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RESEARCH ARTICLE

FACE REGENERATION AND RECOGNITION USING DEEP LEARNING BASED SIFT-HOG ASSISTED GAN MODEL

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Abstract – Face recognition is a vital aspect of computer vision and biometric technology, with applications ranging from security. It is the most critical research direction for identifying criminal activities. The problem of face detection under arbitrary occlusion has become a major concern for social security due to the use of surveillance systems to detect crimes. In complex environments, many researchers use ML-based techniques for face recognition, but there has been no satisfactory recognition accuracy for recognizing faces. In this paper, a novel deep learning-based SH-GAN is proposed for efficient regeneration and recognition of human faces. Initially, the masked face images are gathered from publicly available dataset and these images are pre-processed using bilateral filter to remove the noisy artifacts. Then, the noise-free images are fed in the DL-based U-net for segmenting the masked region to create overlaid images. The segmented mask and overlaid image are given as input to the SIFT integrated HOG based GAN for regenerating the facial images based on the ground truth. Additionally, in SH-GAN the regenerated images are identified as authorized and unauthorized (unknown) faces. The experimental results of the proposed model are assessed using specific metrics like accuracy, F1 score, dice index and jaccard index. From this analysis, the proposed SH-GAN attains the overall accuracy of 98.14% in the recognition of facial images. The proposed SH-GAN framework increases the overall accuracy of 3.99%, 7.94% and 27.17% for Face mesh model, MFNet and Haar Cascade technique respectively.

Keywords *– Face recognition, Masked occlusion, Deep learning, SIFT, HOG Segmentation.*

1. INTRODUCTION

Face recognition is becoming increasingly important in today's digital age, where images and videos are omnipresent across various platforms [1]. In computer vision, one of the most important tasks is to identify and locate human faces in images and videos. [2]. This technique has several uses in a variety of industries, such as biometrics, human-computer interface, security surveillance, and photography. [3]. In today's fast-paced and security-conscious organizational environments, ensuring seamless yet robust access control mechanisms are crucial [4]. Traditional methods of authentication, such as keycards or passwords, often pose security risks and inconveniences [5]. To address these challenges, many organizations are turning to biometric solutions, with face detection emerging as a leading technology for authorization [6].

Face detection, coupled with deep learning, provides a biometric authentication solution that is inherently more secure and resistant to fraud, as it relies on unique facial characteristics that are difficult to replicate [7]. The integration of deep learning-based face detection for authorization in organizations offers several advantages [8]. Firstly, it enhances security by providing a more reliable and tamper-resistant authentication mechanism [9]. Each person has unique facial features, accordingly it's difficult for unauthorized men and women to gain access by using credentials that have been stolen [10]. Secondly, it improves user experience and convenience, as authentication can be performed seamlessly without the need for physical tokens or manual input [11]. This lowers the possibility of human mistake connected with conventional approaches while also saving time [12]. Moreover, deep learning-based face detection systems can be accommodating changing lighting, angles, or facial expressions, among other environmental factors, while still delivering accurate and reliable authentication results [13]. Overall, face detection for authorization represents a cutting-edge solution for organizations seeking to strengthen their security posture while improving operational efficiency [14]. By harnessing the power of deep learning and biometric authentication, organizations can mitigate security risks, streamline access control processes, and safeguard sensitive assets more effectively. In this paper, a novel deep learning-based SH-GAN is proposed for efficient regeneration and recognition of human faces. An overview of this work's primary contribution is provided below,

- Initially, the masked face images are gathered from publicly available dataset and these images are pre-processed using bilateral filter to remove the noisy artifacts.

- Then, the noise-free images are fed in the DL-based U-net for segmenting the masked region to create overlaid images.
- The segmented mask and overlaid image are given as input to the SIFT integrated HOG based GAN for regenerating the facial images based on the ground truth.
- Additionally, in SH-GAN the regenerated images are identified as authorized and unauthorized (unknown) faces.

The remaining tasks have been scheduled as follows: Several recent studies on image retrieval are presented in Section 2. A comprehensive explanation of the proposed face regeneration and recognition method is provided in Section 3. In Section 4, the implications of the proposed system are discussed. Section 5 provides an explanation of the conclusion and future scope.

2. RELATED WORKS

Face recognition remains a complex and compelling area within computer vision and image processing, gaining a lot of interest lately because of its broad applications in many different fields. This section delves into a comprehensive review of recent advancements in face recognition systems, offering insights into the latest research developments in the field.

In 2024, Rostami et al [15] introduced a face detection and recognition model tailored specifically for drones, aiming to improve identification accuracy in scenarios where images are captured from significant heights or distances, limiting the available facial data. Utilizing deep neural networks, the objective was to surpass conventional performance standards in these tasks. Through experimental evaluation against the DroneFace dataset, the proposed framework demonstrated competitive accuracy in both recognition and detection procedures, outperforming existing state-of-the-art models.

In 2023, Hangaragi et al [16] introduced a Face Mesh model tailored for deep neural network-based facial detection and recognition. This model demonstrates robust functionality across diverse scenarios, including variations in background and lighting, owing to its integration with Face Mesh technology. Notably, it effectively handles non-frontal photos of people of all ages, genders, and nationalities. In the experimental analysis, the proposed model achieves an impressive 94.23% accuracy rate in facial recognition tasks.

In 2022 Hariri. W [17] created a DL technique with relevant features and occlusion removal to fix the MFs. For the purpose to extract deep features, the MF region was first eliminated using the pre-trained networks VGG-16, ResNet-50, and AlexNet. Feature mappings were quantized using the Bag-of-Features model and the multi-layer perceptron (MLP) for categorization in the final convolutional layer.

In 2021 Mandal et al [18] demonstrated a deep learning method that can accurately identify persons even when they are wearing face masks. They successfully trained an architecture based on ResNet-50 to recognize masked faces (MFs). This model's results might be simply integrated into the face detection algorithms that are being used to validate security.

In 2020, F. Ding et al [19] suggested a latent component detection (LPD) method to search the MFV and MFI datasets for faces with masks. The LPD model is distinct in that it is trained exclusively on real and fictitious data, acquiring knowledge from start to finish. Rigorous experimentation conducted on MFV, MFI, and artificially masked LFW datasets showcases the LPD model's remarkable performance, surpassing alternative approaches in its ability to generalize effectively across real and fake masked data.

In 2019 Priadana, A., et al, [20] presented a Haar Cascade technique for human face detection. The accuracy rate of 71.48% is clearly exhibited by the method used to identify a human face. The statistical analysis's results indicate that the FP value, which is 33.82%, has a major impact on the machine precision results. The Haar Cascade method can be used to filter images of faces appropriately. The accuracy of the system outcomes is significantly impacted by the FP rate, which statistical results show to be 35.35%.

In 2019 Heusch, G., et al, [21] developed a new database to address the problems that face identification in selfie biometrics is now facing. The recently released database is equipped with several face verification situations and a multitude of baseline checks. Multiple modalities are used to conduct face verification tests in each of the modalities. A convergence of diverse algorithms is then observed, along with the existence of distinct modalities such as RGB, NIR, and Depth maps. The main disadvantages of these approaches include expression, frontal positions, and harsh lighting.

Based on the literature review, current methods exhibit shortcomings in addressing unstrained scenarios, particularly in detecting edges within masked faces. By comparison, the proposed approach reliably recognizes masked faces for every individual by integrating deep learning networks with an edge generating module. Subsequent sections delve into the efficacy of the model in recognizing masked faces amid partial occlusions, showcasing superior performance across varied illuminations and orientations of masked faces. Furthermore, the model demonstrates advancements over prior research endeavours focused on masked face recognition.

3. PROPOSED METHODOLOGY

In this section, a novel deep learning-based SH-GAN approach is presented for efficient regeneration and recognition of human faces. from the available dataset. Masked face images are collected and pre-processed with a bilateral filter to remove noise, then segmented using U-net. The segmented mask and overlaid image are input into a SIFT-HOG-based GAN to regenerate facial images and identify authorized or unauthorized faces. The proposed DL-based SH-GAN approach is displayed in Figure.1.

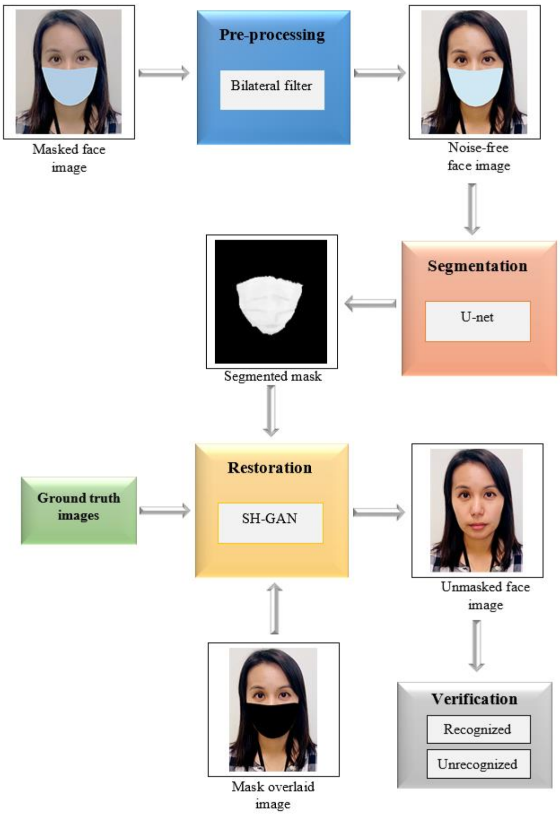

Figure 1. Proposed SH-GAN System

3.1 Data pre-processing

The bilateral filter is a popular method for improving facial image quality from the collected dataset. Cleaner images are the consequence of the bilateral filter's preservation of edge while reducing noise. This is achieved by the filter by combining adjacent pixel values according to their similarity in intensity and spatial proximity. This dual-domain approach ensures that only similar pixels contribute significantly to the denoising process. The bilateral filter at a given pixel location (x, y) can be expressed as follows,

$$B(x,y) = \frac{1}{W_p}\sum_{(i,j)\in\Omega} I(i,j) \times G_{\sigma_s}(d(x,y)) \times G_{\sigma_r}(I(x,y) - I(i,j)) \quad (1)$$

Whereas in the input image, $I(x,y)$ denotes the pixel's intensity at position (x, y), Ω denotes the neighborhood of the pixel (x, y) and W_p is a normalization factor calculated as the sum of the weights applied to each pixel in the neighborhood, ensuring that the output pixel value is properly scaled. $G_{\sigma_r}(I(x,y))$ is the range Gaussian filter, which considers the intensity difference between the current pixel and its neighbors; and $G_{\sigma_s}(d(x,y)$ is the spatial Gaussian filter, which weights the contribution of neighboring pixels based on their spatial distance. Adjusting the values of σ_s and σ_r allows users to control the extent of smoothing and edge preservation, enabling fine-tuning for different denoising requirements.

3.2. Face mask Segmentation

A convolutional neural network architecture called U-Net was created for semantic segmentation tasks; it is well-known for its efficiency in biomedical image segmentation, which includes face mask segmentation operations. A symmetric growing path (decoder) that enables precise localization and a contracting path (encoder) that records context comprises U-Net. There are five convolutional blocks in the down sampling pipeline. Each block has two convolutional layers with filter widths of 3x3, one stride in each direction, and rectifier activation to boost the number of feature mappings from one to 1024. The feature map is reduced in size from 240x240 to 15x15 by utilizing max pooling with step size 2x2, with the exception of the final block. The number of feature maps is decreased by two and their size is increased from 15×15 to 240×240 by the deconvolution layer that appears at the start of each block of the up-sampling pass. By combining the feature map from the encoding pass of each up-sampling block with the deconvolutional feature map, two convolutional layers are eliminated from the total number of feature maps generated. In the down sampling and up sampling passes, all convolutional layers employ zero padding to maintain the output dimension, in contrast to the original U-Net architecture. Finally, after applying a 1×1 convolutional layer, there are just the background and foreground segmentations remaining as feature maps.

(a) (b) (c)

Figure 2. (a) Noise-free image with mask, (b) Segmentation mask and (c) Segmented mask overlaid output

Skip connections are used by U-Net to combine feature maps from the encoder and similar feature maps from the decoder. The segmentation mask is generated by the last layer of U-Net, which classifies pixels in order, as depicted in figure.2. The architecture of U-Net incorporates with its contracting and expanding paths along with skip connections, allows it to effectively capture context and localize features, making it well-suited for tasks like face mask segmentation.

3.3. Face regeneration and recognition

Face regeneration with deep learning-based SIFT-HOG Generative Adversarial Networks (SH-GANs) involves creating realistic facial images. Generator and discriminator neural networks make up a GAN. Realistic images are formed by a generator, whereas actual images are created by a discriminator. During adversarial training, both networks get better until believable outputs are generated. The generator creates a high-resolution image by using input (such as a low-resolution image) or random noise. Mathematically, it can be represented as: $G: z \rightarrow x$, where z is the input segmented mask and x are the generated image. Classifying images as real (from the dataset) or fake (produced by the generator) is the discriminator's goal. The probability that the input image is real is calculated. Mathematically, it can be represented as: $D: x \rightarrow [0,1]$, where *x* is the input image and [0,1] represents the probability of the image being real. The primary objective of the generator is to lessen the possibility that the discriminator would correctly identify its outputs as fake. To maximize the likelihood of accurately identifying both produced and real images, the discriminator operates. This can be formulated using the minimax function:

$$min_G max_D V(G,D) = \mathbb{R}_{x\sim p_{data}(x)}[logD(x)] + \mathbb{R}_{z\sim p_z(z)}[log(1-D(G(z)))] \quad (2)$$

Here, $p_{data}(x)$is the distribution of real images, $p_z(z)$is the distribution of segmented mask, *G*(*z*) is the generated image, and *D*(*x*) is the discriminator's output for real images. In Face Regeneration, the generator learns to map random noise or input data to realistic facial images during training. Furthermore, one of the most crucial stages in the image processing procedure is image matching. The widely used image matching algorithms, SIFT and HOG, have been effective in aligning images. In computer vision, it is used to exclude features from pictures in order to do tasks like matching numerous views of the same item and object recognition. The features that have been retrieved exhibit partial illumination invariance together with scaling and rotation invariance. In order to achieve an adequate technique for imagine adaptation, this research decreases the number of extracting features of SIFT operators and key-point removal operators to a defined number, increasing efficiency and minimizing computing complexity. The item and face are frequently recognized using SIFT features. The primary characteristic of this approach is that it selects the superior key points by leveraging the advantages of a specific strategy. The accomplishment of specific qualities involves four measures.

(a) Scale space extrema detection

The initial phase of the SIFT approach entails detecting stable features, which results in the generation of a scale space where interest points, also called key points, are found. Finding spots of interest in an image that remain constant despite changes in the image's scale allows for their differentiation. This is effectively used by creating a Gaussian pyramid of $G(x, y, \sigma)$ and using an input image to point in local peaks within a Difference-of-Gaussian (DoG) sequence and $I(x, y)$ is,

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (3)$$

Therefore, $G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$ and $*$ is a convolution operator

(b) Removal of key point localization

In this phase, unreliable key points are filtered out since scale-space extreme detection generates a large number of unreliable key point candidates. The optimal ones are chosen by removing the current poor contrast and weak edge localization key spots. Tests of the ratio of major curvatures of each candidate key point eliminate unstable edge key points as a consequence. If the ratio drops below a particular point, the primary argument is maintained.

(c) Orientation assignment

Each major point in this method is given one or more orientations depending at the target locations on the image's local gradient.

(d) Descriptor Calculation

In the end, the local image gradients are calculated around each key point at the specified scale. A 4 x 4 array of histograms is included in every descriptor, and each pixel's neighborhood is calculated 16 times. In a 128-dimensional space, each feature has a vector measurement that is known throughout the key point's neighborhood. Finally, the discriminator learns to distinguish between recognized faces and unrecognized faces. The discriminator gains proficiency in differentiating between faces that have been identified and those that have not, while the generator gains proficiency in creating high-quality facial images through iterative training.

4. RESULTS AND DISCUSSION

In this section, the efficiency of the proposed model is assessed using Matlab-2020b. The masked images of faces for input are gathered from the accessible dataset. Accuracy, F1 score, dice index, and jaccard index have all been used to estimate the analysis of the test samples. The benchmark comprises not only the effectiveness of the suggested model but also the overall accuracy rate, which is thoroughly explained and examined. The results of the proposed model using a sample of masked images from the public dataset are shown in Figure.5, which shows whether the faces in the photographs are identified or incorrect.

Figure 3. Experimental Result of the proposed SH-GAN method

4.1 Performance analysis

This technique is a crucial component of the total face recognition accuracy rate for improving face detection accuracy while reducing the number of false negatives and positives. The experimental results of masked face detection are shown in the table.1. The parameters used for masked face detection are dice index, jaccard index, F1 score, and accuracy which are defined as:

$$accuracy = \frac{tp+tn}{tp+tn+fp+fn}$$

$$F1 = \frac{2(precision*recall)}{precision+recall}$$

$$DI = \frac{2tp}{fp+2tp+fn}$$

$$JI = \frac{tp}{tp+fn+fp}$$

The number of correctly detected mask faces is denoted by tp, the true positive, whereas tn, the true negative, represents the number of correctly recognized non-faces. The number of faces that are misidentified is called false positive (fp) and false negative (fn) respectively.

Table 1. Performance Evaluation of the proposed SH-GAN method**.**

Classes	Accuracy	F1 score	Dice index	Jaccard index
Recognized	98.24	97.51	88.47	87.49
Unrecognized	98.07	97.04	88.14	87.13

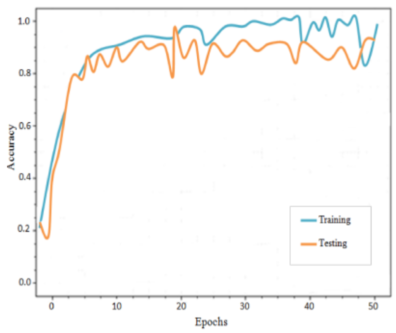

Figure 4. Accuracy curve of the proposed model

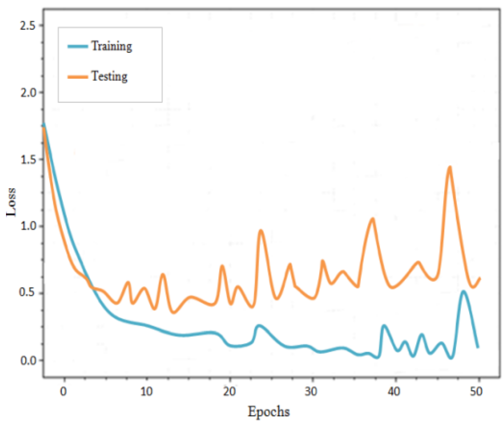

Figure 5. Loss curve of the proposed model

The results of training and testing that the proposed SH-GAN method uses with an organization dataset. The proposed method's epochs are used to evaluate the accuracy of training and testing, and the results are displayed in a figure along with characteristics like accuracy, precision, recall, and F1 score. Additionally, testing and training loss are assessed in order to ascertain the suggested method's epochs, which are displayed in fig. A higher accuracy result could be the result of this lower loss rate.

4.2 Comparative analysis

In this comparison evaluation, the proposed SH-GAN model was demonstrated by comparing its performance with that of present techniques. In a comparative study, the proposed U-Net is compared with the SegNet, Otsu and Grabcut. Table 2 shows the comparison analysis that was done between earlier segmentation techniques.

Table 2. Comparison of traditional segmentation algorithms

Methods	JI	DI
SegNet	86.72	85.61
Otsu	85.21	82.36
Grabcut	91.34	89.01
U-Net	95.64	92.35

Based on the comparison above, compared to segmentation procedures, the suggested U-net produces higher dice and jaccard coefficients. However, in contrast to the U-net, the other networks did not function as well. The ground truth value and the U-net's JI of 0.95 are nearly equal. In contrast to U-net, however, traditional segmentation models do not perform as well. This model achieves an exact dice index of 0.92, which is better than other models. U-Net lowers the false positive rate while improving system performance. The segmentation result illustrates in the figure how the U-net achieves the best results based on JI and DI and operates faster. Figure 6 illustrates how clearly superior U-net is over other segmentation techniques. As a result, the U-net's anticipated results for segmenting the masked regions are quite trustworthy.

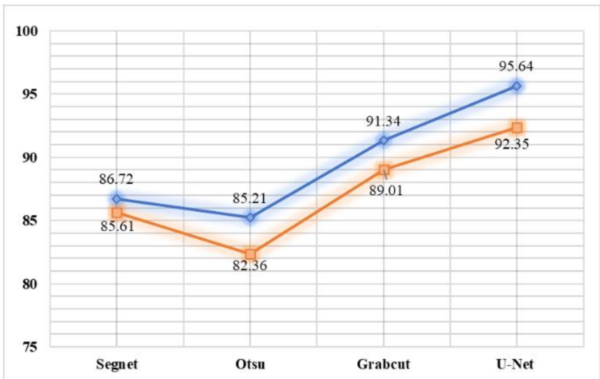

Figure 6. Clearly superior U-net with other segmentation techniques

The proposed approach yields a more efficient result, as demonstrated by an analysis of the performance of current methods. Specificity, sensitivity, and accuracy determine performance. The accuracy rate of 98.15% produced by the proposed approach is higher than that of the current models. The comparison analysis is performed between the proposed model and existing methodologies are presented in table.3.

Table 3. Comparison of classic methods for face recognition

Method	Accuracy	F1 score
SURF	88.24	85.41
SIFT	92.52	91.48
HOG	95.03	94.25
SIFT-HOG	98.15	97.27

Table.3 shows the comparison of traditional face recognition methods with the proposed model. The proposed integration of SIFT-HOG rises the accurateness in face recognition, which performs better than the traditional models. From table.2, the proposed SIFT-HOG method for face recognition attains the accuracy ranges of 98.15%, which comparatively higher than the traditional methods such as SURF, SIFT and HOG.

Table 4. Accuracy evaluation of existing techniques and Proposed model

Author	Method	Accuracy
Hangaragi et al., 2023 [16]	Face mesh model	94.23%
Priadana, A., et al, 2019 [20]	Haar Cascade technique	71.48 %
Wang, and Zhang, 2021[22]	MFNet	90.35%
Proposed model	SH-GAN	98.15%

As shown in Table 4. the testing process comprised measuring the experimental duration of a sample input signal from the gathered dataset in order to verify the correctness of various approaches. Using particular performance criteria, the proper detection accuracy was ensured in order to compare previous methods. The total accuracy for the Face mesh model [16], and Haar Cascade approach [20] an MFNet [22] is increased by 3.99%, 7.94%, and 27.17%, respectively, with the proposed SH-GAN framework. In contrast to the SH-GAN architecture, the current networks have not yet acquired a high degree of accuracy.

5. CONCLUSION

This paper presents a novel SH-GAN is proposed for efficient regeneration and recognition of human faces. Masked face images are pre-processed to remove noise using a bilateral filter. A DL-based U-net segments the masked regions, generating overlaid images. These, along with the segmented mask, are input to an SIFT-integrated HOG-based GAN for regenerating facial images based on ground truth. The SH-GAN identifies regenerated images as authorized or unauthorized faces. The experimental results of the proposed model were assessed using specific metrics like accuracy, F1 score, dice index and jaccard index. From this analysis, the proposed SH-GAN attains the overall accuracy of 98.14% in the recognition of facial images. The proposed SH-GAN framework increases the overall accuracy of 3.99%, 7.94% and 27.17% for Face mesh model, MFNet and Haar Cascade technique respectively. Moreover, the future research directions include integrating emerging technologies like adversarial learning, domain adaptation, and multimodal fusion to improve accuracy, reliability, and fairness in real-world applications.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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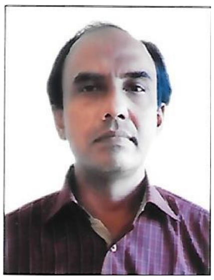

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