extraction and recognition techniques, including LBP, LBPH, Gabor Wavelets, Chi-Square distance, KNN, and SVM. Consequently, they remain vulnerable to challenges such as pose variation, illumination changes, image noise, and computational overhead limitations that become more pronounced in dynamic classroom environments.

Overall, the current body of literature reflects a transitional landscape in facial-recognition-based attendance systems. While emerging multi-face

recognition approaches offer significant improvements in scalability and real-time applicability, they are often constrained by the use of traditional feature extraction and classification methods. Conversely, more advanced deep learning based recognition frameworks demonstrate superior robustness but require substantial computational resources and larger datasets for optimal performance. This synthesis highlights the need for integrated approaches that balance accuracy, efficiency, and environmental robustness to support reliable classroom-scale deployment.

4. CONCLUSION

This systematic literature review examined research on facial-recognition-based attendance systems published between 2020 and 2024, focusing on detection methods, preprocessing techniques, feature extraction approaches, recognition strategies, evaluation metrics, and state-of-the-art implementations in educational and workplace environments. The results show that facial recognition continues to evolve through two dominant paradigms: traditional computer vision pipelines and deep learning-based models. Traditional approaches such as Viola Jones, Haar Cascade, LBP, LBPH, HOG, and Gabor Wavelets remain widely used due to their computational efficiency and ease of deployment on low-resource hardware. Meanwhile, modern deep learning approaches FaceNet, MobileFaceNet, and CNN-based models offer stronger accuracy and robustness but require larger datasets, higher computational resources, and careful fine-tuning.

A key finding of this review is that single-face recognition systems, although accurate, are insufficient for realistic classroom environments, where multiple faces appear simultaneously. Multi-face recognition systems have emerged as promising alternatives, yet most are still constrained by the limitations of traditional detection algorithms, sensitivity to pose and illumination variations, and reliance on distance-based or classical classifiers. Evaluation practices across studies also lack standardization, with most research relying solely on accuracy, providing limited insight into reliability, scalability, or operational performance in dynamic real-world scenarios.

Overall, the synthesized evidence underscores the need for more robust, scalable, and context-aware facial recognition frameworks capable of handling diverse classroom settings, varying environmental conditions, and evolving security threats such as spoofing attacks. The insights from this review provide a foundation for future research directions aimed at advancing facial-recognition-based attendance systems toward practical, secure, and institution-ready deployment.

5. RESEARCH GAPS

A synthesis of the state-of-the-art literature reveals several research gaps that remain unaddressed in the development of facial-recognition-based attendance systems. These gaps emerge not only from methodological limitations but also from constraints related to scalability, robustness, real-world applicability, and evaluation rigor. First, there is a clear lack of scalable solutions capable of handling complex classroom environments with large numbers of participants. Although multi-face recognition systems have been proposed, most traditional pipelines rely on Viola-Jones, Haar Cascade, or HOG-based detection, which degrade significantly under pose variation, occlusion, or uneven lighting. Deep learning detectors such as YOLOv3 and SSD-MobileNetV2 appear in only a few studies, and even these works do not fully investigate performance across diverse classroom conditions such as varying camera angles, crowded scenes, or student movement.

Second, feature extraction techniques used in existing systems show limited robustness toward environmental variability. Traditional approaches such as LBP, LBPH, and Gabor Wavelets struggle with illumination changes, noise, and non-frontal faces, while advanced embedding models like FaceNet require large and well-distributed datasets that are rarely available in institutional settings. None of the reviewed studies explore domain adaptation, contrastive learning, or lightweight embedding models optimized for real-world deployments on edge devices.

Third, classification and matching methods remain overly dependent on conventional algorithms, including Chi-Square distance, Euclidean Distance, KNN, and SVM. These methods are sensitive to noisy inputs and class imbalance, and they do not leverage modern metric-learning or probabilistic approaches that could improve robustness. No studies examine adaptive thresholding strategies, uncertainty-aware classification, or ensemble-based recognition mechanisms.

Fourth, evaluation practices across studies are limited in scope and insufficiently standardized. Accuracy is overwhelmingly used as the primary metric, with very few studies incorporating precision, recall, F1-score, or analysis of false positives/negatives. Real-time performance metrics such as inference time, latency, frame rate, and computational overhead are also rarely reported. This makes it difficult to assess the operational reliability of the proposed systems in practical deployment scenarios.

Finally, most studies lack comprehensive experimentation under real-world classroom conditions, such as varying seat arrangements, illumination changes, large participant groups, spoofing attempts, or device heterogeneity. Only a minority incorporate liveness detection, and even then, the evaluation of spoofing resilience is limited. The absence of benchmark classroom datasets further hampers cross-study comparison and reproducibility.

Taken together, these gaps highlight a pressing need for more robust, scalable, and thoroughly evaluated facial recognition frameworks tailored specifically for classroom-scale attendance systems. These findings inform the subsequent discussion and motivate the need for future research directions that integrate modern deep learning, improved evaluation standards, and real-world deployment considerations.

6. FUTURE WORKS

Based on the identified research gaps, several promising research directions emerge: First, future studies should prioritize the development of scalable multi-face recognition frameworks capable of robust performance in dynamic classroom environments. This includes handling pose variation, occlusion, illumination changes, and crowded scenes. Integrating more advanced detection models such as YOLOv7, RetinaFace, or transformer-based detectors may significantly improve detection accuracy and generalizability.

Second, there is a need for improved feature extraction and embedding models that balance robustness and computational efficiency. Lightweight deep-learning models, domain-adaptive embeddings, contrastive learning, and knowledge distillation offer potential for achieving high accuracy even in resource-constrained devices such as Raspberry Pi or Jetson Nano.

Third, future systems should adopt more advanced recognition and matching strategies, including metric learning, probabilistic classifiers, adaptive thresholding, and ensemble classification. These methods can enhance resilience against noisy inputs, class imbalance, and visually similar identities.

Fourth, evaluation protocols must be expanded and standardized. Researchers should integrate precision, recall, F1-score, FRR, ROC curves, and computational cost into their evaluation pipelines. Real-time performance and system stability under different lighting and seating configurations should also be systematically assessed.

Fifth, real-world deployment studies are needed, involving large classrooms, multi-camera setups, varying camera angles, and continuous monitoring throughout entire class sessions. Large-scale, publicly available classroom datasets would support reproducibility and accelerate benchmarking across studies.

Finally, future research should incorporate stronger security mechanisms, including more advanced liveness detection, anti-spoofing techniques, adversarial robustness evaluation, and multimodal biometric fusion (e.g., face + voice, face + RFID) to ensure integrity and prevent manipulation. Collectively, these research directions provide a pathway toward next-generation attendance systems that are accurate, secure, scalable, interpretable, and ready for real-world institutional adoption.

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