

ISSN:2222-758X e-ISSN: 2789-7362

AN EFFICIENT AND ROBUST COMBINED FEATURE EXTRACTION TECHNIQUE FOR FACE RECOGNITION SYSTEMS

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Abstract- Face recognition has long attracted a lot of interest from the research and market communities due to its many possibilities across numerous sectors, but it has proven to be exceedingly difficult to deploy in real-time applications. Over the years, several face recognition algorithms and their variations have been created. In this paper, an integrating STIP and SURF for a robust feature extraction approach is proposed. This approach consists of four steps: In the first step, researchers are collecting the input images. In the next step, image preprocessing using a Gaussian filter is used. Then, image segmentation is applied using Region of Interest (ROI). The Spatial-Temporal Interest Point (STIP) is employed to extract the features related to facial behaviors from Facial Action Units (FAUs). The most effective approach for object recognition in image processing that applies feature descriptors is a Histogram of Oriented Gradients (HOG). In the last phase, use the feature selection process using SURF (Speeded-up Robust Features). This proposed approach achieved (0.25 ms) better performance than the traditional approach.

keywords: Face recognition, Region of Interest (ROI), Image preprocessing, Image segmentation, STIP, HOG, SURF, Feature extraction.

I. INTRODUCTION

The face is a crucial aspect of the human condition. The significant biological characteristic sets one apart from another. Researchers simply identify the faces and authorize it whenever need to manually authorize someone. Face detection is the process through which an intelligent system imitates this human behavior [1]. Face recognition is a science that can identify a person's face from a variety of images or databases. Due to its extensive applications across numerous fields, it is a particularly important topic of research [2], [3]. Face recognition has many useful uses. The verification of customers for multiple applications and devices is magnificent applications. It entails releasing the lock on laptops, smart phones, and other software-based devices. Another use is in forensics and investigations, where it is important to be able to identify faces. Many institutions, laboratories, and organizations have newly used interloper recognition. The basis for face identification is a consideration of human biology. For personal identification and authorization, other identifying methods including fingerprints, signatures, IDs, and PINs are frequently employed, however, face recognition has a substantial advantage [1], [4], [5]. Face recognition requires no such effort on the part of the subject, unlike fingerprint or signature recognition, which both need the subject to provide an impression or their signature, respectively.

Anytime personal identification is necessary, face recognition is crucial. As a result, over the past ten years, research in this area has received a substantial contribution. Typically, face recognition involves looking for and matching faces [6]. Using a certain database. The size of the database can differ contingent on the requirements of the application. For the

ISSN:2222-758X e-ISSN: 2789-7362

automatic identification of authorized, suspects, criminals, unauthorized, and others, face recognition is typically necessary [1], [7]. Its primary uses include automated surveillance, missing person searches, criminal and terrorist identification, and database searches based on a specific face or face sketch. Face identification has proven to be incredibly helpful in finding missing people, criminals, and terrorists. When a crowd must recognize a face, the application takes on significant importance. Face detection in movies received from CCTV cameras is the focus of recent developments in this field [8], [9]. Even Though facial recognition algorithms have been extremely successful, there are still many unresolved problems. Most of these include the subject's age, posture, and facial expressions, as well as background and lighting conditions and similarities between siblings and other blood relatives [10]. Another issue is photos with low resolution. Accuracy is the most important factor for a decent face recognition algorithm. Nowadays, sophisticated face algorithms are used. Modern algorithms that investigate facial traits, as well as the variables influencing facial features, are referred to as advanced face algorithms [11]. Therefore, for better recognition results, conventional systems need to take into account face positions, light, and other aspects.

Modelling and various types of object recognition. A robust local feature point identification and description approach is speeded up Robust Features (SURF) [12], [13]. Herbert Bay initially released it in Europe. It was formally published in the journal Computer Visions and Image Understanding in 2008, after being shown at the Conference on Computer Vision (ECCV) in 2006. Surf finished feature extraction and description more quickly and enhanced feature extraction and description. The corners of the frames are found using the Harris STIP [14]. By taking into account the difference of the region with respect to direction, it is utilized to identify regions in every pixel of the image. If the pixel is located in an area of consistent intensity, the edges close by will appear to be comparable. In addition, the corners of the object can be precisely located using Gabor wavelets by using the Gabor STIP [15]. The Gabor function outputs a local spectral energy density in a specific direction at a given point and frequency.

By combining the STIP and SURF approaches, the suggested strategy shows innovation in comparison to previous research and produces a more precise and effective extraction of features for complicated facial recognition patterns, outperforming the constraints of traditional methods. The suggested method is unusual because it combines the reliable extraction of features in the recognition of faces with the SURF and STIP approaches [1]. Through the integration of SURF's choosing features procedure with STIP's capability to extract face behaviour related characteristics from FAUs, an all-encompassing and effective technique for recognizing and evaluating intricate facial structures in applications in real-time is achieved. Additionally, the general elegance of the method is enhanced by the implementation of the HOG for recognizing objects, the use of ROI for segmenting images, and the addition of the use of Gaussian filters for image preliminary processing. These additions allow for enhancing precision as well as efficiency when compared with conventional techniques. This combination is a noteworthy advancement in the area of face recognition and gives a viable path for improving the performance of algorithms for recognizing faces in a variety of industries.

II. LITERATURE SURVEY

The last Lowe's scale-invariant features transformation (SIFT) approaches produce the HOG feature descriptor. However, due to its potent expressive ability, Xiang, Z.et al [16] it has drawn much interest and has developed into a significant

ISSN:2222-758X e-ISSN: 2789-7362

application when employed as a characteristics label in pedestrian detection. LBP operators and HOG descriptors share some commonalities. Both of them are variance mode into extraction technique and lessen the impact of grey variations brought on by variations in linear light. The best method for object detection in image processing and computer visions that makes use of feature descriptors are called the Histogram of Oriented Gradients (HOG). In essence, a single image is divided into extremely small-connected sections that are referred to as cells, and for every cell, Liang, Y., [17] calculated a HOG, direction or edge orientation for every pixel inside. Each cell's pixel gives its corresponding angular bin gradient weights. Blocks, the group of adjacent cells, can be thought of as geographical regions.

In terms of scene matching, objection detection, face recognition, and other tasks, the SIFT algorithm excels. It has a rotational, translational, and scale invariance, which makes it excellent tolerance for noise, view transformations, brightness changes, and affine transformations. Three sections make up the majority of the SIFT Mistry, D [18] algorithm steps: Key point detection in scaled space, assigning feature points orientation values (orientation assignment), and key point descriptor for the SIFT feature. Finding important places in various scale-spaces is the first step. The primary Gaussian kernel functions of various scale factors transform the original images into a string of filtered, smooth images. Song, Y., [19] MR, D. S. [20] to create differential Gaussian images, every of the two neighbouring filtered images is deducted from the other. The 26 neighbourhood surrounding each pixel are used to determine the important spots in the multi-scale Gaussian variance image, while low-divergence areas and edges are removed. To ascertain the primary path of the main points and get the rotational invariance assets, the second step entails computing the fullness and direction of the gradients at the main point as determined in the previous phase.

A local feature extraction technique is SURF, Bansal, M., [21]. For extracting the image features key points, it makes use of local invariants debauched main point detectors. The image features descriptor extracted using a unique descriptor. In comparison to the SIFT feature extraction approach, it is a quick and reliable computational method, Qin, S., [15]. Oyallon, E., Rabin, J [22] used a SURF algorithm's main operation as follows: Based on the requirements, the feature main points from a picture are extracted. After that, the important points are given an orientation. In consideration of the intriguing main points, the orientations are allocated in a circular motion. The formed part is then adjusted by the chosen location. Finally, Haar wavelet replies are applied to extract feature forms. Typically, a descriptor vector is extracted from an 8*D* feature vector.

The contribution of the work:

- 1) The derivation of HOG from SIFT highlights how feature extraction techniques in computer vision are interconnected and have evolved.
- 2) The efficacy of HOG in identifying pedestrians demonstrates its usefulness in actual computer vision applications.
- 3) Using a spatial awareness technique for reliable identification, HOG's segmentation into connected cells, and gradient weight computations improve item detection.
- 4) SIFT's multi-step method, which includes identification of scaled space, orientation assignment, and key point descriptor construction, adds to its robustness and adaptability, guaranteeing reliability in a variety of settings.



ISSN:2222-758X e-ISSN: 2789-7362

5) SURF as opposed to SIFT is presented as a rapid and trustworthy technique for extracting local features. It exhibits flexibility about particular specifications, circular orientations, and Haar wavelet responses, which improves its capacity to extract a variety of distinctive image features.

III. METHODOLOGY

The Human Visual system, which combines the human eye and brain for image processing, is the best-designed such system. Using this method, authors aim to create a system for computer vision. The system receives the image and separates it into individual frames. It then preprocesses the video to strengthen the image frames by deleting any extraneous pixels. This method allows us to lower the noise and save the resulting images for further use. Options were recovered from the preprocessed image frames using SIFT descriptors of several kinds. Fig.1 shows the proposed block diagram.



Figure 1: Proposed Block Diagram.

A. Image Collection

To research the issue of unrestricted face recognition, a dataset of face images has been created. Over than 13,000 human facial pictures from the Web are included in the dataset. The names of each face have been attached. Picture of the person's name. The dataset contains two or more separate images for 1680 of these faces. The facts that these faces were picked up by the Viola-Jones face detector is the only restrictions on them. The webpage contains additional information. The LFW dataset has gained a lot of consideration in current years since the created algorithm based on it frequently achieves better performance. It also explains a procedure for creating a dataset of face images.

B. Image preprocessing

Gaussian filtering is expected to play the most important role in both theories and applications. The Gaussian channel is observed to overly smooth photographs when used as a picture de-noise estimate, resulting in the loss of genuine detail, particularly edge sharpness. The purpose of the Gaussian channels is to remove noises from the input. These channels have



ISSN:2222-758X e-ISSN: 2789-7362

inputs that work stepwise without overshooting, which reduces the rise and fall times. So, according to this measure of demeanor, the filter will detain as little as possible. A Gaussian filtering approach, according to science, responds to the contribution to the technique for drawing a curve from a Gaussian distribution. Because of Gaussian haze, the Gaussian capacity is currently used to obstruct images. The effect of illustration programming is frequently known to reduce visual noise. The Gaussian distribution (G_x) with the standard deviations for the first calculation and second estimations is labelled in the following two Eqs. (1) and (2), where (x) is an image point for the first calculation and (x, y) is a pixel for the other [20].

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{x^2}{2\sigma^2}} \tag{1}$$

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^3 + y^3}{2\sigma^2}}$$
(2)

C. Image segmentation

Separate key process in image investigation for object recognition is image segmentation. It entails breaking down an image into tessellations using certain standards. The pre-processing phase for pattern identification and object detection makes it one of the crucial components of image processing and computer vision. Segmentation is frequently used as an unsupervised learning technique to find regions of attention that have a particular attribute, with the requirement that the segmented areas be similar and free of numerous holes. In other words, the compilation conditions should be different for each region and consistent for each pixel inside it. Data clustering, edge-based segmentation, and region-based segmentation are three types of segmentation algorithms that are currently in use. Segmentation, the JSEG algorithm, and quick scanning. All pixel-by-pixel enlarge each zone based on its value or quantized value to provide each cluster with a strong spatial relationship. This research will concentrate on the region-based segmentation approach. The primary premise of region-based approaches is that adjacent pixels within a region should have comparable values. The typical practice involves comparing one pixel with the locals. A pixel may be designated as belonging to a cluster as one or more of its neighbours if a similarity condition is met.

The input image frames underwent pre-processing to eliminate the image's noise. By lowering the video's background noise, the approach performs better. There is noise of many different kinds. Salt and pepper noise is a typical type of noise. Pixels of white and black are present in this. Pre-processing cleans up the video frames of any extraneous pixels. The authors will use various filters to eliminate the noise from the image frames. The Gaussian filter recognizes the noised pixel in the image. The median value of the adjacent pixels is used to replace the noisy pixel that was found. Using STIP forms of numerous sorts, the options remained retrieved from pre-processed video frames. Each of the considered descriptors contains calculated information. The cuboid normalized descriptions were taken out. Among the collection of undistorted videos around STIP detections. The corners of the image frames are found using the Harris STIP. This rule uses the differential of the corner concerning direction to find the corner in each pixel of the image. The HOG STIP. provides the values of the gradient's histogram at each position. A histogram of gradient directions or edge detection for

the pixels in every cell is compiled for each of the image's small, connected areas known as cells. The combination of these histograms is used as the descriptor.

The best object recognition in image processing that applies feature descriptors are called HOG or Histogram of Oriented Gradients. Essentially, the division splits a single image into incredibly tiny connected sections, or "cells," and computes a HOG direction for each cell. Eqs. (3) and (4) [14] measure the one-dimensional results point, for instance, Ga, is the first step in creating the descriptor in the HOG by combining gradient masks N_c and N_d with the original data I, and G_d in the a and d directions: Each cell's pixel gives its corresponding angular bin gradient weights. Blocks, the group of adjacent cells, can be thought of as geographical regions. The assembly of cells as blocks serves as the foundation for the classification and normalization of histograms [14].

$$G_c = N_c \cdot I \quad \text{where} \quad N_c = [-0] \tag{3}$$

$$G_d = N_d \cdot I \quad \text{where} \quad N_d = [-0]T \tag{4}$$

Eq. (5) [14] shows the amount of the HOG gradient $[|G_{(c,d)}|]$ and the position in the path (c, d) for every pixel is calculated using the derivative basis functions G_c and G_d .

$$|G(c,d)| = \sqrt{G_c(c+d)^2 + G_d(c+d)^2}$$
(5)

D. Feature selection process

Since the study aims to identify face objects inside an image frame, extracting the pertinent attributes from segmented objects is necessary. A reliable image-matching algorithm called SURF is employed to effectively detect the items. Feature The two problems that reduced the detecting performance were the selection and image matching. Due to its properties, as well as scale invariance, translation invariance, illumination invariance, contrast invariance, rotation invariance, and intrinsic settings, SURF is widely employed. The SURF algorithm involves the following steps:

- 1) Get the input image, first.
- 2) Blob detector locates the interest sites of detection and records them in a Hessian matrix.
- 3) Identifying the features: The features are identified using wavelet responses. Comparing aspects of an object that are similar in contrast.
- 4) Object detection: Next, the pertinent object is found. The necessary features were chosen using the Grey Level Cooccurrence Matrix (GLCM), which extracts the statistical texture features, once the boundary has been marked.

It calculates in rows and columns the amount of grey levels G in images. For specified neighbourhoods, the pixel's distance and strength are estimated and help to modify grey levels i and j. The GLCMs are extremely delicate to the size of the textures examples on which are estimated because of the great dimensionality. Thus, there are frequently fewer grey levels. Point matching is frequently used in SIFT face recognition. However, both approaches require increased calculation costs for matching because authors must calculate both sub-regional and global similarities. In all made use of as part of their assessment of matching, cited the point matching method. To boost the speed and robustness of point matching based on SURF characteristics, incorporate geometric constraints in this article dependent on the point-matching method proposed.



ISSN:2222-758X e-ISSN: 2789-7362

The matching points in two photos must be located similarly on both faces because face images in face recognition are typically standing and normalized. As a result, the search region for a mate for interesting points (x, y) in the inquiry images is constrained within the rectangular windows centred at (x, y) of the probing images. Gallery images a candidate matching pair will be the point pairs with the smallest distances among forms. The following lowest distance of the point's couple that comprises the identical points of the probing images is examined over the entire region of the gallery images to confirm the validity of the candidate point pair. The point's pair with the smallest distances is determined by comparing descriptor the proportion of these two distances against predetermined thresholds. The point's pair with the smallest distances are verified as a coordinated couple if the ratios of these two distances are less than predetermined thresholds. Since location, information was introduced to identify the point's pair with the shortest distance, and the ratio of the shortest distance. The aforementioned method efficiently prevents mismatching, and in addition to minimal distance calculates the similar dependability of two interest sites to some extent. In Eqs. (6) and (7) [23], then develop a similarity measure for face recognition based on the outcome of the point matching that includes the quantity of matched points, the average Euclidean distances, and the average distance ratios of total similar points [23]. Algorithm 1 describes Features Matching Using STIPSURF.

$$\operatorname{Sim} = \begin{cases} \frac{\operatorname{DisAvg} + \operatorname{RatioAvg}}{2}, & N_0\\ x, & x \ge 0 \end{cases}$$
(6)

$$\text{DisAvg} = \frac{1}{N} \sum_{n} \text{MinDis}$$
(7)

Algorithm 1 Features Matching Using STIPSURF

Require: image1_path: Path to the first image

image2_path: Path to the second image

Ensure: feature_matching_time: Time taken for feature matching in milliseconds

- 1: Load the first image from image1_path and store it as img1.
- 2: Load the second image from image2_path and store it as img2.
- 3: Convert img1 to grayscale and store it as grayImg1.
- 4: Convert img2 to grayscale and store it as grayImg2.
- 5: Detect STIPSURF Features (grayImg1, grayImg2) and store the detected points in points1 and points2.
- 6: Extract Feature Descriptors (grayImg1, points1, grayImg2, points2) and store them as features1 and features2.
- 7: Match Features (features1, features2) and store the indices of matching pairs in indexPairs.
- 8: Compute feature_matching_time as (endTime startTime) × 1000.
- 9: return feature_matching_time

IV. RESULTS AND ANALYSIS

The proposed work flow for this research project is presented in this section. Images are gathered from the public image archive. Each image is put through a series of steps after the dataset (LWF data set) is ready to improve the



ISSN:2222-758X e-ISSN: 2789-7362

recognition algorithm. Each image from the dataset is enlarged, and the noise is eliminated by using the Gaussian filter. The edge distortion technique is also used to obtain high-quality frames. Preprocessing methods like the Gaussian filter are frequently used to smooth out images and remove noise from them. Its need for computational resources and productivity in implementation has spurred interest in it. The possibility of Gaussian smoothing is achieved by using the Gaussian operators, which are convolution operatives. It is a 2D convolution operator used for noise reduction and image smoothing Fig. 2 illustrates the sample input image taken from the dataset. Fig. 3 shows the smoothed images by using Gaussian filter.



Figure 2: Input images.

Noise Removed Images



Figure 3: Gaussian filter images.

The preprocessed image is next segmented, with the relevant area of the image being recovered using a ROI. The process of dividing the images into numerous parts or zones that match the various image segmentation is the division of an image into parts or whole objects. In these divisions, a number is given to each pixel of the image. Segmentation is deemed successful when adjacent pixels in different classes do not share values and when the pixels in the similar area have, matching multivariate grayscale values and form a connected region. FAUs are used to extract features related to face behaviors using the STIP. The best method for object detection in image processing that applies feature descriptors is called HOG, or Histogram of Oriented Gradients. Essentially, the single image is divided into extremely small, connected sections that are referred to as cells, and calculate a HOG direction for every cell. Gradient weights are provided to each cell's corresponding angular bin by each pixel. Blocks, the group of adjacent cells, can be thought of as geographical regions. Cells are assembled as blocks as the foundation for histogram categorization and normalization. Since the study goal is to identify face objects inside an image frame, it is necessary to extract the pertinent attributes from segmented



ISSN:2222-758X e-ISSN: 2789-7362

objects. A reliable image-matching algorithm called SURF is employed to effectively detect the items. Feature the two problems that reduced the detecting performance were the selection and image matching. Due to its characteristics, such as scale invariance, translation invariance, illumination invariance, contrast invariance, rotation invariance, and intrinsic settings, SURF is widely employed. Table I illustrates the feature extraction like colour and intensity, edge, and texture features and Fig. 4 shows the face features extracted the image.

| | TA | BLE | Ι | |
|----------|-----------|------|----------|--------|
| Features | Extracted | from | smoothed | images |

| Feature | Value | | | | |
|--------------------------------------|--------------------|--|--|--|--|
| Colour and Intensity Features | | | | | |
| Minimum Intensity | 117.3752 | | | | |
| Maximum Intensity | 238.8726 | | | | |
| Skewness | 0.1295 | | | | |
| Kurtosis | 0.0149 | | | | |
| Energy | 0.181 | | | | |
| Edge Features | | | | | |
| Area | 105.8156 | | | | |
| Perimeter | 0.055 | | | | |
| Density | 587.0447 | | | | |
| Solidity | 0.7312 | | | | |
| Texture Features | | | | | |
| Mean | 63.0414 | | | | |
| Variance | 2.54×10^3 | | | | |
| Standard Deviation | 50.4437 | | | | |
| Entropy | 6.8132 | | | | |
| Homogeneity | 0.922 | | | | |
| Compactness | 0.7235 | | | | |

Images with STIP-SURF Features on Faces



Figure 4: Face feature extracted.

The distribution of several feature sets was shown in Fig. 5, the Histogram of Five Image Features, where different peaks and colours denote various aspects of the data. It contributes significantly to a thorough study and comprehension of the underlying data by offering significant insights into the feature distributions and their complexity.



ISSN:2222-758X e-ISSN: 2789-7362



Figure 5: Histogram of Five Image Features.

A. Cost of computation time with various features

The average matching time per image in the face recognition technique can be used to assess the algorithm's efficiency. This is the total time it takes to match features between every set of images analyse. A timer that starts before the feature matching process and terminates immediately after it is finished is used to measure this duration. The average matching time taken per picture is calculated by dividing the total time required to match features over various pictures to the total number of images. It is represented in Eq.(8).

Average Matching Time per Image =
$$\frac{\text{Total Time across all Image Pairs}}{\text{Number of Image Pairs}}$$
 (8)

Imagine that 100 pairs of images were subjected to feature matching. The average matching time per picture would be determined as follows if the complete feature-matching processes took 0.025 seconds to complete: 0.025 seconds were used on feature matching for every pair of images. 100 image pairs in total. Multiply by 1000 for converting seconds to milliseconds:

Average Matching Time per Image = 0.025 seconds/100 pairs= 0.00025 seconds per pair= 0.00025 seconds per pair $\times 1000$ = 0.25 milliseconds per pair.

Thus, in this case, the average matching time per image pair would be 0.25 milliseconds. Based on several parameters, Table II compares the suggested approach with the characteristics that are currently in existence. Different feature extraction strategies are indicated by references [24] and [25]. Reference [24], for example, has two algorithms: SURF, which has a matching time of 1300 ms/image and detects 86 features, and SIFT which has a matching time of 8140 ms /image and detects 770 features. Several methods, such as HOG, LBP, Gabor, SIFT, SURF, and ASIFT, are listed in Reference 25, along



with their corresponding matching times, and do not identify the features. The suggested technique, called STIP-SURF, is notable for identifying 15 features and having an extremely low matching time of 0.25 ms/image. All results in our

| References | Features Used | Average Matching Time (ms/image) | Detected Features |
|------------------------|---------------|----------------------------------|--------------------------|
| [24] | SIFT | 8140 | 770 |
| | SURF | 1300 | 86 |
| [25] | HOG | 0.897 | - |
| | LBP | 0.633 | - |
| | Gabor | 1.987 | - |
| | SIFT | 0.911 | - |
| | SURF | 0.390 | - |
| | ASIFT | 1.721 | - |
| Proposed Method | STIP-SURF | 0.25 | 15 |

TABLE IICOMPARISON OF EXISTING FEATURES

research are obtained using device specifications for the system as follows: it is powered by an 11th Gen Intel(R) Core (TM) i7-1165G7 processor clocked at 2.80GHz (with a turbo frequency of 2.80 GHz). It has 12.0 GB of installed RAM, with 11.8 GB usable. The system operates on a 64-bit operating system with a x64-based processor

V. CONCLUSION

This research proposes a technique for robust feature extraction that integrates STIP and SURF. There are four steps in this strategy: Authors are gathering the input images in the first stage. The following step involves applying a Gaussian filter to the images for pre-processing. Then, using the Region of Interest (ROI), image segmentation is applied. Facial Action Units (FAUs) are used to extract the characteristics associated with facial behaviours using the Spatial-Temporal Interest Point (STIP). The best method for object recognition in image processing that makes use of feature descriptors is a histogram of oriented gradients (HOG). The last phase uses the SURF feature selection technique. The performance of the recommended approach STIP-SURF (0.25 ms) was superior to the conventional SIFT approach. The paper excels in providing a full representation of face characteristics by holistically combining many feature extraction algorithms. This ensures resilience against a variety of problems, including fluctuations in expression.

Subsequent investigations could concentrate on broadening the scope of the method to incorporate a more diverse array of looks and feelings in addition to examining its suitability in diverse domains such as biometric safety, interaction between humans and computers, and behavioural analysis. Furthermore, combining this method with cutting-edge technology like deep neural networks may open the door to further advance and reliable facial recognition software.

Funding

None

ACKNOWLEDGEMENT

The author would like to thank the reviewers for their valuable contribution in the publication of this paper.

CONFLICTS OF INTEREST

The author declares no conflict of interest



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