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SURVEY

Face Detection Using Eigenfaces: A Comprehensive Review

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ABSTRACT This paper thoroughly reviews face detection techniques, primarily focusing on applying Eigenfaces, a powerful method rooted in Principal Component Analysis (PCA). The goal is to provide a comprehensive understanding of the advancements, challenges, and prospects associated with Eigenface-based face detection systems. The review commences with exploring the comprehensive facial recognition system framework using Eigenfaces and studying the intricacies of employing Eigenfaces as a foundational element for robust facial recognition. Then, we describe the taxonomies of various Eigenface-based face detection approaches to provide a systematic understanding of the diverse strategies utilized in Eigenface-based face detection systems. Besides, the paper explores benchmarking datasets tailored specifically for facial recognition. These datasets are critically analyzed, highlighting their relevance, limitations, and potential impact on developing and assessing Eigenface-based face detection algorithms. Furthermore, the review details the limitations and open issues inherent in Eigenface-based face detection systems. Addressing concerns such as sensitivity to lighting conditions, occlusions, and scalability, this section aims to guide future research directions by identifying gaps in the current understanding and proposing potential avenues for improvement.

INDEX TERMS Dimensionality reduction, eigenvalues and eigenfunctions, face detection, face recognition.

I. INTRODUCTION

The Facial Recognition system represents a cutting-edge technological advancement designed to efficiently and accurately identify individuals based on their facial characteristics. In today's increasingly technology-driven society, facial recognition has become ubiquitous, finding applications across various domains, including public records management, authentication processes, security protocols, intelligence operations, and numerous other surveillance systems. Notably, the effectiveness of 2D facial recognition has experienced significant enhancements, particularly with the advent of deep learning methodologies. Nevertheless, despite these advancements, the efficacy of such techniques remains challenged by inherent limitations associated with 2D image data, encompassing factors such as varying illumination conditions, diverse facial poses, facial expressions, occlusions, disguises, temporal variations, and image quality fluctuations.

There are two primary paradigms for facial recognition, each characterized by distinct advantages and limitations. The first paradigm encompasses traditional approaches, which typically involve filtering responses, histograms of feature codes, and the distribution of dictionary atoms. These conventional methods aim to discriminate between facial features by relying on simplistic one or two-layer representations. Conversely, the second paradigm revolves around deep learning methodologies featuring Convolutional

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Neural Networks (CNNs). Deep learning approaches employ a cascade of multiple layers of processing units to extract and transform facial features, enabling more intricate and nuanced analysis of facial data.

In essence, the proliferation of facial recognition technology signifies a pivotal milestone in biometric authentication and surveillance systems. While traditional methodologies provide a foundation for facial recognition, deep learning techniques, particularly CNNs, have ushered in a new era of sophisticated facial analysis capabilities. Nonetheless, ongoing research addresses the challenges associated with facial recognition, aiming to enhance accuracy, robustness, and reliability in real-world applications.

The main contribution of this paper is a comprehensive and structured analysis of Face Detection using Eigenfaces. It goes beyond an in-depth overview by incorporating several key aspects. Our contributions are summarized as follows:

- Establishing a taxonomy of the reviewed research, providing a clear organization for researchers to navigate the development of Eigenfaces algorithms.
- Offers a balanced perspective by detailing the advantages and disadvantages of Eigenfaces, along with potential methods for improvement and future research directions.
- Provide detailed discussion regarding compiling a facial dataset since it is a valuable resource for researchers working in various facial recognition and analysis areas, extending its utility beyond the specific domain of Eigenfaces.

The rest of this paper is organized as follows: Section II details the methodologies and search strategies employed to identify relevant research. Section III provides a Top-Down View, presents a high-level overview of the Eigenfaces method, and outlines the general processing pipeline. To facilitate further analysis, Section IV categorizes the identified papers based on specific criteria. Section V delves into the datasets utilized within the reviewed research and introduces some recently emerged face datasets with potential relevance to this field. In Section VI, we address the common challenges associated with Eigenface-based face recognition, fostering a critical understanding of the technique's strengths and weaknesses. Finally, we summarize the key findings and potential future research directions in Section VII.

II. SEARCH STRATEGY

We consulted and analyzed scholarly articles centered on eigenfaces to conduct our investigation.

Figure 1 illustrates the sequence of the proposed method and strategies. Our research initially focused on identifying reputable publishers, such as peer-reviewed journals or academic presses renowned for their rigorous review processes, including IEEE, Springer, MDPI, and others of similar standing. Subsequently, we conducted thorough searches across chosen databases utilizing predefined keywords and filters to pinpoint pertinent literature. Initially, we amassed a comprehensive dataset comprising no fewer than 150 papers relevant to our inquiry. We then sieved through search results by scrutinizing titles, abstracts, and keywords to gauge initial relevance, resulting in a refined selection of 100 papers deemed most pertinent to our study objectives. Following this initial screening process, we meticulously examined each of these papers, conducting in-depth reviews of the full text of potentially relevant papers to assess their alignment with the research objectives and scope. This meticulous curation yielded approximately 70 high-quality, relevant papers that met the stringent criteria established for this survey. Each of these selected papers significantly contributes to advancing knowledge in the research domain, ensuring the integrity and credibility of the survey findings.

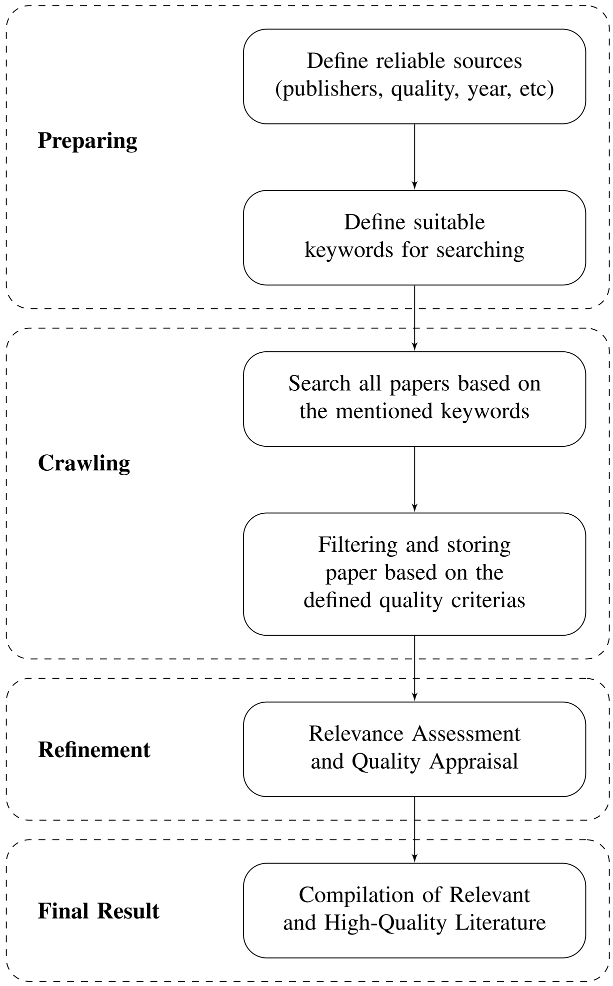

FIGURE 1. The illustration of paper selection strategies.

The distribution of papers across different publishers is illustrated in Figure 2, providing insights into the proportional representation of each publisher within our research corpus. This graphical representation elucidates the breadth and depth of our exploration across various scholarly outlets, highlighting the diversity of sources leveraged in our investigative endeavors.

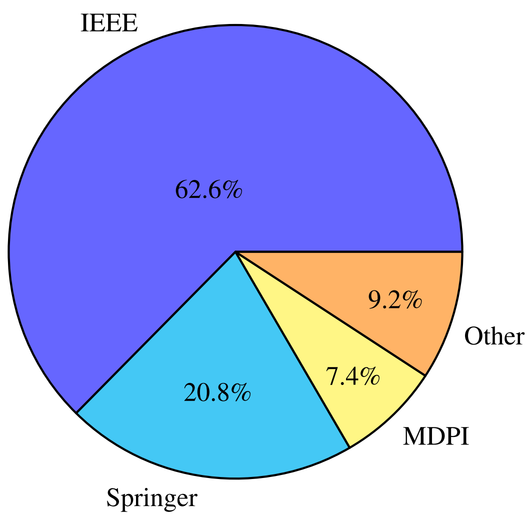

FIGURE 2. Distribution of paper collected regarding publishers.

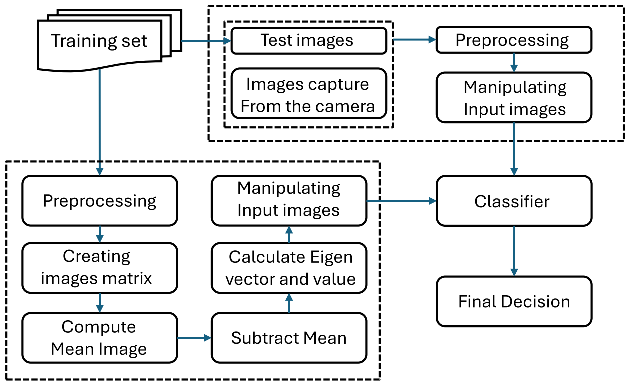

FIGURE 3. Framework for eigenface-based face recognition system.

III. FRAMEWORK OF EIGENFACE-BASED FACE RECOGNITION SYSTEM

A framework of a Face Recognition system employing Eigenfaces methodology encompasses multiple components outlined in Figure 3. This system generally comprises two modules: one dedicated to processing images within the database, while the other handles processing captured images.

A. INPUT IMAGES

The dataset for the Face Recognition system should comprise facial representations. The forthcoming section V will delve into an in-depth exploration of various datasets pertinent to this field. These datasets will be divided into distinct subsets, including the training and testing sets, a practice imperative for ensuring robust model performance. It is important to note that facial images can be obtained in many real-life situations using various devices equipped with cameras. These can range from traditional laptops and mobile phones to the expanding field of Internet of Things (IoT) devices.

B. PREPROCESSING

To achieve optimal classification results and ensure the accurate application of algorithms, it is imperative to undertake preprocessing steps on the images. These preprocessing techniques are crucial in refining the input data, mitigating noise, enhancing features, and standardizing image characteristics. By preprocessing the images effectively, potential sources of variability and distortion can be minimized, thus facilitating more robust and reliable classifier crucial action outcomes. Consequently, preprocessing acts as a foundational step in the image analysis pipeline, enhancing the performance and efficacy of subsequent algorithmic operations.

The preprocessing methodologies encompass a spectrum of essential techniques, including:

- **Face Detection:** The face detection process involves analyzing an image or video frame to determine the locations of all facial regions. The goal is to identify the presence of faces in the image and to determine their position and size. Once a face is detected, additional processing can be performed to extract various facial features, such as eye and mouth positions, head pose, and facial expressions. This information can be used to perform face recognition, emotion detection, and head-tracking tasks.
- **Conversion of RGB Images to Grayscale:** When converting RGB color images into grayscale representations, we can reduce computational complexity by using fewer bits per pixel. Grayscale images typically use 8 bits per pixel, compared to the higher bit depth of RGB counterparts. This reduction in bit depth reduces the computational burden while retaining important image information.
- **Face Alignment:** One crucial step is aligning the detected facial regions to a standard orientation or reference frame. This alignment process corrects any possible variations in the pose or orientation of different facial images, ensuring consistency and making it easier to perform subsequent analysis tasks. Aligning facial features improves the effectiveness of face recognition algorithms, leading to more precise and dependable classification outcomes.

C. TRAINING PHASE

After the preprocessing stage, the system followed by the training stage proposed by Turk and Pentland in 1991, summarized as follows.

1) **Constructing the Face Space:** In this step, all face images in a 2-dimensional matrix are converted into 1-dimensional vectors, e.g., flattened into a single vector. These vectors are then stacked to form a matrix, where each column represents a face vector. Let denote this matrix as X, where each column x_i represents a face image vector.
2) **Calculating the Mean Face:** The mean face vector $\overline{x}$ is computed by taking the average of all face vectors as

Eq. 1

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i, \tag{1}$$

where, $x_1, x_2, x_3, .., x_M$ are face images in the training set.

3) **Subtracting the Mean Face:** Each face vector is normalized by subtracting the mean face vector, as shown in equation 2:

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

This step centers the data around the origin.

4) **Calculating the Covariance Matrix:** The covariance matrix (C) of the normalized face vectors is computed by the equation 3:

$$C = \frac{1}{N}\sum_{i=1}^{N} \hat{x}_i \hat{x}_i^T \tag{3}$$

5) **Computing eigenvector and eigenvalue:** The eigenvectors of the covariance matrix C are calculated. These eigenvectors are the principal components or eigenfaces. They represent the directions in the high-dimensional space where the data varies the most. The eigenvectors v_j satisfy equation 4:

$$Cv_j = \lambda_j v_j \tag{4}$$

where λ_j is the corresponding eigenvalue, these eigenfaces are sorted based on their eigenvalues in descending order.

6) **Calculate Eigenfaces:** While the covariance matrix C holds valuable information in its eigenvectors and eigenvalues, the sheer number of dimensions (N for a matrix of size $N \times N$) can be computationally expensive. Additionally, the concept of rank - the maximum number of linearly independent vectors in a matrix - imposes a natural limit on the number of relevant eigenvectors. In the context of image training sets, this rank is limited by the number of images (M). This translates to, at most, $M - 1$ non-zero eigenvalues and their corresponding eigenvectors. Fortunately, a theorem in linear algebra offers an alternative approach by finding eigenvectors and eigenvalues of matrix A^TA denoted by ν_i and ν_i, respectively:

$$A^TA = \mu_i \nu_i \tag{5}$$

multiply both sides of equation 5 with A, we obtain a set of consecutive equations as shown in equation 6:

$$\begin{aligned} AA^TA\nu_i &= A\mu_i\nu_i, \\ AA^T(A\nu_i) &= \mu_i(A\nu_i), \\ C(A\nu_i) &= \mu_i(A\nu_i) \end{aligned} \tag{6}$$

Since the eigenvector corresponding to the lowest eigenvalue captures the least variance (information spread), eigenvalues typically exhibit an exponential decay. This implies that a significant portion, often around 90%, of the total variance can be captured by just the first 5-10% of the eigenvectors [2]. To exploit this property, we prioritize eigenvectors based on their eigenvalues. By sorting them in descending order, the first eigenvector in the resulting matrix, denoted by E, corresponds to the highest variance. These eigenvectors are then normalized to ensure unit length. Stacked as column vectors, they form the new basis matrix E with dimensions $N \times D$, where N is the original data dimensionality and D represents the chosen number of eigenvectors for dimensionality reduction. This matrix E serves two key purposes: 1) projecting the data matrix A onto the subspace spanned by these principal components, and 2) calculating the transformed data points, represented by the vector y_i in the resulting matrix $Y = (y_1, \ldots y_m)$. The calculation of Y is done using equation 7:

$$Y = E^TA \tag{7}$$

D. INFERENCE PHASE

The trained model recognizes faces in unseen images during the inference stage. The process typically involves the following steps:

1) **Preprocessing:** Similar preprocessing steps applied during training, such as normalization and alignment, are performed on the input facial image.
2) **Projection:** The preprocessed image is projected onto the Eigenfaces space, resulting in a low-dimensional representation of the input face using the previously computed Eigenfaces. This is done by computing the dot product between the normalized face vector and each Eigenfaces as shown in equation 8:

$$w_i = V^T\hat{x}_i \tag{8}$$

where V is the matrix containing the selected eigenfaces as columns.

3) **Recognition:** The last step is face recognition. Here, classification is achieved by calculating the distance, denoted ϵ_i, between w_i and each vector y_i within the transformed data matrix Y. Euclidean distance is the most prevalent metric for this purpose, but other distance measures can also be employed [3]. The formula for calculating Euclidean distance is shown in equation 9:

$$d(A, B) = \sqrt{\sum_{i=1}^{D}(a_i - b_i)^2} = ||A - B|| \tag{9}$$

Manhattan Distance also could be considered as equation 10:

$$d(A, B) = \sum_{i=1}^{D} |a_i - b_i| \tag{10}$$

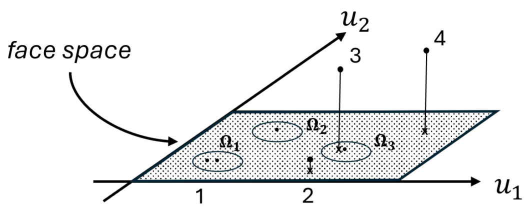

FIGURE 4. **Simplified face space illustration [1].**

Furthermore, it is crucial to establish a threshold value. The face is classified as unknown if the minimum distance between an inferred face and its corresponding training image surpasses this threshold. Conversely, if the distance falls below the threshold, the face is recognized, and the corresponding identity can be determined as $s = argmin_i[\epsilon_i]$, where ϵ_i represents the distance between the inferred face and the i^{th} training image. A face recognition system lacking a threshold would erroneously validate individuals even if they have not appeared in the database. There is no definitive formula to calculate the optimal threshold. However, a common approach involves computing the minimum distances between each image in the training dataset and all other images. These distances are then stored in a vector *rast*. The initial threshold is then typically set at 0.8 times the maximum value within this vector, as shown in equation 11:

$$\theta = 0.8 \times \max(rast) \tag{11}$$

IV. TAXONOMIES

In order to ensure a clear understanding of the methodologies employed in this survey, we have categorized them into distinct classifications. These classifications encompass foundational and didactic expositions, the imperative of preprocessing, algorithmic enhancement strategies, hybrid methodologies that combine multiple techniques, real-world applications and implementations, comparative analyses, strategies and frameworks for safeguarding privacy, and miscellaneous categories. A visual representation of this taxonomy is provided in Figure 5. Notably, our taxonomy includes a dedicated class for "hybrid" methodologies, which encompass solutions that integrate two or more feature extraction techniques to improve the efficacy of face recognition systems. This approach fosters a streamlined and user-friendly taxonomy by minimizing redundancy and overlaps between sections. Furthermore, we have meticulously employed well-established terminology throughout the taxonomy to enhance accessibility and ensure intuitive understanding for all readers.

A. FOUNDATIONAL AND DIDACTIC EXPOSITIONS

In this category, we will explore the foundational principles and didactic expositions. We will delve into the fundamental concepts, theories, and methodologies that underlie different fields of study, providing clarity and insight to both beginners and experienced practitioners.

Sirovich and Kirby explained the conceptual foundations of the Eigenfaces algorithm in their seminal work titled "Low-dimensional procedure for the characterization of human faces" published in 1987 [4]. Subsequently, Turk and Pentland [1] provided a formalized exposition of the algorithm in their significant contribution, "Face Recognition Using Eigenfaces", presented at the 1991 Conference on Computer Vision and Pattern Recognition (CVPR). These academic publications are essential to the development of computer vision research, specifically in the area of facial recognition. A simplified face space model is utilized to demonstrate the outcome of mapping an image into this space as Figure 4. The model comprises two eigenfaces (denoted as u_1 and u_2) and identifies three distinct individuals (denoted as Ω_1, Ω_2 and Ω_3, respectively).

In a study by Wahyu Mulyono et al., they explored the Eigenfaces approach across three diverse face datasets. Their findings showed recognition accuracy spanning ranges from 67% to 100%, with an average of approximately 85%. This underscores both the potential and the challenges in applying Eigenfaces to real-world scenarios [5].

A manuscript that provides an in-depth analysis of the classical Principle Component Analysis (PCA) method has been written. The manuscript highlights challenges when applying it to very small or very large high-dimensional datasets, such as Eigenfaces. The tutorial focuses on the mathematical foundations of classical PCA and its practical applications, drawing on insights initially introduced by Marukatat [6].

Singh et al. took these theoretical concepts and brought them to life by implementing Eigenfaces algorithms using MATLAB and Python. Their work culminated in creating a web application capable of accurate face detection. This fusion of theory and application showcases the transformative potential of Eigenfaces in real-world settings [7].

B. THE IMPERATIVE OF PREPROCESSING

Preprocessing in face recognition encapsulates many techniques aimed at refining raw input data, typically images or videos, to extract pertinent facial features effectively. It serves as the crucial initial phase where data quality is enhanced, noise is mitigated, and irrelevant information is filtered out, laying a robust foundation for subsequent feature extraction and classification stages. As such, the imperative of preprocessing cannot be overstated, as its efficacy profoundly impacts face recognition systems' overall performance and applicability in real-world scenarios. Moreover, this section underscores the interdisciplinary nature of preprocessing in face recognition, drawing insights from diverse domains such as image processing, machine learning, and signal processing. By amalgamating insights from these disparate fields, researchers can harness a synergistic approach toward devising innovative preprocessing strategies that transcend

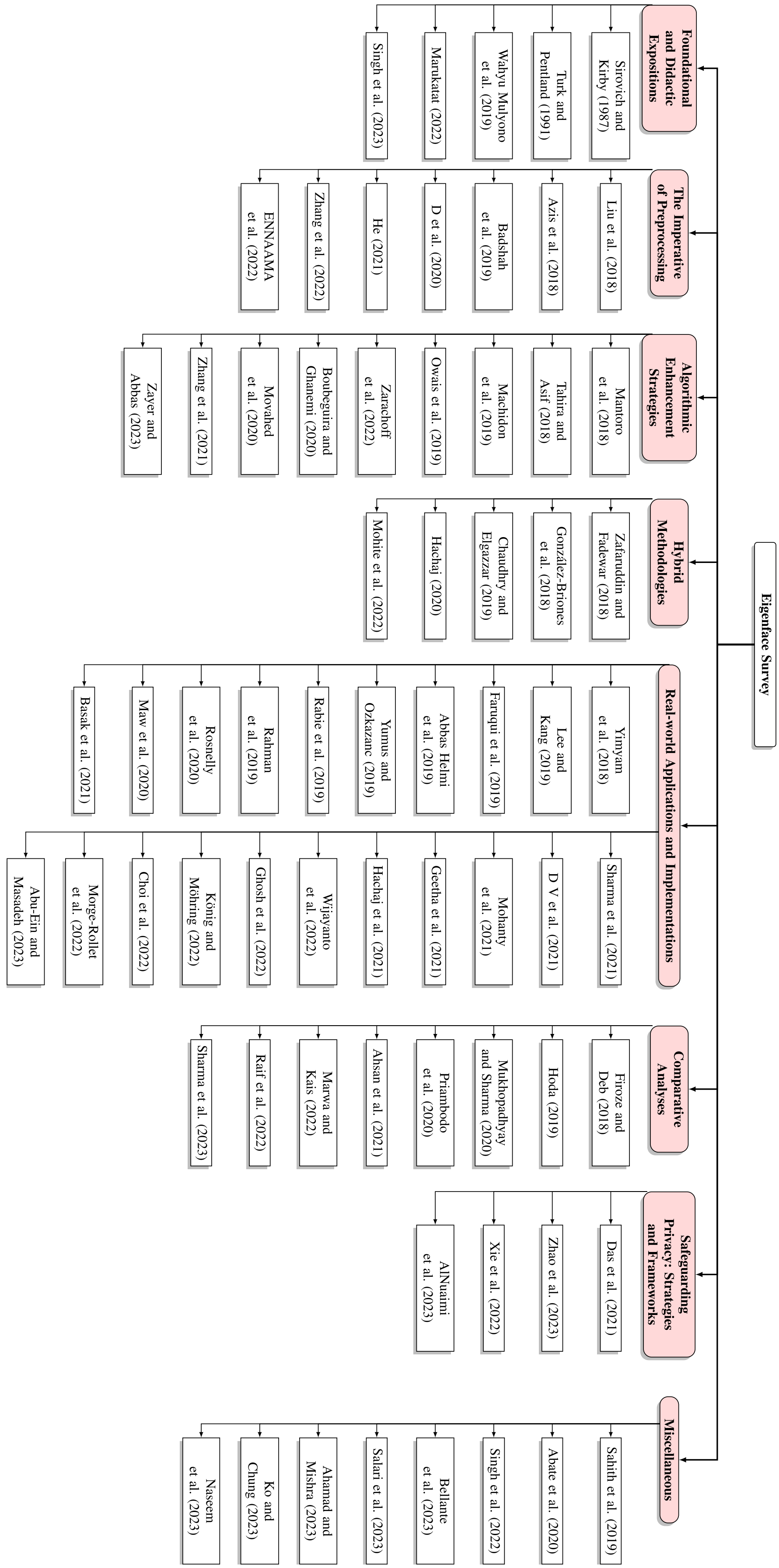

FIGURE 5. Structure of taxonomy.

conventional boundaries, thereby fostering advancements in face recognition technology.

A study conducted by Liu et al. highlights the shortcomings of traditional face recognition systems, such as inefficiency and the complexity associated with statistical analysis, prompting the proposal of a novel check-in system. Comprising three primary stages, initially, computer cameras capture images of individuals, followed by the application of image preprocessing techniques and feature extraction employing Eigenfaces. Subsequently, a database containing participant information is established, coupled with the features extracted in the previous stages. The preprocessing phase encompasses geometric normalization, which ensures the geometric stability of images, followed by gray-scale normalization. This latter procedure aims to address potential issues of low contrast in original images stemming from environmental constraints. By equalizing the contrast levels across images, this procedure serves to improve visual quality and facilitate the identification of salient features within the images [8].

In some situations, Face Recognition Systems may not work accurately due to low light conditions, making them difficult to operate. To address this issue, Azis et al. conducted a thorough investigation to develop a robust system that can accurately identify human faces even in low-light conditions. They achieved this by implementing image restoration techniques such as Histogram Equalization, Contrast Limited Adaptive Equalization, and Local Enhancement. These techniques were used to enhance image quality and refine images exhibiting contrasting brightness and overexposure. By improving image quality, Azis et al. achieved a remarkable enhancement in Face Recognition Systems accuracy, achieving an impressive 50% improvement from previous non-functional or unreliable performance levels [9].

In a study conducted by by Badshah et al., three principal filtering methodologies were scrutinized: Linear Predictive Coding, Mean Filtering, and Homomorphic Filtering. The findings indicate that the mean filter exhibits a marginally superior performance in comparison to its counterparts. This finding is crucial in addressing challenges such as limited dataset availability, image perturbation, variations in lighting, and fluctuations in background color [10].

The authors of the paper titled "ID Photo Verification by Face Recognition" [11] described a detailed set of image processing techniques used to improve the quality of input data. These techniques involve converting images to grayscale, normalizing histograms, reducing noise to minimize random intensity fluctuations, and classifying skin. This thorough enhancement protocol aims to speed up the process of face detection while also reducing the number of false positive identifications.

In a scholarly work by He, the author suggests using familiar methods like histogram equalization and median filtering, except for single-scale Retinex. The term Retinex is a combination of the words retina and cortex. It has been found that the algorithm used for human eye recognition based on Retinex theory is unsuitable for machine recognition. On the other hand, techniques such as histogram equalization and median filtering have shown effectiveness in removing image noise and improving contrast. Additionally, implementing grayscale normalization algorithms can significantly improve the accuracy of machine recognition [12].

According to Zhang et al.'s research, the authors utilized questions and hypotheses to determine the factors that affect the accuracy of face recognition systems. The findings indicate that face angle and masking have a positive impact on face recognition, with masking being the most significant factor [13].

Facial recognition can be challenging when individuals wear masks, as it obscures a significant portion of their faces, making identification difficult. ENNAAMA et al. proposed an innovative approach that involves using skin detection techniques to supplement facial recognition. The results of the evaluation of this method are promising, indicating that it has the potential to overcome the challenges posed by facial masks and improve recognition accuracy [14].

To summarize, the discussion aims to explain the crucial role of preprocessing in the field of face recognition. By exploring the fundamental concepts, practical approaches, and emerging trends, this section aims to create a deeper understanding of the intricacies involved in preprocessing, while emphasizing its essential role in unlocking the full potential of face recognition technology.

C. ALGORITHMIC ENHANCEMENT STRATEGIES

Achieving optimal performance in face recognition systems requires significant emphasis on preprocessing. This phase is critical as it lays the foundation for the accuracy, efficiency, and robustness of subsequent recognition tasks. Within preprocessing, algorithmic enhancement strategies emerge as essential tools, offering advanced techniques to refine raw input data and effectively extract discriminative facial features.

Mantoro et al. conducted research to enhance face recognition by combining Haar Cascades and Eigenfaces methods and applying them in the preprocessing and feature extraction stages. This study was published in 2018. The proposed approach achieved a recognition accuracy of up to 91.67 % for detecting and recognizing multiple faces, both during daytime and nighttime (under good lighting conditions). However, it is worth noting that this method is limited to frontal-facing or $\pm 15°$ head rotation faces [15].

The study "Effect of Averaging Techniques on PCA Algorithm and its Performance Evaluation in Face Recognition Applications" by Tahira and Asif (2018) compared three different PCA methods based on mode, mean, and median. The findings revealed that using mode could enhance the face recognition rate and reduce computational complexity as compared to using mean. However, further research is necessary to evaluate the effectiveness of this technique under varying conditions and more advanced facial databases [16].

In 2019, Owais et al. researched methods to improve human face recognition, also utilizing PCA and individual faces. The results demonstrated that this approach achieved high performance on test datasets, with high recognition rates and low computational complexity. One strength was the use of a minimal number of eigenfaces to represent the face space, enhancing the classifier's performance. However, the study only focused on minor variations in facial expressions and poses [17].

Also, in 2019, Machidon et al. introduced the gaPCA (geometrical approximated PCA) method to reduce the computational complexity of traditional PCA in face recognition. The results showed that gaPCA achieved comparable performance to traditional PCA, with an overall average difference of less than 4%. GaPCA offers flexible options and reduces the number of training iterations for neural networks. However, further research is needed to assess the performance of gaPCA in different situations and conditions of variation [18]. In a paper "GPU-Accelerated implementation of Eigenfaces (PCA) algorithm using memory optimization" of Boubeguira and Ghanemi (2020) introduced a novel approach to Eigenfaces PCA face recognition algorithm implementation leveraging GPU acceleration and memory optimization techniques. By utilizing CUDA on an NVIDIA GeForce 750M GPU with 3.0 capability, the study explores various memory access methods, including uncoalesced and coalesced memory accesses, with shared memory yielding the most significant performance improvements. Experimental results conducted on the Yale Face Database B demonstrate a 3x faster overall execution compared to existing algorithms. The authors plan to extend their implementation to real-time applications, particularly for face detection in live videos in future research endeavors [19]. To enhance the performance and reliability of face recognition systems, Movahed et al. (2020) proposed a method that integrates the Eigenfaces algorithm with image registration techniques, which optimizes the facial recognition process to improve accuracy and efficiency across various scenarios. Their approach utilizes preprocessing steps and image registration techniques to create a flexible and diverse system, resulting in better recognition capabilities compared to traditional methods. However, it's worth noting that this method may encounter relatively long processing times, requiring optimization for optimal performance in the future [20]. The study conducted by Zhang et al. (2021) introduces a face recognition method that integrates principal component analysis (PCA) and support vector machine (SVM) algorithms. PCA is employed to transform face images into a new feature space, reducing dimensionality and eliminating correlation and noise among features. Subsequently, SVM is used for classification, with additional samples from the test set added to the training set to improve recognition accuracy. Experimental results demonstrate a 5% improvement in detection accuracy compared to classical algorithms [21]. In contrast, Zarachoff et al. (2022) presents a Two Dimensional Multi-Band PCA (2D-MBPCA) method for ear recognition, inspired by PCA-based techniques for multispectral and hyperspectral images. By dividing input images based on pixel intensity and applying PCA, the proposed method significantly outperforms standard PCA and Eigenfaces techniques, achieving up to a 56.41% improvement in matching accuracy [22].

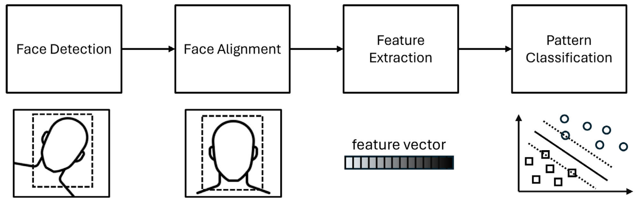

FIGURE 6. Automated gender and age classification flowchart [25].

Furthermore, Zayer and Abbas (2023) proposes an enhancement to face recognition under varying illumination using Normalized Eigenfaces with Histogram Equalization. By mitigating errors caused by background and lighting variations, the method achieves high recognition accuracy, particularly for low-light and shadowed images. Experimental results indicate an enhancement of recognition efficiency by 13.586-222.967% compared to the Eigenfaces method and 0.389-10.294% compared to the Normalize Eigenfaces method [23].

Algorithmic enhancement strategies play a vital role in optimizing face recognition systems, offering avenues for refining raw input data and extracting discriminative facial features efficiently. These approaches contribute to improving recognition accuracy, reducing computational complexity, and addressing challenges such as variations in lighting conditions and pose.

D. HYBRID METHODOLOGIES

The integration of a "hybrid" class within our taxonomy represents a pivotal advancement in the categorization of feature extraction techniques for face recognition systems. This classification facilitates a streamlined and intuitive framework by strategically amalgamating two or more methodologies, minimizing redundancy and overlap across disparate sections. This deliberate structuring not only enhances accessibility but also fosters a deeper understanding of the diverse strategies employed in face recognition.

In the study "Face Recognition Using Eigenfaces" of Zafaruddin and Fadewar (2018) introduces a face recognition system that combines PCA with neural networks. This method achieves a high recognition rate of approximately 93% on the ORL database and demonstrates flexibility in experimenting with various numbers of hidden neurons and eigenfaces [24].

Figure 6 shows that the pipeline of study by González-Briones et al. (2018), a multi-agent system integrates Fish-

FIGURE 7. Misclassified faces by eigenfaces [26].

erfaces, Eigenfaces, Local Binary Patterns, and Multilayer perceptron for gender and age classification from images, alongside Gabor and Sobel filters for dimensionality reduction. While this method demonstrates high classification accuracy and flexibility in configuration, it requires high-quality preprocessing and careful selection of appropriate methods and filters [25]. In 2019, Chaudhry and Elgazzar proposed research that combines Eigenfaces, Fisherfaces, and Local Binary Patterns Histograms for enhanced accuracy in face recognition. Experimental results reveal that the hybrid approach outperforms individual algorithms, particularly in handling background shadows, with Fisherfaces showing the most efficient performance [26]. However, there are still cases where faces cannot be accurately classified, as depicted in the figure 7 that show face is unable to classify using the Eigenfaces method. The reason for this is that the background may cause issues in the face recognition classifier. Particularly, images of closed eyes cannot be recognized.

Next, Hachaj introduces a classifier for human facial feature annotation, designed for low-power consumption autonomous microcomputer systems in 2020. The proposed method combines a Histogram of Oriented Gradients (HOG) face detector with neural networks, achieving comparable accuracy to deep neural network architectures but with less memory usage and no need for additional coprocessors. The research showcases the feasibility of performing facial attribute annotation on incoming video data captured by RGB cameras without additional coprocessors. This work contributes valuable insights for developing autonomous systems capable of facial image annotation on low-power devices [27]. Until 2022, "Thermal and Visual Face Recognition using Eigenfaces and Transfer Learning" by Mohite et al. presents a hybrid approach that combines Eigenfaces with transfer learning to enhance face recognition. Utilizing pre-trained deep learning models for feature extraction, the system achieves reduced complexity that is suitable for small embedded devices. Despite achieving promising accuracy rates of 62.9% for thermal images and 91.93 % for visual images, limitations arise due to the scarcity of thermal datasets for model training, potentially impacting feature extraction quality. Nonetheless, the hybrid approach offers a promising direction for improving thermal face recognition systems by integrating transfer learning techniques [28].

Overall, these hybrid approaches offer versatile solutions for enhancing face recognition systems, providing improved accuracy, flexibility in configuration, and feasibility for deployment on various hardware platforms, including low-power devices.

E. REAL-WORLD APPLICATIONS AND IMPLEMENTATIONS

In recent years, the advancement of face recognition technology has catalyzed a transformative shift in numerous industries and sectors, ranging from security and surveillance to marketing and healthcare. This burgeoning technology, once confined to the realm of science fiction, has become an integral component of our daily lives, revolutionizing how we interact with our environments and each other. In this section, we delve into the myriad real-world applications and implementations of face recognition technology, exploring its multifaceted roles, ethical considerations, and implications for society at large.

In 2018, Yimyam et al. proposed a face-detection system for CCTV cameras to spot criminals in action by comparing eigenvectors. The result reaches 95% in single-person detection and 87% in group face recognition [29].

Lee and Kang introduced the human-face emotion estimate system based on Japanese female facial expression (JAFFE) and Cohn-Kanade (CK+) dataset in 2019. The authors imply that RMSE values computed by linear regression get a good result and are even better with less computation with PCA dimensions [30].

Faruqui et al. proposed a high-speed and lightweight system that is used to detect unethical behavior of proxy test-takers in examination in 2019. The approach uses Euclidian distance to distinguish between candidate faces. The result not only got a good speed performance but also exceeded a high accuracy of 97.88%, which can be helpful for exam invigilators [31].

For the class attendance study case, Abbas Helmi et al. proposed the FRACAS system in 2019 to scan and recognize student and lecturer faces using the Eigenfaces algorithm. However, due to its algorithm's comparison by face feature, the work needs to improve in further research to avoid the misrecognition of human faces when deformed [32].

In 2019, Yumus and Ozkazanc proposed a supervised method to handle the land cover classification problem. The paper presented some feature extraction methods and K-mean clustering combined with Kernel PCA to get the best silhouette of 85.71% for VH and VV polarization. Figure 8 demonstrates the classification result effect by the value of k. With $k = 2$, there are only two clusters, and even a better look at 3 clusters of building, wetland, and forest comes with the distinction of sea and forest [33].

Rabie et al. proposed 2 approaches for palm vein classification in 2019. The first approach combines PCA for feature extraction with an MLP neuron network for detection. The second is a Bag of Features (BOF) with SURF and SVM.

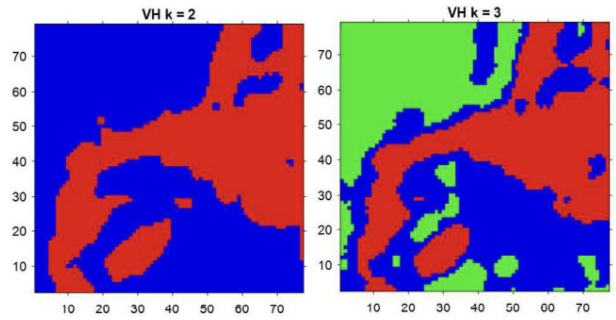

FIGURE 8. Land cover result for k = 2 and k = 3 [33].

The paper shows that the BOF technique provides a better result with an accuracy of 98%, indicating better performance than PCA and MLP [34].

Rahman et al. introduced a facial motion and emotion detector to calculate the stress level of employees in 2019. Eigenfaces were used to extract features from facial parts. Then, the authors used Euclidian distance to identify faces and emotions. A fuzzy classifier was used to measure stress levels by comparing the features from the database. The author also mentioned the system needs to improve to achieve better accuracy for real-life applications [35].

In the year 2020, Rosnelly et al. presented the laptop camera face recognition by comparing extracted face features with eigenvector values. The system can identify human faces from different angles and expressions [36].

Maw et al. also uses the JAFFE dataset to perform facial recognition in 2020. Eigenfaces are again used for feature extraction, and then KNN and multi-SVM classifier algorithms are employed to determine face emotions. The approach reaches 84.29% in accuracy. The author mentions in future work, the system will be re-trained and tested again with other datasets to get consistency detection [37].

In 2021, Basak et al. performed a classification system on Thermal tomographic images by manipulating the Eigenfaces and PCA to calculate the heat volume between uniform and non-uniform heating. The work may contribute to the fuel industry [38].

In quarantine, the explosion of social media such as Facebook is one of the reasons Sharma et al. introduced an Auto-tagging system that can apply to social media applications using different approaches: Eigenfaces technique, local binary pattern (LBP), and linear regression. The author concludes that linear regression archives have high accuracy due to their pattern recognition, while the Eigenfaces usually fails when little significant changes in features occur and needs more improvement in the future [39].

Due to the widespread use of ATMs, improving the safety of goods is necessary. For that purpose, in 2021, D V et al. proposed a solution to add Face-id for the transaction using the Eigenfaces algorithm. The method performed a prominent result, enhancing the security ability. The Adaboost recognition reaches 75%, while the Eigenfaces produces the accuracy rate at 80%. Hence, the author mentioned that 3D Face-id will be the mainstream for this study [40].

The attendant system of In 2021, Mohanty et al. brings the attendant system into a new step with the classroom management system, combining face recognition with student sound analysis for taking student present and lesson quality using Eigenfaces and CNN methods. The result shows that both approaches obtain a notable false acceptance rate (FAR) and false rejection rate (FRR), especially since CNN accurately recognizes all attended students with FRR equal to zero. Note that this system was not tested on a standard class size.

The Covid pandemic has changed the way students study, with everyone having to attend online classes. Reference [36] approach despite being good at detecting but incomplete, Rosnelly et al. proposed the method to intergrade Eigenfaces with the SVM classifier to perform performance on real-time recognition and attendance checks. The author states that the system obtains a high speed at recognition and extends the accuracy of 61%. In the future, the author will try several algorithms, such as SURF, SIFT, and Fisher Faces, to examine and improve the execution [41].

Within the diversity metadata and internet attackers, Hachaj et al. introduced the steganography technique by novel transform domain with Eigenfaces linear vectors. Using a unique approach, the eigenfaces-based steganography technique involves hiding messages within facial images. The process includes extracting a face image with embedded secrets, subtracting a mean face from the image, visualizing selected eigenfaces, generating Eigenface-based features through a linear combination of coefficients, and scaling high-order coefficients to represent secret data. To recover the original data, specific equations are applied to these coefficients. This technique utilizes the concept of eigenfaces to encode and decode hidden information within facial images, offering a novel and effective approach to steganography in the digital domain [43]. Figure 9 illustrates the secret encoding process. After isolating the face from the image(A), the representative average face is removed (B). Step (C) displays a selection of these representative faces, which are visualized as two-dimensional images. Eigenfaces create a mathematical representation of the face image (D). Some of these coefficients have a smaller impact on the overall appearance of the reconstructed face (E). By replacing these less significant coefficients with a secret message encoded as numbers, we can hide information within the image using equation 12, with s_i as the i-th binary coefficient of vector s (F):

$$s_i' = \frac{2 \cdot s_i - 1}{\mathrm{div}} \tag{12}$$

To complete the process, the average face (removed earlier) is added back to the modified face image(G). Finally, the resulting image containing the hidden message is inserted back into the original image(H). The author mentioned that

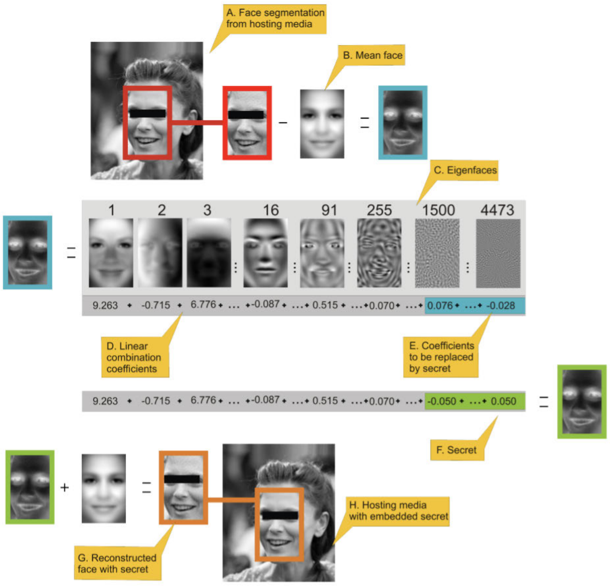

FIGURE 9. Eigenfaces steganography encoding pipeline [43].

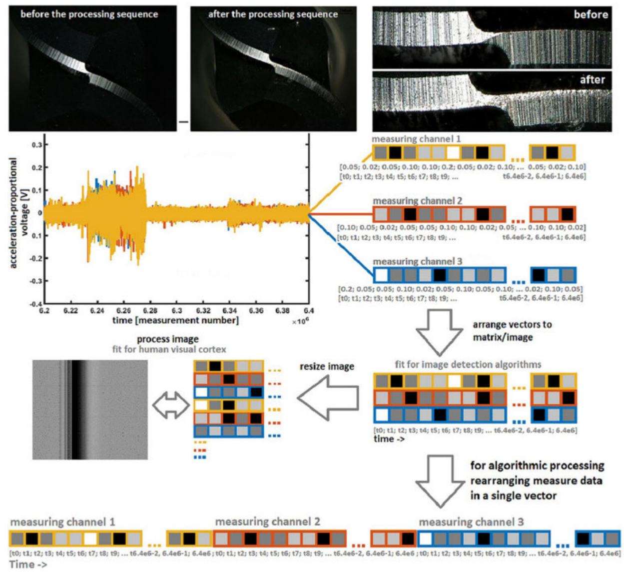

FIGURE 10. Preprocessing image data for efficient image processing tasks [46].

robustness against downscaling attack improvement will be the future work of this study.

In a study by Wijayanto et al., the authors developed an IoT device leveraging AI and the Eigenfaces method to distinguish between Organic and Non-Organic Waste, achieving accuracies of 75% and 70%, respectively. The accuracy was influenced by the dataset's limited variation and changes in the physical condition of the objects. In their work, Wijayanto et al. proposed a method for detecting the similarity of illuminance images through real-time processing with a wireless server-client network, utilizing Eigenfaces with PCA as the foundational algorithm [44]. In 2022, König and Möhring introduced a novel approach for monitoring tool wear in milling by applying the Eigenfaces algorithm to multi-sensor data, thereby overcoming the traditional challenges of tool wear monitoring and enhancing machining process analysis with advanced data fusion and machine learning techniques. Figure 10 shows the preprocessing for razor images to achieve better efficiency [46].

In 2022, Choi et al. introduced QR-EFA, a method to improve classification accuracy in BCIs by tackling the challenges of non-stationary datasets through the combination of Eigenface Analysis (EFA) and CNN techniques, particularly for motor imagery classification. This approach involves converting BCI signals into standardized and shareable QR images and employing systematic data augmentation during training to enhance classification performance [47]. Moreover, Abu-Ein and Masadeh 2022 unveiled RF Eigenfingerprints, utilizing SVD for feature learning, the Ljung-Box hypothesis test for feature selection, and statistical modeling for decision-making, showing high classification performance with potential IoT applications [70]. This powerful technique is employed in RF Eigenfingerprints to automatically learn significant features by decomposing the signal data matrix M. Finally, Abu-Ein and Masadeh in 2023 developed a proof-of-concept application employing the Eigenfaces method to identify absent students during live online exams, aiming to improve the Binus Online attendance tracking system by automating the process and minimizing the potential for attendance fraud. This prototype achieved an average accuracy rate of 94.08% across five tests in recognizing faces [49].

However, the proliferation of face recognition technology also raises profound ethical and privacy concerns, necessitating careful consideration of its societal implications. Issues such as data security, consent, bias, and the potential for misuse underscore the importance of implementing robust regulatory frameworks and ethical guidelines to govern the development and deployment of these systems. As such, while acknowledging the remarkable potential of face recognition technology, it is imperative to approach its implementation with a critical lens, balancing innovation with ethical considerations and safeguarding individual rights and liberties.

F. COMPARATIVE ANALYSES

The efficacy of a face recognition system hinges on its ability to accurately identify individuals across varying environmental conditions, poses, and facial expressions while mitigating the impact of factors such as illumination changes, occlusions, and noise. Traditional methods, such as Eigenfaces, Fisherfaces, and Local Binary Patterns (LBP), rely on handcrafted feature extraction techniques and statistical classifiers to achieve recognition. While offering simplicity and computational efficiency, these methods often struggle to generalize across diverse datasets and exhibit limited robustness in unconstrained environments.

In 2018, the research from North South University and Columbia University by Firoze and Deb aimed to enhance face recognition speed without sacrificing accuracy in a controlled setting, such as a classroom. By partitioning faces from an image into three levels and employing a hybrid model combining classical and CNN algorithms, they achieved a 33.43% faster recognition time compared to CNN alone while maintaining accuracy [50]. This approach was tested on a dataset of classroom faces under various conditions, demonstrating its potential for improving real-time face recognition efficiency. Along with that, in the year 2019, Danish et al. evaluates the error rates of state-of-the-art face detection algorithms, specifically Eigenfaces, Fisherfaces (using PCA and LDA, respectively), and LBPH, under various challenging conditions such as changes in environment, lighting, and facial features (e.g., hair, mustache). The analysis, which utilized the Yale dataset and datasets generated from internet images and live camera captures, revealed that Eigenfaces and Fisherfaces are more susceptible to errors than LBPH. The findings underscore the impact of environmental variations on face detection accuracy and highlight LBPH's relative robustness under such conditions [51]. A paper presented in 2020 by Mukhopadhyay and Sharma introduces a framework for real-time facial expression and emotion recognition using Eigenfaces, Local Binary Patterns Histograms (LBPH), and Fisher algorithms. It uses these biometric techniques to differentiate individuals based on physical or behavioral attributes, such as facial features, to validate identities or understand emotions. The research highlights the use of these algorithms for detecting facial expressions, thereby providing insights into a person's feelings or intentions, with applications extending to security, interactive systems, and helping disabled individuals communicate. The methodology encompasses image processing and machine learning techniques to classify facial expressions by comparing features extracted from images against predefined models. The findings underscore the potential of combining these algorithms to enhance the accuracy and efficiency of facial expression recognition systems, indicating a step forward in developing intelligent, responsive technologies that can interpret human emotions and intentions in real time [52]. In the same year 2020, Priambodo et al. evaluates Local Binary Pattern (LBP) and Eigenfaces algorithms for predicting drug use based on facial recognition technology. Using a dataset of images before and after drug use, the research found LBP to be more effective, achieving a 75% accuracy rate. This suggests the potential for more targeted drug testing in educational settings [53].

In a paper published in 2021, Ahsan et al. evaluates Eigenfaces, Fisherface, and Local Binary Pattern Histogram (LBPH) facial recognition methods under different weather conditions using a newly developed dataset, LUDB, alongside AT&T and 5_Celebrity datasets. LBPH outperformed other methods in terms of accuracy on the LUDB and 5_Celebrity datasets, ideal for unconstrained environments. Fisherface showed the least execution time across all datasets.

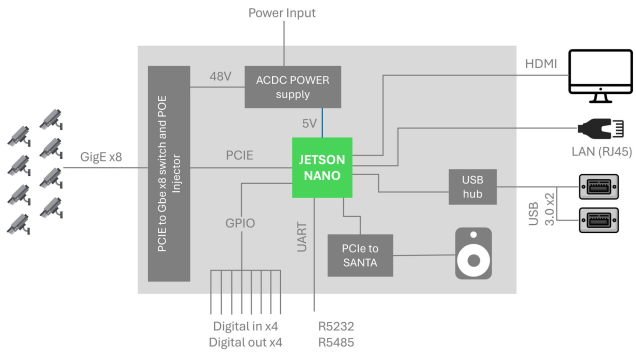

FIGURE 11. Jetson Nano B01 Synthetic deepstream gstreamer workflow [56].

The findings suggest that LBPH is optimal for varied weather scenarios, which is a significant step towards robust facial recognition in challenging conditions [54].

A research in 2022 conducted by Marwa and Kais evaluates classical facial recognition techniques like Eigenfaces and Fisherfaces and compares them against a more modern approach involving a deep learning model based on an improved VGG-16 architecture. The emphasis here is on the effectiveness of both traditional and cutting-edge methods in achieving high accuracy in facial recognition tasks, with a notable improvement seen in applying deep learning techniques [55]. The study of Sharma et al. in 2022 proposes a cost-effective, trusted system for smart parking and intrusion detection using the JetsonNano board as shown as in figure 11, focusing on the application of Eigenfaces and Local Binary Pattern Histogram algorithms for facial recognition [56]. It introduces metamorphic testing to evaluate the system's resilience to variations such as weather conditions, pixel noise, and distortion. The study demonstrates the potential of edge computing in smart city applications, highlighting the efficiency of Local Binary Pattern Histogram over Eigenfaces in handling extreme conditions and advocating for the importance of metamorphic testing in developing reliable machine learning models.

And especially during the year 2023, Sharma et al. extends the use of facial recognition technologies into the realm of public safety and emergency response. By leveraging Haar-Cascades for face detection and a combination of Eigenfaces, Fisherfaces, and LBPH for recognition, the proposed system aims to enhance road accident reporting and victim identification speed and accuracy. This application underscores the societal benefits of facial recognition technologies, especially in critical, life-saving situations [57].

This comparative analysis explores the nuances of different face recognition approaches, examining their performance across various benchmarks and datasets, computational requirements, scalability, and applicability to real-world scenarios. By synthesizing insights from academic research, industry developments, and case studies, we aim to provide a comprehensive overview of the current landscape of face recognition technology, elucidating key trends, challenges, and opportunities for future advancements.

G. SAFEGUARDING PRIVACY: STRATEGIES AND FRAMEWORKS

Face recognition technology is increasingly used in various aspects of society, such as security, commerce, healthcare, and entertainment. However, growing concerns exist about how this technology could infringe on people's privacy and misuse their data. The ability to collect, store, and analyze biometric information poses unique risks to individuals' privacy and civil liberties. Therefore, robust safeguards and ethical frameworks are necessary to mitigate potential harm. This section explores the multifaceted challenges of protecting privacy in face recognition systems. We will analyze strategies and frameworks to balance innovation with protecting fundamental rights. The proliferation of face recognition systems has raised significant apprehensions regarding collecting, storing, and utilizing biometric data, often without adequate consent or transparency. Unlike traditional forms of identification, such as passwords or ID cards, biometric identifiers are inherently immutable and irreplaceable, rendering individuals vulnerable to identity theft, surveillance, and unauthorized profiling. Moreover, integrating face recognition technology into public spaces, such as airports, shopping malls, and urban environments, has heightened concerns regarding mass surveillance and the erosion of privacy in everyday life.

Face recognition is widely used for authentication purposes, but face images often contain sensitive personal information that can be misused if leaked. In 2021, a system was proposed by the Das et al. that utilizes face recognition for authentication and proposes a more secure method of communication by modifying the AES algorithm. This modified algorithm uses variable irreducible polynomials in the $GF(2^8)$ finite field. The face detection process uses Haar-classifiers, which achieve high accuracy for still images and video recordings. Additionally, two algorithms are used for face recognition: LBPH and Eigenfaces. The modified AES algorithm enhances communication security by generating a new S-Box and inverse S-Box using different irreducible polynomials each time. This makes it difficult for intruders to crack the modified AES and ensures a more secure communication method [58].

Zhao et al. proposes a privacy-preserving face recognition framework called PriFace that maintains the privacy of face images while achieving accurate and efficient face recognition. PriFace utilizes eigenfaces and locality-sensitive hashing (LSH) techniques to reduce the dimension of face images and introduce randomness for privacy preservation. The framework involves three stages illustrated in Figure 12, and PriFace achieves accurate recognition of registered users and rejection of unregistered users with an accuracy of approximately 100%. PriFace balances privacy preservation and recognition performance, making it suitable for security, finance, and social networking application [59].

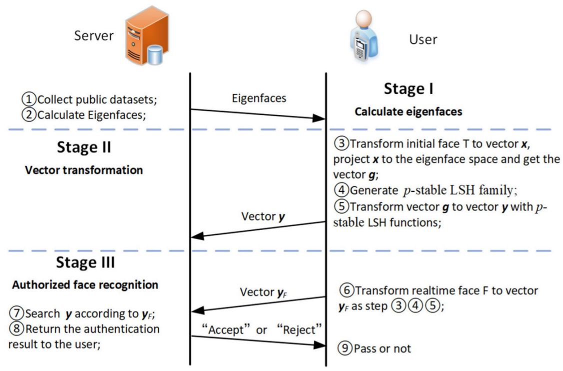

FIGURE 12. PriFace system framework [59].

Xie et al. introduce a two-fold approach called PEEP (Privacy using EigEnface Perturbation) to address privacy concerns in emotion recognition systems. PEEP first extracts eigenfaces and then adds specific noise to the facial data. This process ensures that identities remain anonymous while the system can recognize emotions accurately. By distorting the facial features through perturbation, the images become unrecognizable, yet the system can still perform emotion recognition with high accuracy. Finally, the perturbed images are encrypted and securely stored in the cloud to ensure maximum privacy protection [60].

The study by AlNuaimi et al. introduces a framework for protecting privacy in edge-based face recognition (EFR) systems. This framework addresses the concern of data privacy breaches that may occur in IoT-based face recognition systems. The EFR system consists of three layers: local terminals, edge network centers, and a remote cloud server, as shown in Figure 13. The framework uses Eigenfaces to perturb the Eigenfaces matrix and enhance privacy protection. The proposed scheme does not require a trusted third party and achieves a maximum balance between privacy protection and data utility by adjusting privacy budget parameters based on the proportion of principal component feature information [61].

H. MISCELLANEOUS

While the applications of face recognition technology extend far beyond security and privacy concerns, exploring its diverse array of uses unveils a realm of innovative possibilities and transformative potential. Beyond its traditional roles in authentication and surveillance, face recognition technology has catalyzed advancements across various fields, from healthcare and education to entertainment and social media. In this section, we embark on a journey through the miscellaneous applications and future directions of face recognition technology, uncovering novel use cases, emerging trends, and untapped opportunities for innovation.

In 2019, Sahith et al. proposed a Wireless Sensor Network (WSN) system using sensors to identify and recognize people if they detected any motions. When the light sensor

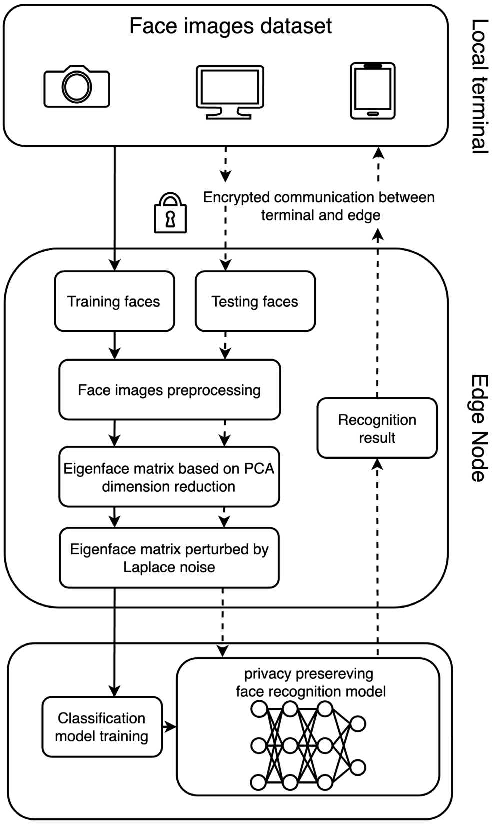

FIGURE 13. Flowchart of EFR system [61].

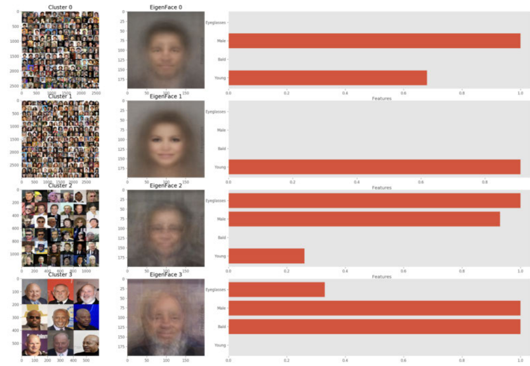

FIGURE 14. Apply weights to clusters [63].

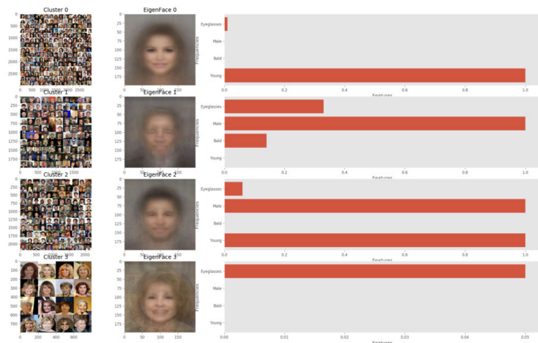

FIGURE 15. Apply no weights to clusters [63].

notices any human motions, the Pi camera proceeds to capture images, and then Eigenfaces are deployed to encode and decode faces in approximately real-time. The author noted that this will be applied to a smart home system. The success of face detection and recognition is blooming, yet it is still a trending topic to exploit, especially soft biometrics [62].

In 2020, Abate et al. introduced an approach for face component detection using pre-trained CNN model. The output of the CNN model will be grouped and examined to the nearest input face by K-means, Iterative Self-Organizing Data Analysis Technique Algorithm (ISODA), and DBSCAN clustering algorithm. The result shows that it returns better accuracy than other approaches mentioned in the research and comes with the advantages of K-means compared to the other 2 cluster methods [63]. Weight strategy was also deployed to enhance the effectiveness of the process. The influence of this weighted approach is illustrated in Figures 14 and 15.

When it comes to unfavorable conditions such as low light and motion blurring, face recognition usually does not correctly detect the right faces. Singh et al. proposed an approach to reduce noises based on super-resolved faces algorithm and enhance the image resolution with a CNN-VGG16 combined architecture (super-resolution - SR) to increase recognition accuracy, reflecting in the result. After applying the SR technique and resizing to 96 × 96, low-resolution images yield an increment of 5-6% each integrated [64]. The author will continue to study this approach's application, speed, and visual accuracy.

Bellante et al. proposed a quantum machine learning algorithm for face recognition based on the eigenfaces method. This algorithm enhances nearest neighbor/centroid classifiers by incorporating concepts from principal component analysis, enabling automatic outlier detection and finding applications beyond face recognition in anomaly detection domains. The experimental results demonstrate effective outlier recognition while maintaining good classification accuracy, with reasonable running time parameters that could provide advantages even on small datasets. The author referred to exploring further large-scale datasets, efficient error models, and block encoding [65].

Computer resources become crucial to calculating tasks, and face recognition is not exceptional. For that reason, Salari et al. proposed a quantum face recognition algorithm for 2D recognition named QPRP (quantum pattern recognition processor) based on quantum principal component analysis (QPCA) and quantum independent component analysis (QICA). Figure 16 specifies the process pipeline of the algorithm. The author introduced a novel algorithm based on log-determinant divergence metrics to calculate the matrix distance for dissimilarity measure seeking. The system has a low running time with highly efficient recognition for every image dimension, from 64 × 64 to 2028 × 2028 [66].

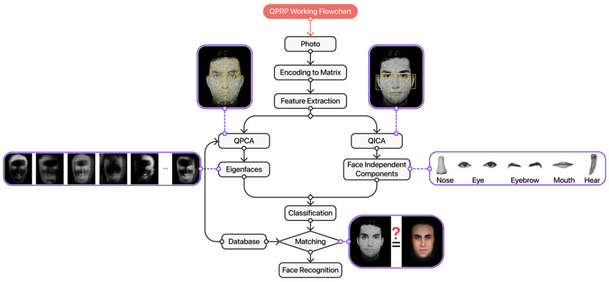

FIGURE 16. **Quantum face recognition algorithm pipeline [66].**

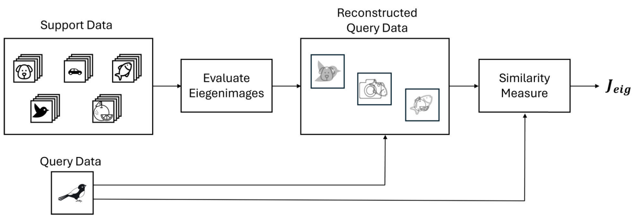

FIGURE 17. **Architecture of the eigen loss function [68].**

In time, most video surveillance systems (VSS) over IoT devices did not achieve an accuracy over 90% since video/image qualities, lighting conditions, geometries, and using a restricted number of Eigenfaces for PCA play a vital role in this task. To acknowledge that problem, Ahamad and Mishra introduced a hybrid face and object detection system through UAVs. The accuracy, benchmarked on many different datasets, results in a far higher rate than existing systems in 2023, implying a robust, reliable system that can be applied in real-world efficiency [67]. 2023 proposed an additional Eigen loss function to reduce overfitting on the Few-shot learning algorithm by comparing query images and eigenimages of support data. The architecture of the proposed method is shown in 17. The performance archived is significant with any input data. Furthermore, Eigen loss can be applied with another few-shot learning model, increasing the speed and accuracy for state-of-the-art execution [68].

The real-world environment is still a challenge to the recent video surveillance systems. For that reason, Naseem et al. proposed an enhanced method using Dynamic Image-to-Class Warping (DICW) with the Structural Similarity (SSIM) index in 2023. The DICW system does not need the image training process. The SSIM index checks the structure after decreasing the noise density and then compares two images together. On the AR Face dataset, the proposed improved DICW-based returns a better result with an increase of 5 to 6 percentage points. In the future, the author will continue to examine different SSIM techniques and weights on the image to simulate the realistic condition [69].

V. DATASET FOR FACIAL RECOGNITION

A suitable facial recognition research or development dataset is crucial for training and evaluating algorithms. This section discussed several popular datasets widely used in facial recognition. The detailed statistics of these datasets are shown in Table 1.

FERET [71] is a database for evaluating facial recognition systems. It was created in 1993 by Harry Wechsler and Jonathan Phillips. It standardizes facial images for benchmarking, facilitating the comparison of different algorithms. It has 14,126 images of 1,199 individuals, including 365 duplicate sets from different days, collected between 1993 and 1996.

The ORL Database of Faces [72] contains ten unique images for each of 40 distinct individuals. For certain individuals, the images capture variations over time, including changes in lighting, facial expressions (such as eyes open or closed and smiling or not smiling), and facial features (like wearing glasses or not). Each image was captured against a dark, uniform background, with the subjects positioned upright and facing forward, allowing for slight lateral movements.

The Yale Face Database [73] comprises 165 grayscale images in GIF format featuring 15 individuals. Each subject is represented by 11 images, each corresponding to a distinct facial expression or configuration: center-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleepy, surprised, and wink.

The Japanese Female Facial Expression (JAFFE) Dataset [74] contains 213 images containing a variety of facial expressions from 10 Japanese female participants. Each participant was requested to display seven facial expressions, including the six fundamental emotions and a neutral expression. These images have been annotated with average semantic ratings for each facial expression by 60 annotators.

The AR Face Database [75], developed by Aleix Martinez and Robert Benavente at the Computer Vision Center (CVC) of U.A.B., comprises over 4,000 color images of 126 individuals' faces (70 males and 56 females). The images display frontal views of faces with varying facial expressions, lighting conditions, and occlusions (sunglasses and scarves). These photographs were captured at the CVC in a highly controlled environment. Participants were not restricted in attire (clothing, glasses, etc.), makeup, or hairstyle. Each individual took part in two sessions, held two weeks apart, with identical photographs taken in each session.

The Georgia Tech face database [76] includes 15 color JPEG images of 50 individuals captured over two or three sessions from June 1 to November 15, 1999, at the Center for Signal and Image Processing at Georgia Institute of Technology. The images have a resolution of 640×480 pixels, and the size of each face averages 150×150 pixels. The collection features a variety of facial expressions, lighting conditions, and scales.

The Caltech Face Dataset 1999 [77] includes 450 JPEG images of faces with a resolution of 896×592 pixels. The dataset contains about 27 individuals captured under varying backgrounds, expressions, and lighting conditions.

TABLE 1. Compilation of facial datasets.

Dataset Name	Release time	Number of samples
FERET Database [71]	12/1993 - 08/1996	14,126
The Database of Faces (AT&T)(formerly 'The ORL Database of Faces') [72]	04/1992 - 04/1994	400
The Yale Face Database [73]	1997	165
The Japanese Female Facial Expression (JAFFE) Dataset [74]	1998	213
The AR Face Database [75]	1998	4000
Georgia Tech face database [76]	16/01/1999 - 15/11/1999	15
Caltech Face Dataset [77]	1999	450
Yale Face Database B [78]	2001	5850
The Extended Yale Face Database B [79]	2001	16128
Caltech 10k Web Faces [80]	2005	7,092
FEI Face Database [81]	06/2005 - 03/2006	2800
Labelled Faces in the Wild (LFW) [82]	2007	13,233
Grimace [83]	2009	360
CK+ (Extended Cohn-Kanade dataset) [84]	2010	593 video sequences
ChokePoint Dataset [85]	2011	48 video sequences & 64,204 face images
IMDB-Wiki [86]	2015	524,23
Large-scale CelebFaces Attributes (CelebA) Dataset [87]	2015	202,599
VGG Face2 [88]	2016	3.31 millions
UMDFaces [89]	2017	22,000 videos & 367,888 images
iQIYI-VID [90]	2018	600,000 Face videos
Digi-Face 1M [91]	2022	1.2 million

The Yale Face Database B [73] contains 5850 images of 10 individuals. Each subject was photographed in 9 different poses under 64 different lighting conditions. Additionally, ambient lighting captured an image for each subject in every pose. The compressed database size is approximately 1GB. The Extended Yale Face Database B [79] contains 16,128 images of 28 people in 9 poses and 64 lighting conditions. The format is the same as that of the Yale Face Database B.

The Caltech 10k Web Faces dataset [80] contains 10,524 human faces from a Google Image search. It includes coordinates for facial features and can be used to align and crop faces or as a benchmark for face detection algorithms. The images have varying resolutions but an average of 304 $\times$ 312 pixels.

The FEI face database [81], created at the Artificial Intelligence Laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil, from June 2005 to March 2006, includes 2,800 colorful images of 200 individuals (14 per person). These images, which feature a white background and vary slightly in scale, showcase a frontal view with up to 180 degrees of profile rotation. The original resolution is 640 $\times$ 480 pixels. Subjects, aged between 19 and 40, include students and staff at FEI, offering a variety of appearances, hairstyles, and accessories.

Labeled Faces in the Wild (LFW) [82] is a database of facial photographs intended to study unconstrained face recognition. Created and maintained by researchers at the University of Massachusetts, the dataset comprises over 13,000 face images sourced from the web. Each image is tagged with the name of the individual featured. Among these individuals, 1,680 have two or more unique photographs within the dataset.

The Grimace dataset [83] includes 20 images per person, captured with a stationary camera. In the sequence, the individual moves their head while intensifying their grimaces, with the strongest expressions occurring at the end. The setup is similar to that of Faces95, with a gap of about 0.5 seconds between each frame.

The Extended Cohn-Kanade (CK+) Lucey et al. [84] is a dataset of 593 videos from 123 individuals aged 18 to 50, with diverse genders and heritages. Each video captures the transition from a neutral facial expression to a peak expression and is recorded at 30 frames per second with resolutions of 640 $\times$ 490 or 640 $\times$ 480 pixels. 327 videos are annotated with seven emotional expressions: anger, contempt, disgust, fear, happiness, sadness, and surprise.

The ChokePoint Dataset [85] is a video and image dataset designed to test person identification and verification in real-world surveillance scenarios. It consists of three cameras positioned above various portals and natural choke points for pedestrian traffic. As people pass through these portals, a series of facial images, or ''face sets'', are captured, exhibiting variability in lighting, pose, focus, and alignment due to automated face detection. The strategic placement of the cameras increases the likelihood of obtaining a face set with a subset of near-frontal images.

The IMDB-WIKI dataset [86] is a compilation of over half a million face images from IMDb and Wikipedia. The dataset spans a wide age range and diverse demographics, making it ideal for developing and testing facial analysis machine learning models. It's tailored for age and gender prediction and provides metadata to facilitate these estimations.

CelebFaces Attributes Dataset (CelebA) [87] is a large-scale face attributes dataset with over 200,000 celebrity images, each annotated with 40 attributes. It includes 10,177 identities, 202,599 facial images, and five landmark locations, with 40 binary attribute annotations per image. It's ideal for computer vision tasks such as face attribute recognition, detection, landmark localization, and editing and synthesis.

The VGGFace2 dataset [88] is a collection of 3.31 million images used for face recognition. It contains images of 9,131 individuals, with an average of 362.6 images per person. These images were obtained from Google Image Search and showcase various poses, ages, lighting conditions, ethnicities, and professions, including actors, athletes, and politicians. The dataset is divided into two sets: a training set with 8,631 individuals and a test set with 500 individuals.

UMDFaces [89] is a comprehensive facial dataset divided into two parts: Still Images and Video Frames. The Still Images section contains 367,888 facial annotations across 8,277 individuals, featuring details such as manually verified bounding boxes, estimated poses, keypoint locations, and gender information. On the other hand, the Video Frames segment encompasses over 3.7 million annotated frames from 22,075 videos featuring 3,107 subjects, providing pose estimations, keypoint locations, and gender details. Both parts utilize annotations derived from a pre-trained neural network to offer rich data for facial recognition research.

iQIYI-VID [90] is a comprehensive video dataset designed for multimodal person identification. It consists of 600,000 video clips featuring 5,000 celebrities. These clips are hand-picked from a vast collection of over 400,000 hours of online video content, including movies, variety shows, TV series, and news broadcasts. Each video clip undergoes a thorough human annotation process, which ensures a label error rate of below 0.2%.

Digi-Face 1M [91] is a synthetic face recognition dataset that solves three major challenges of large-scale face recognition datasets - ethical concerns, labeling noise, and data bias. It uses high-quality head scans from a few individuals with consent to generate digital faces, ensuring privacy and consent. Synthetic data guarantees labeling accuracy, and the data pipeline ensures equitable data distribution and diversity, avoiding reliance on celebrity images with lighting, makeup, and racial representation biases. The dataset's samples are illustrated in Figure 18.

FIGURE 18. Digi-Face 1M Dataset samples [91].

Addressing the ethical implications surrounding human identity, the paper titled ''Quantum face recognition protocol with ghost imaging'' [66] paper delves into the challenges aforementioned by Digi-Face. Utilizing the tool known as thispersondoesnotexist.com,[1] which employs StyleGAN2, the research generates synthetic human faces that do not correspond to any real individuals.

VI. DISCUSSION, LIMITATION, AND OPEN ISSUES

The Eigenfaces algorithm has demonstrated compromise and efficacy in face recognition and image analysis. As an appearance-based approach, employing the PCA effectively reduces the dimensionality of facial images and captures the most salient features. It's evident that when compared to various other face recognition techniques, the Eigenfaces approach stands out for its simplicity and efficiency. It effectively reduces the complexity involved, making it not only easier to implement but also significantly more efficient in terms of computational resources and time.

In Eigenface-based facial recognition systems, raw intensity data from facial images are used directly for learning and recognition without significant low-level or mid-level processing. Moreover, eigenfaces lie in their ability to perform facial recognition without relying on detailed geometric measurements or explicit modeling of reflectance properties. The geometry of a face refers to its distinct features, such as the eyes, mouth, nose, and chin, and involves measuring their relative position, width, and other parameters.

By retaining only the top eigenfaces corresponding to the largest eigenvalues, PCA effectively captures the essential features of facial images while discarding less significant variations. The resulting low-dimensional subspace is a compact representation of the original high-dimensional facial data. Each facial image can be projected onto this subspace, yielding a set of coefficients that encode the image's representation in the selected eigenfaces. Since the dimensionality of the subspace is significantly lower than that of the original image space, this representation achieves data compression by reducing the amount of information needed to describe each facial image and facilitates efficient storage.

[1] thispersondoesnotexist.com

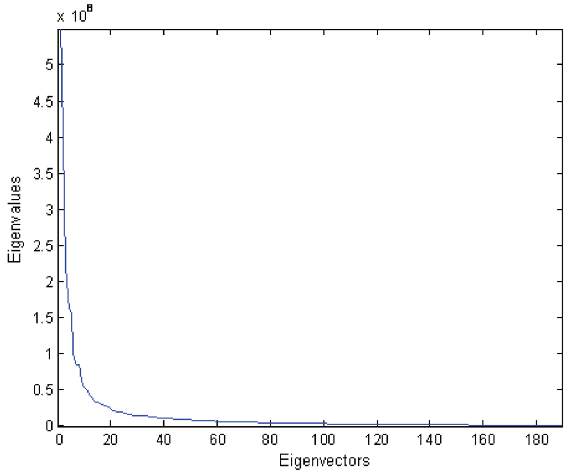

FIGURE 19. Eigenvalues and eigenvectors [2].

However, despite its success, several considerations must be discussed to understand its capabilities and limitations further.

Eigenfaces heavily relies on the assumption that facial images lie in a linear subspace, which may not always hold in real-world scenarios. Variations in lighting conditions, facial expressions, and pose can introduce nonlinearities that challenge the algorithm's performance. While preprocessing techniques such as normalization can mitigate some of these issues, more robust approaches may be necessary to handle complex variations effectively. The Fisherface projection method addresses the illumination issue by maximizing the between-class and within-class scatter ratio. However, finding an optimal projection method that simultaneously separates multiple face classes is almost impossible.

Despite the direct use of raw intensity data in Eigenface-based facial recognition systems, it's crucial to note that they can be sensitive to scale variations in facial images. Therefore, low-level preprocessing steps, such as scale normalization, are often necessary to increase the accuracy and reliability of the recognition process.

People should be concerned about the following question: How many principal components should be taken in Eigenfaces? Existing research, such as the work presented in a paper titled "Face Recognition Using Eigenfaces Approach" [2], suggests that a significant portion of the informative variance can be captured by utilizing only a subset of the total eigenvectors. As illustrated in Figure 19 and Table 2 of their study, roughly 10% of the eigenvectors hold eigenvalues with substantial magnitude, while the remaining eigenvectors exhibit negligible eigenvalues, whereas, for the remaining vectors, the eigenvalues are approximately zero. However, it is important to acknowledge the computational cost associated with employing a larger number of eigenvectors. Recognition speed can be negatively impacted as the dimensionality of the representation increases. Therefore, a trade-off exists between achieving high accuracy and maintaining efficient processing time. Furthermore, incorporating an excessive number of eigenvectors can lead to overfitting, where the system prioritizes capturing idiosyncrasies specific to the training data, potentially hindering its ability to generalize and recognize novel faces not present in the database.

TABLE 2. Eigenfaces vs. recognition rate.

Number of Eigenfaces	Recognition Rate	
	Euclidean distance	Manhattan distance
5	77.5%	80.0%
10	92.5%	95.0%
20	97.5%	97.5%
190	97.5%	97.5%

Eigenfaces, while computationally efficient and straightforward, still struggle with various light conditions, facial expressions, and large datasets. On the other hand, Deep Learning-based methods, particularly CNNs, offer high accuracy and robustness by extracting complex, hierarchical features from raw image data. However, they require substantial computational resources and large labeled datasets. Furthermore, they often operate as black-box models, making them less interpretable and more resource-intensive. Hybrid methods aim to combine the efficiency of Eigenfaces with the robustness of deep learning. One approach involves using PCA for initial dimensionality reduction, making the data more manageable for deep learning models. This preprocessing step can reduce computational load and improve training efficiency. Another strategy is to fuse features from both Eigenfaces and deep learning at the feature extraction stage or at the decision-making stage to create a more comprehensive representation. Additionally, pre-trained deep learning models can be fine-tuned with Eigenface-based features, leveraging their generalization capabilities while incorporating the specificity of PCA-based methods. These hybrid methods offer a balanced solution by combining the quick, efficient nature of traditional methods with the advanced, adaptable features of deep learning.

VII. CONCLUSION

In summary, this systematic survey examines approximately 70 scholarly papers related to eigenfaces from 2018 to 2023. The survey explains the methodological approach, including search strategies, defining paper sources, and rigorous paper assessments. Our work also provides an in-depth overview of the eigenfaces face recognition pipeline. We grouped papers together in a way that helps make sense of the wide variety of uses and methods linked to researching eigenfaces. We also gathered a diverse range of face datasets to meet the varied needs of researchers working on everything from recognizing faces to detecting emotions and conducting surveillance. Our study also looks at the pros and cons of the eigenfaces approach. By carefully explaining the advantages and disadvantages, we aim to give researchers a deeper insight into what can be achieved with eigenfaces and their limitations. Additionally, we address some ongoing challenges and offer practical tips for researchers dealing with the intricate details of the eigenfaces method. In essence, this systematic survey consolidates and synthesizes existing knowledge on eigenfaces while empowering researchers with the requisite insights and guidance for navigating eigenfaces research. Through rigorous methodology and comprehensive analysis, the study contributes meaningfully to the burgeoning discourse surrounding eigenfaces methodology and its myriad applications.

In our future research, we intend to group datasets into specific categories and carry out comparative experiments. This approach will help us conduct a detailed quantitative analysis to highlight the advantages and limitations of both traditional and contemporary face recognition techniques. By segmenting the datasets, we aim to gain a better understanding of how each method performs in various contexts and applications, thereby improving our knowledge of their strengths and weaknesses. While our current study does not address deep learning techniques for face detection separately, we acknowledge their importance and intend to incorporate a comparative analysis in our future research. This will enable us to compare traditional Eigenface-based methods with contemporary deep learning approaches, facilitating a comprehensive evaluation of their effectiveness and areas for improvement. These future efforts will contribute significantly to the ongoing development and enhancement of face recognition technologies, ensuring that our work remains at the forefront of the field.

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