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FACE RECOGNITION IN ATTENDANCE SYSTEMS: A COMPREHENSIVE REVIEW

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Abstract--**This paper conducts a comprehensive exploration of the historical and current evolution of face recognition-based attendance systems, analyzing their practical implications and persistent challenges. It critically evaluates the progression of these systems, emphasizing the imperative for continuous improvement. By surveying implemented models and methodologies for face recognition, it offers insights to contribute to ongoing efforts in enhancing attendance systems through this technology. Through a chronological approach, it illuminates the advancements and obstacles in this field, providing a foundation for future research and development. The paper aims to foster a deeper understanding of the potential and limitations of facial recognition technology in attendance marking. It seeks to stimulate discussions and guide future work toward more effective and reliable attendance solutions.**

I. INTRODUCTION

The evolution of face identification has become a focal point in recent years, particularly in image analysis. The task of creating a fully automated model capable of accurately pinpointing human faces has proven challenging [1]. Face IDs play a pivotal role in attendance management systems, where non-automated processes are time-consuming. The need for a highly qualitative and quantitative investment of time to yield reliable output has driven the exploration of solutions, one of which is the utilization of biometric attendance structures [2]. However, challenges persist, especially in high-volume classroom scenarios where it is arduous to verify each pupil, potentially disrupting the teaching process.

Researchers acknowledge the constraints of current biometric systems, often costly and demand substantial interaction with students, resulting in time inefficiencies. Consequently, developing an ideal system capable of detecting, recognizing, and recording student attendance is deemed a formidable challenge. Previous research has suggested remedies that provide quicker processing with a commendable level of efficacy, smoothly integrating with Computer Vision technology. Presently, face identification methods follow two approaches: localized models that focus on specific facial features such as the nose, mouth, and eyes for matching, and global models that consider the entire face during feature extraction. These approaches are supported by unique algorithms, encompassing systematic processes from image acquisition to feature extraction and database creation [3]. The intermediary process is crucial, as meaningful feature extraction is imperative to bolster the facial recognition process. The process culminates in face matching, involving face comparison, although each project typically involves post-processing after face matching [3].

Various algorithms play a significant role in face matching operations. Popular ones for pupil detection include 'Haar Cascade' and 'Viola Jones,' while identification processes are supported by algorithms like 'Eigen Face,' 'PCA,' 'Fisher Face,' 'LDA,' and 'LBPH' [4]. The selection of algorithms and the outcomes obtained depend on the application, whether it is intended for single face recognition or multiple face recognition scenarios. The subsequent sections delve into a review of various algorithms that have been used and continue to be utilized in the current decade, providing a comprehensive understanding of their workings and applications [4].

II. LITERATURE SURVEY

Tripathi et al. [1] introduced a real-time system dedicated to monitoring student attendance in a classroom. The system utilized images captured at a constant rate through a webcam, employing techniques for face detection and recognition. The authors utilized AdaBoost and Haar cascade classifiers for pupil identification, while OpenCV libraries, PCA, and LDA were employed for face exposure and recollection. The document highlighted the distinctions between LDA and PCA, emphasizing the system's accuracy, which is contingent on the database and image size used.

Ms. Pooja Humbe et al. [2] implemented a model using a 360-degree rotating camera for pupil detection in classrooms. The system's functionality relied on software components such as XAMPP controller, NetBeans, and Java Advance for front-

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end and back-end, along with MySQL. Principal component analysis (PCA) was employed for facial characteristics, and once registered, attendance records were sent via email to parents and teachers.

Shireesha Chintalapati et al. [3] presented the Viola Jones Face Detection Algorithm, asserting its superior performance in various lighting conditions. The authors integrated multiple Haar classifiers to improve output rates and used LBPH algorithm for feature extraction and SVM classifier for classification. The study employed an 80-person database, demonstrating the system's performance under various conditions.

E. Varadharajan et al. [4] detailed an Automatic Attendance Management system based on Face Detection. The system performed background subtraction and recommended the use of Eigenface for simplicity and performance in facial recognition. The authors observed varying detection and recognition rates for veiled and unveiled faces, emphasizing gender-based differences.

Akshara Jadhav et al. [5] incorporated the Viola Jones face detection algorithm and PCA algorithm for face recognition, with support for machine learning and SVM for extraction functionality. The system employed reprocessing, including histogram equalization, and discussed the potential of semi-supervised learning using facial recognition support vector machines.

Nirmalya Kar et al. [6] utilized Haar cascade for face detection and Eigen face for confirmation, achieving high detection and recognition levels at facial orientations of approximately 0 degrees. The study observed a gradual decrease in frequency as facial orientation increased, with overall performance ranging from 0 to 90 degrees.

Smit Hapani et al. [7] expanded on a face-distinguishing model using Haar classifiers for detection and Fisher face for recognition. The system demonstrated efficacy up to 50% within 15 pupils, handling variations such as caps and spectacles. The proposed system utilized video frames for face identification, enhancing the overall model's rate and accuracy.

Krishna Dharavath et al. [8] focused on preprocessing noisy images, implementing face cropping, resizing, and filtering. The study compared PCA, DCT, and combined spatial and frequency domain approaches, emphasizing the combined form's high face recognition rate and resilience to preprocessing influences.

Priyanka Wagh et al. [9] presented a multiple face recognition system using Viola Jones for face detection and Eigen face for face recognition. characterized as invariant to illumination, combining both Eigen face and PCA. The study acknowledged challenges in facial recognition rate at longer distances and varying lighting conditions.

Nazare Kanchan Jayant et al. [10] designed an automatic attendance system based on Viola Jones facial detection and face recognition. The study created a database with various head poses, evaluating the efficiency of the face finding and recognition algorithms regarding the quantity of faces detected.

Firoz Mahmud et al. [11] utilized UMIST and ORL databases, implementing PCA and LDA for face recognition. The study emphasized the impact of face alignment on recognition accuracy, with front-aligned faces exhibiting better accuracy.

Refik Samet et al. [12] implemented a cell phone-based system for attendance automation utilizing Viola-Jones for face detection and Eigen face, Fisher face, and LBP for recognition. The study compared precision for the recognition methods and developed a smartphone application for automatic attendance generation.

Sathyanarayana n et al. [13] introduced an Automated Attendance system using facial recognition, employing Viola Jones for face detection and MSE for face recognition. The study highlighted the system's security and accuracy improvement with increased training images, achieving identification at face angles up to 60 degrees.

D. Nithya et al. [14] proposed an Automated Attendance System on MATLAB, utilizing Eigen facial approach for ease, speed, and learning ability. The study calculated Euclidean distance for face recognition, emphasizing the system's functionality with regard to accuracy.

Rajashree P. Suryawanshi et al. [15] described a system with Raspberry PI and a wired camera, employing Haar Cascade Classifier for face detection and PCA for face recognition.

K.L.P.M Liyanage et al. [16] introduced a system with separate and web-based applications, utilizing Haar cascade for face detection and PCM for face recognition. The system included a natural language processing (NLP) component for employee license applications.

Professor Arun Katara et al. [17] implemented a real-time assistance system using Raspberry PI, OpenCV libraries, and feature extraction techniques like PCA and LBP for multiple facial recognition.

Kennedy Okokpujie et al. [18] utilized Viola Jones for face detection and Fisher face algorithm for recognition, implementing a webcam to build the database. The study noted decreased face recognition rates in different lighting conditions.

Nilesh D. Veer et al. [19] developed an automatic attendance system using Viola Jones for face detection and PCA for face recognition. The study achieved nearly 100% facial recognition rate for a limited group of students.

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A Majumdar et al. [20] examined the efficiency of Fisher face subspace and LDA, comparing various methods to improve detection and recognition rates. The study highlighted consistent results with Viola Jones and superior performance with Fisher Face's LDA algorithm.

III. RECOGNITION PROCEDURE

Our research is inspired by reference [21] and revolves around the idea that a feature selection method capable of identifying distinguishing features within a set of faces should also perform well with new faces. Reference [9] utilized an eigenface approach. However, traditional eigenface techniques, relying on principal component analysis, tend to emphasize directions of maximum variance in the image space, neglecting differences between individuals. To address this limitation, [21] adjusted the eigenface method to maximize variation among classes. In the work, simpler yet effective approach is adopted: the Fisherface technique, which employs linear discriminant analysis. Fisherface is renowned for its ability to discern features that optimize inter and intra-subject discrimination. Although Fisherface typically necessitates multiple samples per class, the dataset comprises only one facial image per individual. To circumvent this challenge, we augment the dataset with a separate collection containing multiple samples per person. We then apply Linear Discriminant Analysis (LDA) to this augmented dataset, deriving a Fisher subspace that effectively discriminates between faces. The transformation matrix obtained from mapping the original image space to the Fisher subspace serves as our feature selection method, effectively capturing distinguishing features within the dataset, the transformation matrix can generalize to other faces. Next, apply this transformation matrix, obtained from LDA on the augmented dataset, to extract discriminating features from each image in our original dataset. By multiplying each facial image with this matrix, thus obtain a dimensionality-reduced subspace specific to that image. This ensures all images are mapped to a uniform subspace. While testing, the test image is mapped to this subspace by multiplying it with the transformation matrix. Subsequently, employ a simple distance-based classifier, such as the K-Nearest Neighbor, to determine the class closest to the test sample in this subspace. It's important to note that this subspace, although not strictly Fisher, can be termed a pseudo-Fisher subspace as it wasn't derived directly from the original training images using LDA. A visual representation of methodology is presented in Figure 1.

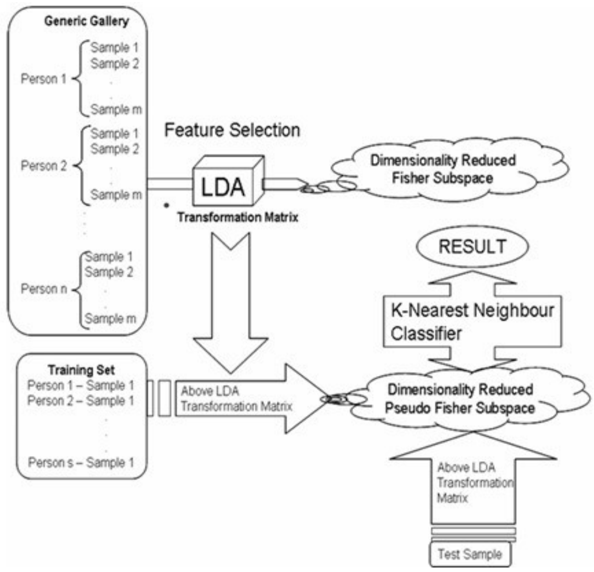

Fig 1.Recognition scheme [24]

The procedure outlined above operates entirely within the spatial domain. However, the aim is to extend this method to the transform domain based on recent findings [22, 23] suggesting improved face recognition in wavelet domain compared to spatial domain. Additionally, studies on curvelet [24] and contourlet [25] transformations have demonstrated promising results in face recognition. Leveraging transform coefficients instead of pixel values is expected to enhance recognition accuracy. The proposed scheme, depicted in Figure 1, remains unchanged, but we will utilize the transform coefficients (wavelet, curvelet, or contourlet) of corresponding images as inputs to the Linear Discriminant Analysis (LDA) scheme. Experiments are conducted with Principal Component Analysis (PCA) alongside LDA for feature selection. However, LDA consistently yielded superior recognition results, rendering PCA comparisons unnecessary for this discussion. Hence, focus solely on LDA-based outcomes and compare them with Sparse Principal Component Analysis (SPCA) [32] and Eigenface Selection [21]. For mathematical formalization of the curvelet and contourlet transforms, readers can refer to works by Candes and Donoho [26] and Do and Vetterli [27]. We implemented the curvelet transform using the Curvelab 2.0 [28] toolbox and the contourlet transform using the Contourlet [29] toolbox. For additional understanding of various multivariate methods in spatial domain face recognition, readers may consult the work of Delac et al. [30]. Regarding our classification method, which employs a K-Nearest Neighbor classifier, interested readers can refer to [31] for a comprehensive understanding. In summary, our extension involves employing transform coefficients in place of pixel values, with LDA for feature selection, and compare the results with SPCA and Eigenface Selection methods.

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IV. RESULTS

The test is conducted with two types of face databases: one containing frontal face images and another with images showing various head movements. Specifically, utilizing the Faces94 database [33] for frontal images and the AtnT database [34] for images with head tilts. Sample images from both databases are depicted in Figures 2 and 3.

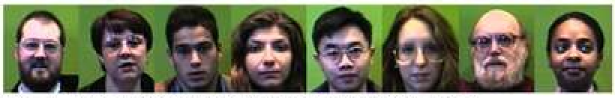


Fig. 2. Images from Faces94 Database (Frontal)

Fig. 3. Images from AtnT Database of Faces (With Head Tilt)

The Faces94 database comprises images of 152 individuals, each photographed 20 times, while the AtnT database includes images of 40 individuals, with 10 samples per face. Given that the recognition method requires a generic face database, it's crucial to select a database aligned with the intended application. For instance, if the objective is to recognize frontal faces,then select a generic database primarily consisting of such images. Conversely, if the task involves identifying faces with varying head positions, we opt for a generic database containing images with head tilts.

To construct the generic databases , partition each dataset into two halves. For Faces94, randomly 76 individuals are selected, each with 20 samples, to form the generic database. Regarding the AtnT database, 20 individuals, each with 10 samples, constituted the generic database.

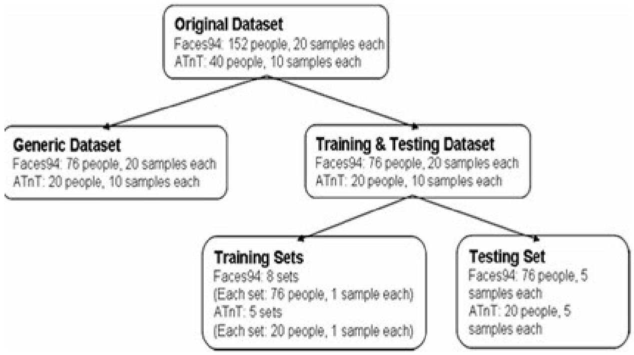
This approach ensures that the generic databases align with the specific recognition requirements, whether focused on frontal faces or accommodating variations in head position.

In adherence to the problem's condition stipulating the separation of training and testing images from the gallery images, distinct training and testing sets are formed. For Faces94, these sets comprised images from the remaining 76 individuals, while for the AtnT database, they consisted of images from the remaining 20 individuals.

To construct the test set, five images are seledted at random from remaining Faces94 set and five from the remaining AtnT set.

Following the methodology outlined in previous work [32] concerning face recognition from single prior samples, we generated multiple training sets. For the AtnT database, we created five training sets by choosing one sample at random for each of the 20 individuals in each training set. Similarly, for Faces94, eight training sets were formed by randomly choosing a single image for every single one of the 76 individuals in each training set.

The division of the datasets into different sets is illustrated in the following diagram.



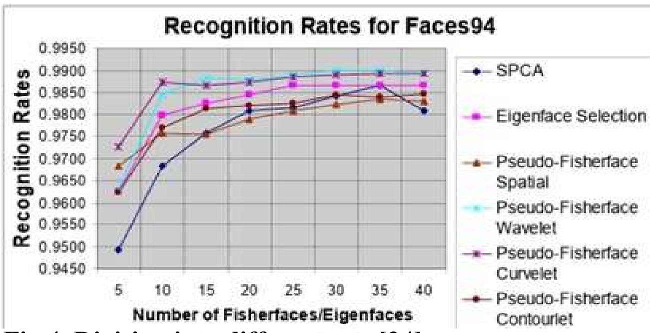


Fig 4. Division into different sets [24]

As a preprocessing step, we converted the color images in the Faces94 database to grayscale and normalized all images to a resolution of 128x128.The results presented in the subsequent graphs represent the average outcomes obtained across multiple training sets. These graphs compare the effenciency of our proposed technique against SPCA [32] and Eigenface Selection[21].

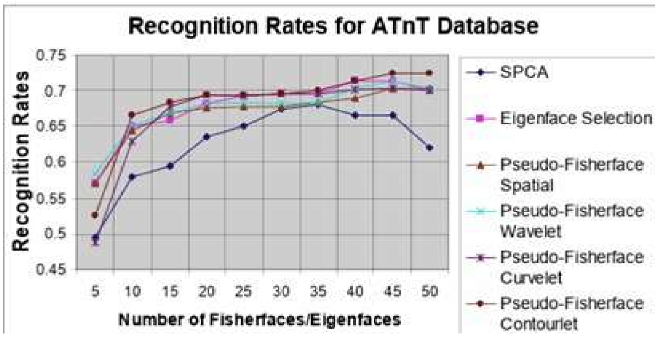


Fig 5. Recoginition Rates for Faces94 [24]

Fig 6. Recoginition Rates for ATnT [24]

In summary, the methodology ensures the separation of training and testing images from the gallery images, while also incorporating multiple training sets for robustness. Preprocessing steps such as grayscale conversion and normalization were applied, and the outcomes are contrasted with those already in existence methods through graphical analysis.

The proposed Pseudo-Fisherface method demonstrates superior performance compared to both SPCA and Eigenface Selection. Specifically, provide the most optimal findings on the Faces94 database, consisting of frontal faces, were achieved by the Pseudo-Fisherface method in the Wavelet domain, attaining a recognition accuracy of 99.01%. On the contary, for the AtnT database containing images with head tilts, the Pseudo-Fisherface method yielded the highest recognition accuracy of 72.4% in the Contourlet domain.

V. CONCLUSION

This review extensively delves into various methodologies aimed at improving detection and recognition rates in facial recognition systems. The Viola-Jones algorithm, leveraging Haar Cascade, consistently exhibits robust detection rates, while the Fisher Face algorithm, employing LDA, consistently outperforms its counterparts with superior performance and faster results. In addition to these approaches, we have incorporated the methodology of Fisher Face, further enriching the scope of our analysis. Despite concerted efforts to adapt these algorithms for multi-face scenarios, challenges persist in both detection and recognition, prompting a paradigm shift towards Deep Learning, specifically the adoption of Convolutional Neural Networks (CNNs). This strategic transition is driven by the ambition to overcome the identified limitations and meet the evolving requirements of facial recognition applications. The integration of traditional algorithms, including Viola-Jones and Fisher Face, with cutting-edge technologies underscores a commitment to achieving heightened accuracy and efficiency in facial recognition systems. This inclusive approach aims to harness the strengths of both classical and modern methodologies, forming a cohesive strategy for advancing the field of facial recognition.

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