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RESEARCH ARTICLE

FACE RECOGNITION APPROACH USING DLIB AND K-NN

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ABSTRACT: The face serves as a unique topographical map that reflects an individual's distinct features. Face recognition has gained prominence as a popular biometric method, especially in security control applications. In this study, we introduce a system developed using a Haar cascade classifier and a Hog-based Dlib face detector for human face detection. Face features are extracted with the Dlib deep metric learning library, and classification is performed using the k-NN algorithm. The system underwent testing on benchmark data within the framework of an exam access control system, demonstrating an accuracy of up to 90% in the Orl_Face dataset. The measurement results were compared with other face recognition systems for validation. Beyond accuracy assessments, the proposed system was also benchmarked against similar training tools, fostering a comprehensive discussion of its performance and capabilities.

1. INTRODUCTION

The rapid advancement of technology, marked by increasingly compact computers, expanded memory capacities, and accelerated video and graphics processor speeds, has propelled the evolution of image processing technologies. Digital image processing has become ubiquitous, finding applications in various fields such as medicine, media, space exploration, pattern recognition, self-driving vehicles, and quality control [1], [2]. Among the essential tasks in pattern recognition and computer vision, face recognition stands out [3]. Face recognition systems are favored in the security practices of airports and government institutions due to their contactless nature and the distinctive features of a person's face, including the nose, chin, cheeks, and eye contours [4], [5]. In this context, the use of a face recognition-based exam access control system is proposed for examinations conducted by ÖSYM (Measuring, Selection, and Placement Center) in Turkey [6]. The issue being addressed is the unauthorized substitution of individuals during central and local examinations. To address this problem, an examination admission control system has been designed and implemented. During registration, the system captures and records face photographs of candidates, which are then stored in the dataset. These photographs serve as reference points for comparison during the examination, ensuring that the candidate in the examination room matches the registered individual.

In this study, the Dlib library was utilized for extracting facial features, and the K-nearest neighbors (k-NN) classifier was employed to match these facial features. This combined approach has contributed to the development of a streamlined version of the exam entry system mentioned earlier. The article begins with a general overview of the methods employed in face detection and recognition systems in the background section. The methodology section outlines the libraries and methods utilized in the study.

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Moving on to the results section, a comparison with other works is presented. Finally, the conclusion section offers a comprehensive assessment of the study and outlines the planned methods for future work.

2. BACKGROUND

The use of intensive and local Histograms of Oriented Gradients (HOG), initially proposed by Dalal [7], is integrated into the system to operate under various ambient conditions. Karakaya et al. selected the HOG method for real-time object recognition to ensure independence from ambient conditions during object detection. The primary goal of this method is to represent the image as a collection of local histograms, with each histogram containing the orientation numbers of gradients in a local image area [8]. In this method, the classifier is trained using an intermediate representation instead of the pixel-based representation of the image. Ideal representations, often referred to as property vectors, compile information that is valuable for classification but remains consistent against small variations in lighting and other environmental variables. The HOG method integrated into the approach is supported by the sliding window method and operates under the Dlib face detector.

The Haar cascade classifier, proposed by Viola and Jones, stands as an active object detection method primarily focused on texture and face geometry [9]. This method is notably responsive to changes in lighting and exposure due to its reliance on collecting pixel integrals in images. Since the exam recording occurs in a more controlled and standardized environment with minimal environmental variables, the Haar cascade classifier is employed for determining face photos.

In the early 1990s, the Eigenface method, recommended by Turk and Pentland [10], emerged as a significant milestone in pattern recognition, particularly in face recognition systems. This method has been utilized for decades in various studies. Face recognition systems are categorized as subclasses of pattern recognition systems because they involve the comparison of numerous patterns along facial lines.

Sultan et al. proposed an attendance system for university halls based on Histograms of Oriented Gradients (HOG) and Dlib [11]. Fayyoumi and Zarrand developed a face recognition-based authentication system for online exams similar to Kanimozhi [12]. During student enrollment, face expressions were received over a 2-second video. The best image from these expressions, obtained through video recording with another application, was chosen to mitigate issues caused by light and resolution. The selected face photos were then compared with the candidates' submitted photos. However, this study lacks specification on methods, results, and algorithms [13]. In a video-based automatic classroom input system recommended by Raghhuwanshi and Swami, PCA (Principal Component Analysis) and Linear Discriminant Analysis (LDA) were utilized as face recognition methods. The system's workflow involves creating a video recording, face detection, and face recognition [14]. Similarly, in a face recognition-based absence control system recommended by Adrian et al., the same methods as PCA (Eigenface) and LDA (Fisherface) were preferred. Upon examination, Eigenface yielded better results than Fisherface [15].

Lu et al. proposed a face recognition method based on deep metric learning, exploring deep neural networks to understand deep metrics on facial features [16]. In recent years, deep learning-based methods have gained preference due to their high success rates compared to traditional methods like PCA [17].

Face recognition systems are built upon two main foundations, as observed in the studies mentioned above. In the Face Detection section, methods commonly used in object detection systems were employed [9], [10]. However, these methods differ in sensitivity to performance and environmental impacts. Given that exam environments can vary, the HOG method [8] addresses environmental challenges in the proposed system. In the second stage of face recognition, the most common methods include the PCA-based Eigenface method [10] and approaches that involve the k-NN algorithm [18]–[20]. The k-NN algorithm, a machine learning technique, is commonly used in face recognition systems for the classification of face photographs. Nowadays, 3D face recognition systems, relying on both 3D facial features (combining 2D features with depth), have gained prominence over traditional 2D recognition systems [21], [22]. Accomplished systems have explored various types of data. Dealing with real-world data collection challenges, such as noisy labels and privacy concerns, has led researchers to create synthetic data, as demonstrated by Qiu et al. [23], [24]. Many unimodal systems face challenges due to a lack of detection capabilities for obscured faces, such as those wearing masks, glasses, helmets, or any obstruction in the detection scene. To address this issue, researchers tend to prefer multimodal systems capable of handling different feature extraction problems [21]. Researchers like Qi and Min have specifically focused on conditions that affect the retrieval of facial features [25].

3. METHODOLOGY

In the face recognition module, we employ the Dlib pretrained face recognition_resnet model, featuring 29 convolutional layers. This model is a modification of the ResNet architecture proposed by Kaiming He et al. [26] , with a few layers removed, and the number of filters per layer halved. The ResNet architecture is distinctive for reformulating layers as learning residual functions concerning the layer inputs, rather than learning unreferenced functions. The authors provide extensive empirical evidence, demonstrating that these residual networks are easier to optimize and can achieve increased accuracy with considerably greater depth.

Evaluating residual networks on the ImageNet dataset [27], the authors assessed depths up to 152 layers, which is eight times deeper than VGG (Visual Geometry Group) nets [28] while maintaining lower complexity. An ensemble of these residual nets achieved a remarkable 3.57% error on the ImageNet test set, winning 1st place in the ILSVRC 2015 classification [26]. In simpler terms, a deep convolutional neural network involves stacking several layers and training them for a specific task, learning various low/mid/high-level features towards the end of its layers. In residual learning, the focus shifts to learning residuals instead of specific features, where residuals are understood as the subtraction of the features learned from the input of that layer. ResNet achieves this using shortcut connections, directly connecting the input of the nth layer to some $(n + x)th$ layer. It has been demonstrated that training networks in this form is easier than training simple deep convolutional neural networks and effectively addresses the problem of degrading accuracy.

The network was trained from scratch on a dataset comprising approximately 3 million faces aggregated from various sources, including images from Face Scrub [29], the VGG dataset [30], and a substantial number of images scraped from the internet. The pretrained model conducts face recognition by segmenting face images into 128-dimensional vectors and mapping faces using deep metric learning [31].

These challenges can be mitigated to a certain extent with the development of face recognition systems. To execute face recognition, tracking, and expression detection, it is necessary to automatically detect faces first. Feature extraction is then applied to the detected faces, and the comparison process is carried out with other individuals. In face recognition, a feature based on deep metric learning using the Dlib library is employed for feature extraction. The flow diagram of this method is depicted in Fig. 1 [16]. For a given face image x_1 and x_2, the same property as $h_1^{(2)}$ and $h_2^{(2)}$ are matched to a subspace using a hierarchical array of nonlinear transformations. The similarities of the outputs at the top level are calculated, determining whether the photographs belong to the same person.

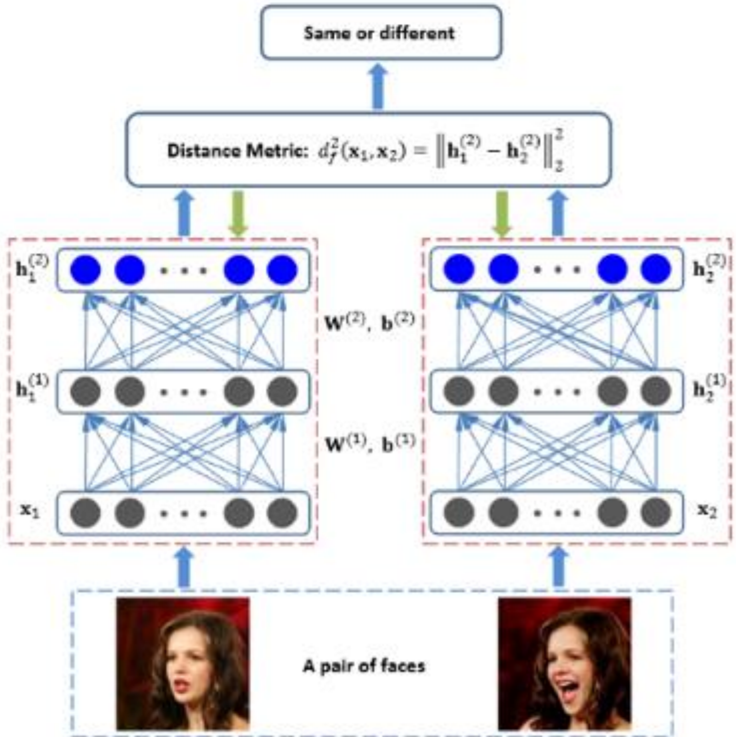

FIGURE 1. Flowchart of the method based on deep metric learning.

3.1 Haarcascade and Dlib with face detection

Dlib is a modern library encompassing machine learning algorithms and tools designed to address real-world problems, aiding in the development of sophisticated software. Its applications span various domains, including robotics, embedded devices, mobile phones, and large high-performance computing environments [32]. In the proposed approach, the Dlib library and the Haar cascade method are integrated into the system for face detection and recognition.

The Haar cascade leverages the integral representation of face images, enabling calculations at any scale or fixed time. The removal of image integrals aims to prevent the summation of individual pixel values, reducing system resource utilization and accelerating the face detection process.

In Fig. 2 [9], two features are presented in the top row and superimposed on a typical training face at the bottom. The first feature measures the difference in density between the eye area and the upper cheek, based on the observation that the eye area is generally darker than the sides. The second feature compares the density of the eye region with the nose bridge. This feature analysis, which separates other objects from the face, is applied by superimposing these characteristics on each face photograph, effectively isolating the face from other objects.

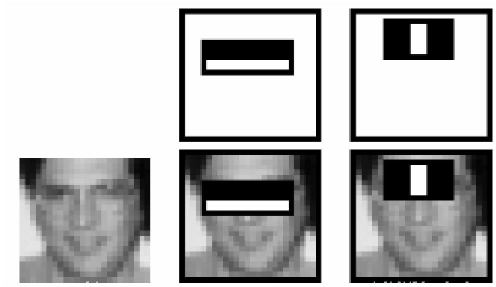

FIGURE 2. Adaboost first and second property selection.

Another versatile system suitable for various environments is the Hog-based Dlib face detector. HOG is frequently employed in computer vision, pattern recognition, and image processing to identify visual objects, such as faces. HOG-based detectors can offer enhanced comfort in face detection compared to existing systems, addressing issues arising from illumination conditions and scale variations, among others [33]. One of the primary reasons for this efficacy is the utilization of a “generic” feature to perceive the face rather than a collection of 'local' features. In simple terms, unlike many property vectors representing smaller portions of a person, all individual properties are captured by a single property vector. The HOG-based Dlib face detector employs a sliding detection window that traverses the view, as illustrated in Fig. 3 [34].

FIGURE 3. Hog face detection.

At each position of the sensor window, a HOG identifier is computed for the detection window. This identifier is then fed into the trained Support Vector Machine (SVM), which classifies it as either "face" or "not face" [35].

During the exam registration, photographs are captured in the dataset using an automatic classifier with a Haar cascade classifier. However, in examination rooms, there are more environmental variables compared to the registration exam. The face detection with the Hog-based Dlib face detector is illustrated in Fig. 3.

The Hog-based Dlib face detector, known for its higher processing power than the Haar cascade classifier, is adapted for use in exam room systems. This adaptation aims to minimize the error ratio and maximize the detection rate (performance).

Using the Dlib face detector, photographs where faces are missed are detected and recorded in the person's log file, as shown in Fig. 4.

```
MORE FACE COUNT 0
NO FACE NUMBER 0
dataset/DuringExam/muratigde 3.jpg,unknown_person 04:09:57.266338
dataset/DuringExam/semihcelal 4.jpg,unknown_person 04:09:57.475720
dataset/DuringExam/muharremhoca 9.jpg,muharremhoca9  CANDIDATE ACCESS EXAM 04:09:57.617145
```

FIGURE 4. Log file for entrant.

3.2 Face recognition using Dlib and k-NN

The face recognition module in the Dlib library is employed for face recognition [31]. The underlying principle of this module relies on deep metric learning. Dlib accomplishes face recognition by segmenting face images into 128-dimensional vectors and mapping faces using deep metric learning.

The Euclidean algorithm is utilized for distance measurement during the module's learning from deep metrics. The distance-measured 128-dimensional vectors highlight differences in face contours relative to other individuals [31]. The k-NN method is a learning-based classification algorithm. The result of a new sample inquiry is classified according to the k-NN majority. This algorithm classifies the object based on intended qualities and training samples [36].

The k-NN classifier is initially trained on many labeled (known) faces. In the training set, the most similar faces are classified according to the nearest face features determined by the Euclidean distance algorithm [37] (the matrix of distances between the points), and the person in the image is identified.

For instance, with $k = 3$, if two of the three nearest faces in the training set are labeled as "Taha" and one as "Oğuzhan" for a given image, the recognition result will be "Taha".

In the comparison process over a photograph, the face lines of the person are determined using the Dlib library. The numerical data of the positions and shapes of the contour lines are extracted. This numerical data includes distinguishing features for each candidate. Each candidate undergoes training in the face recognition part of the exam room through a program based on the k-NN algorithm. Candidate photographs are then compared with the current photographs taken of those candidates entering the hall, and the application is executed.

Face recognition is conducted by comparing photographs of individuals in the developed system using Dlib and k-NN.

A sample of face recognition is illustrated in Fig. 5. If the calculated face recognition accuracy is low (below 80%), real-time monitoring of the person can be initiated via a camera. An example situation is depicted in Fig. 6.

FIGURE 5. Recognized face display.

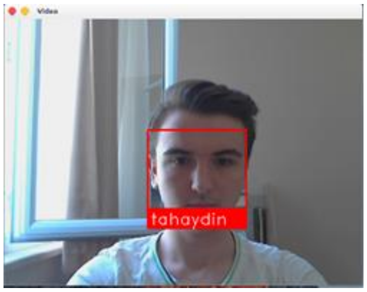

FIGURE 6. Dlib real time face recognition.

4. RESULTS

At the outset of the study, the system developed using the PCA and k-NN method underwent testing. However, in alignment with the literature, new methods were explored when the performance results were suboptimal. It was observed that performance results improved notably when utilizing the k-NN algorithm from the Dlib library based on deep metric learning.

In each recognition process, the system logs candidates matching other candidates in the dataset in a log file. This log file is instrumental in determining the correct match status of the intended candidate and showcasing similarities with other candidates.

As depicted in Fig. 7, the system identifies initial faceless photos. Before the face recognition system engages, the face detection system is activated first, ensuring that unidentified faces or non-face photographs are not introduced into the recognition system. The “MORE FACE COUNT” counter identifies photos with multiple faces and tracks their number.

```
WARNING: No faces found in dataset/BeforeExamTest/taha/taha 8.jpg. Ignoring file.
MORE FACE COUNT 0
NO FACE NUMBER 1
dataset/DuringExam/tahaydin 2.jpg,taha 4  CANDIDATE ACCESS EXAM 15:12:53.325312
dataset/DuringExam/oguzhanhoca 1.jpg,unknown_person 15:12:53.528608
```

FIGURE 7. Log file of face recognition.

The primary objective of the system is to compare the candidate's photograph taken before the exam with all the individuals belonging to that hall. Upon correct recognition, the system outputs “CANDIDATE ACCESS EXAM”, accompanied by the system clock indicating that the candidate can enter the test. Unmatched faces are documented in the file as “unknown_person”.

For accuracy and precision computations in the system, true positives, true negatives, false positives, and false negatives are considered for the processed faces. Lines in the log file containing “Candidate Access Exam” correspond to True Positives (TP). True Negatives (TN) are instances where “Candidate Access Exam” is not present. False Positives (FP) represent cases where the precision computation program indicates a match, but the result does not correspond to the exposed person. False Negatives (FN) are instances where a face photograph of a candidate subject to comparison in the dataset does not match any photos in the dataset of the person, or if it is one of the photos where no face is detected or contains more than one face. These values are computed by analyzing files created for each candidate using Equations (1), (2), and (3). The results are presented to the user as illustrated in Fig. 8

```
Project$python precision.py /oguzhanmenemencioglu
100 positive, 75 unknown, 0 no face detect, 107 access
Precision: 0.934579
Recall: 1.0
Accuracy: 0.934579
```

FIGURE 8. Accuracy, precision and recall representation.

Table 1 presents accuracy values and details on the methods, algorithms, and datasets employed in selected studies from the literature. A meticulous selection process was undertaken to identify the most prevalent methods, algorithms, and datasets in these studies.

$$Accuracy = (Tp + Tn) / (Tp + Tn + Fp + Fn) \tag{1}$$

$$Precision = (Tp) / (Tp + Fp) \tag{2}$$

$$Recall = (Tp) / (Tp + Tn) \tag{3}$$

TABLE 1. The Overview of literature.

Approach	*Methods*	*Dataset*	*Accuracy (%)*
[15]	Pca+Lda (without black background)	-	70
[20]	Pca+k-NN	Unique, 270 persons	77.50
[16]	Deep Metric Learning (DML)	Youtube_Faces	82.34
[19]	Pca+k-NN	Unique, 180 persons	89.97
[18]	Pca+k-NN	Unique, 70 persons	92.47
[39]	Pca+Hog+Svm	LFW	64.6
[40]	Metric Learning (ML)	LFW	89.73
Proposed	**Dlib (DML) + k-NN**	**LFW**	**75.2**
[41]	Pca+Svm	BioId	67.39
[39]	Pca+Hog+Svm	BioId	75.67
Proposed	**Dlib (DML) + k-NN**	**BioId**	**84.6**
[14]	Pca+Lda	ORL_FACES	66-80
[38]	Class wise+Pca	ORL_FACES	86.67
Proposed	**Dlib (DML) + k-NN**	**ORL_FACES**	**90.6**

4.1 Proposed Approach Test on Commonly Known Data Sets

The proposed approach was applied to commonly used face recognition datasets, with practical testing involving the division of datasets into 70% for training and 30% for testing. Accuracy percentages derived from these tests are provided in Table 1.

4.2 Proposed Approach Test on Unique Data Set

A distinct dataset consisting of 10 face photographs from each of 8 volunteer colleagues at our university was created.

Table 2 illustrates precision measurements obtained from the system. For each person, measurements were conducted on 10 photos, calculating precision separately for each candidate's photograph as minimum, maximum, and average values. This involved comparing each of the 10 photographs in a person's dataset with all individuals in that exam hall.

As a result of this comparison, for instance, the precision was measured at a minimum of 90.90% and a maximum of 100% for person 1. The average precision is the mean value calculated over the 10 photographs of each candidate.

Algorithm runtime was computed on a computer with an Intel i5 4-core processor and 8 GB RAM. The training time for the k-NN algorithm, involving 8 people, was 4.78 seconds. Individual face recognition time ranged between 0.45 and 0.65 seconds, contingent on feature inference. The total recognition time for 8 people was 5.13 seconds.

TABLE 2. The Precision and accuracy of the local dataset.

Person No	Min Prec. (%)	Max Prec. (%)	Avg. Prec. (%)	Avg. Acc. (%)
1	90.9	100	99.09	97.82
2	42	81	60.5	60.5
3	100	100	100	96.56
4	100	100	100	100
5	76	100	95.2	93.45
6	45	100	75	71.94
7	90.9	100	98.18	98.03
8	100	100	100	100
Total	42	100	91	89.79

4.3 Discussion

The face recognition-based exam admission control system utilizes the mentioned before libraries and algorithms. With the support of the Dlib library, our system achieved a 90% accuracy result on the widely used Orl_Face dataset. In comparison, a similar study, a class survey system using the same dataset [14], achieved an accuracy range of 60% to 80% with the Pca-Lda method. Another study with a different purpose but utilizing the same dataset [38], achieved an accuracy of 86.67% through a class-wise PCA approach. Our study demonstrates higher accuracy on the same dataset compared to these studies. A similar scenario is observed with the BioId and LFW datasets [39], as presented in Table 1. The proposed approach in this paper doesn't exhibit a clear advantage over our study when considering accuracy values. However, considering the initial attempt in the field, accuracy results, and system cost together, the proposed approach can be deemed qualified for use as an exam admission control system.

Comparing our work with papers by Kanimozhi [12] and Fayyoumi [13], which are face recognition applications for online exams and share similarities with our study, our work stands out by providing truth tables on the detection and identified faces. This inclusion enhances the reliability of our work by offering transparency in accuracy and precision measurements, which is lacking in these applications.

5. CONCLUSION

In this study, we developed an approach by integrating the Dlib face recognition library with the k-NN classifier, implemented within an exam access control system. We calculated accuracy values and compared them with similar studies. The Dlib library, combined with the k-NN algorithm, demonstrated high-performance results in accuracy and precision for the face recognition system. Consequently, the proposed approach is considered semi-novel, and the system serves as a successful prototype for an exam access control system, exerting a deterrent effect on those attempting to substitute someone else's place.

For future work, the primary goal is to train convolutional neural networks for specific customized purposes and involve them in the implementation. Another crucial aspect is optimizing the process time for comparing photographs. Some individuals exhibit lower recognition accuracy, around 60% or 75%, likely due to challenges in handling changes in lighting and capturing suitable images of these faces. Additionally, facial feature similarity among certain individuals may reduce precision. We believe that refining the implementation beyond the prototype and incorporating self-training can address these specific challenges, improving accuracy.

Furthermore, by adapting the proposed approach, it can be compatible with online exam applications. Its applicability extends beyond this specific use case to various fields, including airports, stadiums, shopping malls, bus stations, and more.

Conflict of Interest

The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

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