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Comparative Study on Face Identification Algorithms

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ABSTRACT: This article describes an experimental investigation of the potential for celebrity recognition from visual content that was conducted in the applied field of organic image processing. Unlike typical state-of-the-art research, more focus is placed on situations where the face is partially or not entirely out of frame (lateral. views, small occlusions, etc.) and/or where the illumination changes without warning. After conducting a cutting-edge investigation, we evaluate two traditional face identification algorithms—the Haar Cascade Classifier and the Max-Margin object identification along with two traditional face-recognizing models—the CNN-based Pruned ResNet and the Local Binary Pattern Histogram. The experimental task is to assess the four potential pairings between the mentioned two face identifications and two techniques for facial acknowledgment. For this investigation, an image database has been arranged. A public image database including 31 frontal face photos of celebrities is taken into consideration. Overall, we found that, with an accuracy of 85%, the MMOD combined with a Pruned ResNet model appears to better fit the odds of the organic image processing use case. The study also highlights and analyses the variations in the quantitative outcomes attained for the two categories of database content (pictures of celebrities' faces versus organic image footage).

KEYWORDS: Face identification, face acknowledge, organic image, Haar Cascade Classifier, Max-Margin object identification (MMOD), Local binary pattern histogram (LSBH), Pruned ResNet

I. INTRODUCTION

It is normal for humans to identify and recognize other people, but it might be challenging for a machine to do the same. Face recognition, also known as facial acknowledgment, is a computer technique based on artificial intelligence (AI) that locates and recognizes human faces in digital photos and images. Face identification technology is frequently used for real-time tracking and surveillance of people. Among the industries that use it are social media, entertainment, law enforcement, biometrics, and security. Artificial neural network (ANN) and machine learning (ML) technologies are used in facial identification, which is essential to face tracking, face analysis, and facial recognition. In face analysis, face identification uses facial expressions to identify the regions of an image or picture that require attention to extract data regarding emotions, gender, and age. Data on face identification is required in a facial make a faceprint and compare it with other stored photos by acknowledging the system. Facial recognition technology allows for the identification or verification of an individual's identity. Facial recognition software can be used to identify people in photos or in real time. Facial recognition is a subset of biometric security. Other biometric software includes voice, fingerprint, and iris or retinal identification programs. The main applications of the technology are in security and law enforcement, while interest in other areas is expanding.

Face identification applications utilize a combination of machine learning, AI, statistical analysis, and image processing to identify faces within larger images while distinguishing them from non-facial elements such as buildings, landscapes, and other body parts. Before face identification begins, the media being evaluated undergoes preprocessing to improve its quality and filter out images that may hinder identification.

Typically, face identification algorithms initiate by searching for human eyes, which are among the simplest facial traits to identify. Subsequently, they scan for additional facial features such as lips, nose, irises, eyebrows, and nostrils. The algorithm conducts supplementary tests to confirm the identification of a face once it has located a facial region.

To ensure accuracy, algorithms are trained on extensive datasets comprising hundreds of thousands of both positive and negative images. This training process boosts the algorithms' ability to detect faces within an image and precisely determine their locations. The following area few methods employed in face identification applications: Background removal. The facial boundaries can be seen when the background of an image is removed, especially if it is a predetermined, static background or a simple, monochromatic one. Color of skin. Skin tone can occasionally be used to identify faces in color photos, albeit this may not be effective for all skin tones. Move. Another method for finding faces is to use motion. Users of this method have to compute the moving area because faces in real-time video are almost always moving. This method's possibility of misunderstanding with other things moving in the background is one of its drawbacks. Combining these techniques can result in an all-encompassing face identification technique.

Face Recognition

When referring to face identification, the words "face detection" and "face recognition" are sometimes used interchangeably. Still, facial recognition is essentially just one of the most important applications of face detection. In addition to biometric authentication, facial recognition software is utilized to unlock phones and mobile apps. Facial recognition is used by the banking, retail, and transportation sectors to lower crime and stop violence. To put it briefly, facial recognition technology can identify a face in addition to simply detecting its presence. A computer program is used in the procedure to take a digital picture of a person's face, sometimes from a video frame, and compare it with pictures in a database of previously saved records.

II. SIGNIFICANCE OF THE SYSTEM

Face identification plays a crucial role in various sectors:

1. Security and Surveillance: They are widely applied in surveillance systems to identify individuals in public spaces, airports, and banks, bolstering security measures and deterring criminal activities.
2. Access Control and Authentication: Facial recognition offers a secure and convenient means of verifying identities, replacing traditional authentication methods in devices like smartphones and laptops.
3. Biometric Identification: It's an integral part of biometric systems used across sectors such as immigration, law enforcement, and healthcare, aiding in identity verification and fraud prevention.
4. Personalization and User Experience: These technologies enable tailored experiences in social media, advertising, and e-commerce by customizing content and recommendations based on user demographics and preferences.
5. Emotion Analysis and Behavioral Insights: Facial recognition analyzes facial expressions for market research, customer feedback, and psychological studies, providing insights into consumer behavior to improve products and services.
6. Healthcare and Medical Diagnosis: They assist in medical diagnosis, patient monitoring, and treatment planning, aiding in identifying individuals in health records and detecting medical conditions.
7. Human-Computer Interaction: Enabling natural interactions in gaming, virtual reality, and augmented reality, face detection, and recognition control characters or objects based on facial expressions and gestures.

In summary, these technologies have diverse applications impacting security, privacy, convenience, and personalization. However, ethical considerations regarding privacy, consent, and bias require careful attention for responsible deployment and usage.

III. LITERATURE SURVEY

Comparable to object recognition is this. The majority of human faces appear to be similar to one another, with very little variation. Even though every face is the same, there are a number of variables that affect how each one looks. It falls under the following categories: variables both internal and external. Intrinsic signifies a face's purpose [1]. There are two categories: intrapersonal and interpersonal.
The Eigen face approach Kirby and Sirvoich first demonstrated Eigenfaces' recognition approach. For the same reason, Pentland and Turk improved their research by using the Eigenfaces approach based on Principle Component Analysis. A Karhumen-Loeve transformation is PCA [2]. As seen in Fig. 1, PCA is a realized linear dimensionality reduction technique used to identify a set of mutually orthogonal basis functions. The sample covariance matrix's vanguard eigenvectors are used to describe the lower dimensional.

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The Fisher Face Method

A variation of Fishers Linear Discriminant (FLD), which uses linear discriminant analysis (LDA) to obtain the huge discriminant structures, Belhumeur proposed the Fisher Face approach in 1997. The methods used to create a subspace projection matrix, PCA and LDA, are comparable to the Fisher face and Eigen face techniques [3]. LDA explains When compared to the Eigen face technique, a pair of projection vectors that simultaneously form the lowest in the class scatter matrix and the largest between-class scatter yield lesser error. Using LDA, six distinct classes with significant variability within them but little variance between them. When compared to the conventional Fisher face, which is based on the second order statistics of an image set without taking into account the high-order statistical dependencies, Kernel FLD outperforms the conventional method in extracting the most distinct features in the feature space, which is common to the nonlinear features in the reference input space [4]. A selection of contemporary LDA-based algorithms consists of: Direct LDA can solve problems with limited sample sizes by creating the image scatter matrix from a typical two-dimensional image. Furthermore, the Dual-Space LDA algorithm needs all of the face's discriminative information in order to tackle the same problem. Direct-Weighted LDA combines the usage of weighted pair-wise Fisher criteria privileges with LDA [5]. With the block LDA technique, the entire image is divided into many blocks and arranges each block in a row vector form. The row vectors for each block that are derived from the two-dimensional matrices are subjected to linear discrimination analysis. Using LDA and PCA, the K-Nearest Neighbor (KNN) and the Nearest Mean (NM) techniques were fused. The AT&T and Yale datasets were employed for the study.

Assistance Vector Systems

Support vector machines (SVMs) were developed to enhance the classification performance of PCA and LDA subspace features [6]. Typically, SVMs are trained using supervised learning approaches. SVM is trained on a group of images in order to estimate the Optimal Separating Hyperplane (OSH). reducing the possibility that two classes of images in a feature space may be misclassified. This method was used for facial recognition by Guo et al. Using binary tree classification algorithms, he continually classified facial images into one of two classes. Until the two classes represent distinct subjects and a final classification choice can be made, a binary tree structure is utilized [7]. Some researchers have chosen SVM for facial recognition to achieve good outcomes.

Haar Cascade

A technique for object detection called Haar cascades gained popularity in the field of face detection. This method was created as a component of the Viola-Jones facial recognition system. Simple rectangular patterns called Haar-like features are employed in object detection. They are essential to Haar cascades because they identify pertinent patterns in pictures [8]. A computational method essential to Haar cascades, integral pictures allow for the effective computing of Haar features. An algorithm called the Viola-Jones algorithm is used to identify faces in pictures. It employs a cascade classifier architecture, whereby progressively higher classification levels are applied to filter out non-face regions. To increase detection accuracy, features are chosen and refined iteratively during the training phase. A number of performance evaluation measures are used to evaluate the Viola-Jones framework's efficacy [9].

MMOD

MMOD, or Mixture of Deep Object Detectors, represents a cutting-edge technique for object detection, offering advanced capabilities in identifying objects within images. It can be defined as a method that combines multiple deep learning-based object detectors to achieve superior performance in detecting various objects of interest [10].
MMOD has emerged from the evolution of traditional object detection methods, incorporating advancements in deep learning. Initially, object detection relied on conventional techniques such as Haar cascades and handcrafted features. However, with the rise of deep learning, particularly convolutional neural networks (CNNs), the concept of mixture models was adapted to create more sophisticated object detection frameworks capable of handling complex visual data.
A mixture of detector architecture, which integrates several object detection models, is one of MMOD's primary constituents[11-15] Together, these models depict a variety of patterns and traits found in many things. Furthermore, in order to evaluate the probability of an object's presence, MMOD uses probabilistic modeling, which produces more precise and nuanced detection results.

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CNN BASED PRUNED_RESNET_34

CNNs are deep learning models specifically designed for processing visual data, such as images and videos. They consist of multiple layers of neurons that perform operations like convolution, pooling, and nonlinear activation to extract features from input images. CNNs have revolutionized computer vision tasks by achieving state-of-the-art performance in various domains, including image classification, object detection, and image segmentation [16].

Pruning techniques involve removing redundant connections, weights, or entire neurons from a neural network to reduce its computational complexity and memory footprint. By eliminating unnecessary parameters, pruned models can be more efficient for deployment on resource-constrained devices or in scenarios where computational resources are limited. Pruning techniques have been extensively studied and applied to deep neural networks to achieve faster inference times and reduce memory requirements without significantly sacrificing model accuracy [17].

A variation of the ResNet (Residual Network) architecture known for its deep structure and utilization of residual connections is called ResNet34.ResNet34 consists of 34 layers, including convolutional layers, pooling layers, and shortcut connections (residual blocks). These residual connections allow ResNet models to effectively train very deep networks without suffering from the vanishing gradient problem [18]. ResNet34 has been widely adopted in various computer vision tasks due to its balance between model complexity and performance.

CNN-based pruning techniques have evolved from traditional model compression methods, driven by the need for more efficient and compact neural network models. Initially, model compression techniques focused on reducing the size of neural networks through techniques like weight quantization and low-rank factorization. With the rise of deep learning, pruning methods specifically tailored to CNNs have emerged, aiming to identify and remove redundant parameters while preserving model performance [19].

ResNet architectures, including ResNet34, have evolved with improvements in architecture design and training methodologies. The development of deeper and more efficient variants of ResNet models has led to their widespread adoption in both research and practical applications across various domains, including image classification, object detection, and image segmentation [20].

Pruning methods applied to ResNet34 have evolved to address the specific challenges posed by deep neural networks with residual connections. Techniques have been developed to identify and prune redundant parameters in residual blocks while preserving the integrity of the network's representation. Additionally, fine-tuning and retraining strategies have been devised to recover or even improve the performance of pruned ResNet34 models after the pruning process.

IV. METHODOLOGY

The author of this work compares the effectiveness of various algorithms for face detection and recognition. This experimental study examines two classic face acknowledge models (LSBH and CNN-based Pruned ResNet) and two classic face acknowledge algorithms (MMOD and Har Cascade Classifier) selected through state-of-the-art research. The discussion is on the open-source software implementation of Viola and Jones's ML object identification algorithm, the Haar cascade classifier. We considered a publicly available program that is open source. In particular, the MMOD Convolutional Neural Networks model is designed for non-frontal images captured from different perspectives. The LBPH-based face acknowledge algorithm is an upgraded ML-based face acknowledge method, according to its open-source version available at. We thought of utilizing a condensed form of ResNet-34 is utilized for DL-based facial acknowledgement, as detailed in. The OpenCV library provides this. We are designing this method because MMOD and ResNet34 perform better in both detection and recognition tasks.

Dataset Description

For the experiment we considered a dataset of celebrities, the number of images of each celebrity under different lighting conditions, with different Facial expressions for training and testing the algorithms. The image material has varied resolutions, spanning from 360x640 pixels to 1080x1920 pixels, and is encoded at a rate of 30 frames per second. Both professional and amateur cameras are used, and the shooting conditions are totally unrestricted.

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Figure 1. Images of facial samples for the ML-Based Face Acknowledge dataset (several perspectives from the same subject are needed)

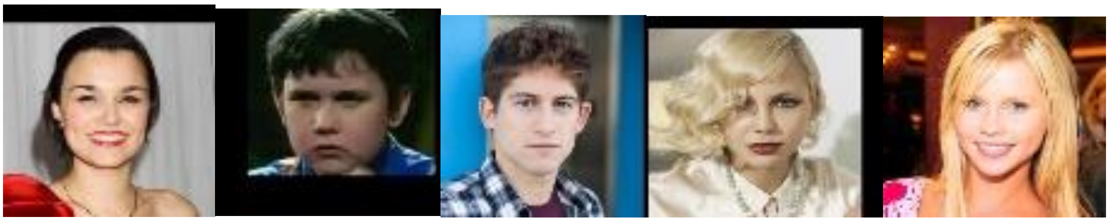

Figure 2. Images of facial samples (several viewpoints from the same subject are required) for the ML-Based Face Acknowledge dataset

A) Data Pre-processing

Data gathering and annotation: Compile a wide range of face-containing photos into a dataset for training and assessment. Add annotations to the dataset to show the faces' locations and/or landmarks in each picture. Image Resizing and Cropping: To guarantee uniformity throughout the collection, resize the images to a consistent resolution.
If the photographs are part of broader scenes, you can crop them to highlight the faces or other parts of interest. Data Augmentation: To improve the dataset's diversity, use modifications like rotation, scaling, flipping, and translation. Enhancement contributes to the models' increased resilience and ability to generalize to new inputs. Normalization: Set each image's pixel value to a standard scale, such as [0, 1] or [-1, 1].
Normalization guarantees that the model converges effectively and stabilizes training.

V. EXPERIMENTAL RESULTS

The test findings show that four possible combinations of two face identification methods and two face acknowledge methods can be used to recognize celebrities in order. Figures 3 and 4 provide examples of representations that include basic frontal views and more intricate material, which combines numerous faces at different angles to the camera with partial occlusions. Figure 3 illustrates how the four approach types act very similarly in the basic tasks (no occlusion, anterior face locations). Figure 4 illustrates a different response for complicated and varied content, indicating that the MMOD trimmed by the ResNet model would perform better in practice than the other three combinations.
Take note of the details of each face identification and identification feature. The findings of applying machine learning (ML)-based identification approaches to an organic image (refer to Figure 5) are very deceptive, with accuracy and error values of 45% and 55%, respectively. DL methods increase these values by 25% and 75%, respectively. It can be inferred from a comparison of these two sets of data with the findings displayed in Figure 6 (i.e., for the second dataset corresponding to the celebrity-front view) that the bad performance is more likely to be related to the kind of material than the techniques. by himself. The results of a face acknowledge function rely on the type of sensor as well as the sensor itself. The ML detector in the organic image (refer to Figure 5) functions appropriately for the faces that it has identified.

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Values for accuracy and error indicate 95% and 5%, respectively. However, when applied to face regions identified by DL, the same detector yields subpar results (accuracy = 63%, error = 37%).
99% accuracy and 1% error for both ML and DL-recognized facial regions indicate similarly good performance. Figure 6 displays the facial acknowledge outcomes from processing the second database. Keep in mind that a direct comparison of the results displayed in Figures 5 and 6 may not be fair due to the tiny size of this database. Table 1 displays the combined performance of two databases and four operational setups. The findings indicate certain limitations with organic image content. Accuracy = 85% is the best configuration (MMOD with Pruned ResNet model), which is 5% less than the celebrity database. It should be noted that the recall is quite less even though the precision values are always equal to their ideal limit: recall = 0.8 for the organic picture database and the same DL-DL.
Fig.5 shows how the working implements, celebrity dataset is uploaded and training &accuracy loss graph is obtained as shown in Fig.6. The image to be acknowledged is fed to test the image and identify the parson in the image.

Original image The frontal facial image experimental findings.

Figure 3. The frontal facial image experimental findings

Original image Illustration of the non-frontal face picture experimental outcomes.

Figure 4. The frontal facial image experimental findings

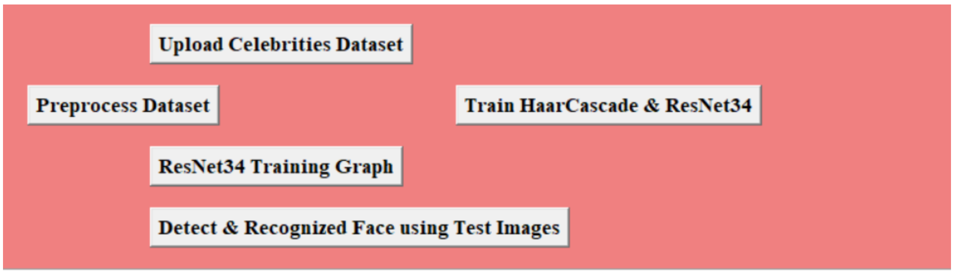

Figure 5: Framework of the proposed model

In Figure 6. In the above graph x-axis represents the training epoch and y-axis represents training accuracy and loss. In the above graph red line represents loss and the blue line represents accuracy with each increasing epoch accuracy increased and reached to 1 and loss got decreased and reached to 0. Now click on the 'Detect & Recognized Face using Test Images' button to upload images and recognize faces.

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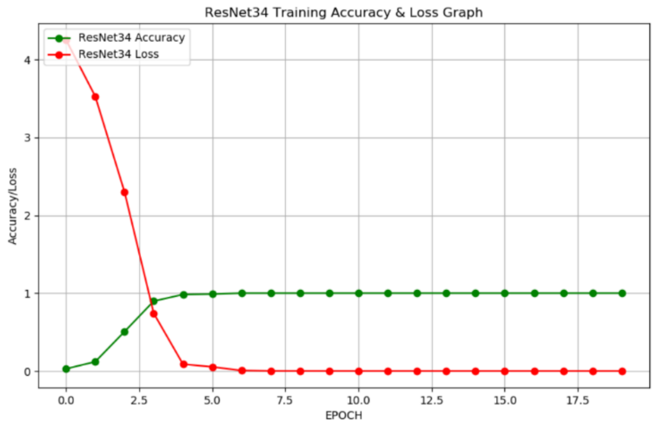

Figure 6. Training accuracy and loss graph

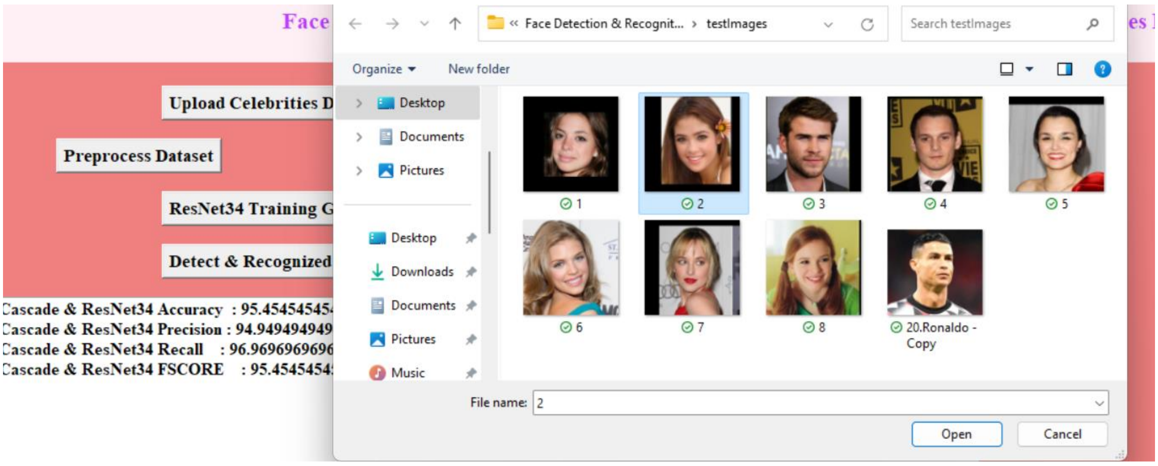

Figure 7: Uploading the images from the dataset

Figure 8: The image is recognized correctly as Gia Mantegna

VI. CONCLUSION AND FUTURE WORK

The Experimental research on the application of contemporary face detection and identification algorithms in the organic image application framework is presented in this paper. The organic image application framework is a different area of image processing that offers virtually all possibilities for information distribution and storage. Objective evaluations and subjective, applied evaluations as shown in Figures 3 and 4 show that the combination of MMOD and the Pruned ResNet model will be practically superior to the other three combinations. original picture with great accuracy compared to the other three cases, which are associated with a lack of perception during the process. During this research, an organic database of photos has been developed and is being made available. The task of face identification and detection will be expanded upon in the future to include more difficult multi-semantic/multi-contextual information recognition. From all the possible cases we worked on MMOD and Pruned Resnet to identify and acknowledge the image from the celebrity database.

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