Sensors and Materials, Vol. 37, No. 6 (2025) 2521–2532
MYU Tokyo

S & M 4072

Substandard Facial RGB-sensing Pixels with Motion or Gaussian Blur Improved by DeblurGAN Blur Alleviation for Performance Evaluations of VGGNet Identity Classification

Ing-Jr Ding[1*] and Meng-Chuan Hsieh[2]

[1]Department of Electronic Engineering, National United University,
No. 2, Lienda, Miaoli 360302, Taiwan
[2]Department of Electrical Engineering, National Formosa University,
No. 64, Wunhua Rd., Huwei Township, Yunlin County 632, Taiwan

(Received January 22, 2025; accepted June 3, 2025)

Keywords: substandard face image, motion blur, Gaussian blur, DeblurGAN, VGGNet identity classification, recognition accuracy

Identity recognition using the biometrical characteristics of facial pixel information extracted from the person has been undoubtedly an important AI technique issue in security and surveillance applications. In identity recognition using facial RGB-sensing pixels, an undesired situation in which classification performance would be degraded is to encounter a blurred face image composed of substandard facial pixels hybridized with blur noise. The generative deep learning network, deblurring generative adversarial network (DeblurGAN), is well known to be effective in removing blur noise from the blurred image to help object detection. Such object detection applications that are focused on the issue of public safety accomplish person detection by using detection networks (such as YOLO) in fast flows of walking or running pedestrians. DeblurGAN in person detection enhancements mainly improves only the images with motion blur. Another typical type of substandard image that is also frequently used in surveillance applications with the high protection of personal privacy is an image with Gaussian blur. However, studies on exploring the effectiveness of blur alleviation of Gaussian-blurred images by DeblurGAN as well as evaluating the performance of visual geometry group network (VGGNet) identity classification are rare. To tackle this issue, in this study, DeblurGAN is used to alleviate blurring in face images with motion or Gaussian blur, followed by the evaluation of the recognition performances of VGGNet identity classifications using two different types of substandard facial pixels with blurring. A series of performance analysis and comparison experiments are carried out using designed face image datasets composed of sharply focused faces without blur disturbance, motion-blurred and Gaussian-blurred faces with different degrees of blur, and DeblurGAN-restored faces with blur alleviation in the VGGNet identity recognition task. Various important points are constructively identified in this study on the basis of the recognition performance results observed in identity classification experiments, which will provide a fine reference for the development of practical application systems in real life by

*Corresponding author: e-mail: eugen.ding@gmail.com
https://doi.org/10.18494/SAM5562

ISSN 0914-4935
https://myukk.org/

VGGNet identity classification incorporated with the online blur detection and DeblurGAN blur improvement of the blurred face image.

1. Introduction

Identity recognition using biometrical characteristics extracted from the person has undoubtedly been the mainstream approach in related secure applications. Nowadays, popular biometrical-feature-based identity recognition includes mainly face recognition,[1,2] fingerprint recognition,[3] iris recognition, and speaker recognition.[4,5] Among these biometrical identity recognition techniques, face recognition is one of the most popular approaches owing to its rapidness and convenience in applications for using facial characteristics to perform unlock actions immediately.[1,2] Face recognition is viewed as an effective and acceptable way of performing the authentication of a person's identity in applications of "command-enabling face verification" to access the control of doors or unlock handheld devices (e.g., notebooks, smart phones, and panels). On the other hand, face recognition is also frequently used in another type of application, "person-monitoring face identification." The objective of such a face recognition application is mainly to maintain the security of a specific environment by performing surveillance using a fixed camera or a mobile vison-based robot (also known as a guardian robot).[1,2]

In either the command-enabling or person-monitoring face recognition application, the face image captured by a full-color camera to obtain facial RGB-sensing pixels is sometimes substandard as it contains blur; such an image is generally called a "blurred face image". Such substandard face images with the blur phenomenon are undesirable and will lead to the extremely low recognition performance of face recognition. "Motion blur" and "Gaussian blur" are two typical blur conditions that frequently occur in the face images from an RGB camera.[6,7] In face recognition in which a camera at a fixed location is deployed for the surveillance of a specific environment, the captured face image can be blurred and substandard for recognition owing to fast motions of walking or running pedestrians.[6] In smart manufacturing, smart hospital, and smart service field applications, a mobile vison-based robot containing an appropriately deployed image sensor will also encounter undesirable blurring since the image capture action is usually accompanied by a fast or unstable movement of the robot. The face image captured for accessing unlock control in command-enabling face verification applications will also sometimes suffer from unexpected blurring due to the unsteady rocking of the recognized object or the image-sensing camera while performing verification. The blurred face images obtained in the above-mentioned situations are viewed as images with motion blurring. On the other hand, in person-monitoring face identification, which is performed in home, laboratory, or office applications for security purposes, because of the demand for high personal privacy protection, the image processing of Gaussian blur is usually adopted to significantly reduce the level of detail of the captured face image.[4] Such Gaussian-blurred face images can effectively avoid the violation of personal privacy. Focusing on face sensing data hybridized with these two different types of blur, that is, Gaussian and motion blurs, the deblurring generative adversarial network (DeblurGAN) deep learning model belonging to the generative adversarial network (GAN) category is employed for removing the blurring phenomenon from facial images.[8,9] The convolutional neural network (CNN)-based face recognition approach will then be used to evaluate the effectiveness of the removal of motion and Gaussian blurs by DeblurGAN on the basis of recognition accuracy. The CNN of the well-known visual geometry group network (VGGNet) structure is adopted for performance evaluations of classifications of facial images with removed blur in this work.[10,11] The comparison results of face recognition performances investigated in this study will be able to provide a reference to various application areas in which face clues are used for identity recognition.

2. Generative Deep Learning of DeblurGAN for Clean Image Generation by Removing Blur from Camera-captured Substandard Facial Pixels

It is well known that GANs of the generative deep learning type are driving more and more artificial intelligence application developments in various fields.[6] Compared with other nongenerative categories of deep learning frameworks in which only a single computation model is trained for the purpose of classification, detection, or verification, the GAN requires two calculation models, the generator model and the discriminator model (generally called modules D and G, respectively), in the training phase. When completing the training procedure, only module G (trained generator) is employed for object generation in the test phase (online inferring phase). The generative deep learning of the DeblurGAN structure is mainly based on the GAN framework.[8] In the model training of DeblurGAN, adversarial training between the two computation modules D and G is performed, where the goal is to deceive D. That is, it should be difficult for D to clearly distinguish between the restored image with blur removed (i.e., the fake sample obtained through computations by G with blurred image I_B as the input) and the clean image I_C (i.e., the real sample). The training goal of DeblurGAN is to achieve an acceptable model loss value. The total model loss value of DeblurGAN in training is composed of two different types of losses, the perceptual loss (also known as the content loss) of the generator, $Loss_g$, and the adversarial loss (also called the discriminator loss) of the overall DeblurGAN model, $Loss_d$, as follows:[8]

$$Loss = \lambda_1 \cdot Loss_d + \lambda_2 \cdot Loss_g, \tag{1}$$

where $Loss_d$ is a distance, which is also well known as the Wasserstein distance of Wasserstein GAN, between the restored and original clean images derived from the critic network, $Loss_g$ indicates the difference between the VGGNet (in general, VGG-16 or VGG-19 VGG-CNN adopted) convolution feature maps of the restored and original clean images, and λ_1 and λ_2 are two tunable weight parameters. On the other hand, when performing model inferences of the well-trained DeblurGAN in the online test phase, only G of DeblurGAN will be employed to remove the blur appearing in the provided input image. The CNN architecture of the DeblurGAN generator computes a residual correction image, I_R, of the input image with blur, I_B, to recover a clean image with blur alleviations, I_C, which is shown as[8]

$$I_c = I_B + I_R. \tag{2}$$

Such generative deep learning of DeblurGAN is generally used in object detection applications to support the detection performance of the object detection deep learning network, such as the popular YOLO network.[12] In object detection estimates using DeblurGAN, the DeblurGAN generator first carries out blur removal, then sends the blurred image to the object detection network. In addition, the blurred image in object detection applications with DeblurGAN has only motion blur (resulting from the fast walking or running of people, as mentioned previously). For surveillance applications with high privacy protection, an additional process of Gaussian blurring is applied to the captured clean image. To tackle these problems, we will evaluate the DeblurGAN performance in another application field of CNN-based identity classifications where the recognized object will be substandard facial pixels hybridized with either motion or Gaussian blur.

3. Blurred Images of Substandard Facial Pixels with Motion or Gaussian Blur Improved by DeblurGAN for CNN-based Identity Classification

In this section, we will first describe RGB-camera-captured blurred images with substandard facial pixels hybridized with motion or Gaussian blur to be processed by DeblurGAN. Then, to evaluate the effectiveness of removing the two types of blur using DeblurGAN on the basis of the classification accuracy of identity recognition, the CNN-based identity classification approach with a blur detection scheme for the recognition of the input facial pixel data containing the different types of blur will be explained.

3.1 Substandard facial pixels with motion or Gaussian blur

As mentioned, motion blur results from the fast motion of the object to be captured or the unstable shaking of the deployed camera (on the mobile robot) and will be an adverse factor in the constructed application system. For DeblurGAN training, the preparation of a database comprising a series of image pair sets, each of which includes the original clean image and its corresponding blurred image, will be difficult if only a general camera is used for image capture.[8] Although cameras with a high frame rate can be employed to simulate blurred images, the simulation process will be complicated and exhausting. Linear motion kernels have also been designed to effect a proper convolution with the clean image to generate a synthetic image with blur.[6] Other more varied and realistic motion kernels have also been developed, where trajectory vectors from the statistical Markov procedure are further generated to enable the blur kernel to have a smooth form with different degrees of nonlinearity.[8] In this work, the motion-blurred image corresponding to the original clean image (mainly facial pixels from an RGB camera) is constructed using the blur tool of Adobe Photoshop. Such a motion blur tool mainly provides a high-speed-motion trail to the target image where two selected items, the angle and the distance, are inputs to generate a desired motion blur kernel [e.g., 60 image pixels are averaged along the motion direction of −58° with the specific setting of (distance, angle) = (60, −58), see Fig. 1]. To create motion-blurred face images for use in the evaluation of the performance of CNN identity classification with DeblurGAN in this study, two categorizations of images containing motion blur are generated, namely, $I_B(Motion, pixel = 60)$ and $I_B(Motion, pixel = 80)$, denoting light and heavy blur values on movement effects, respectively.

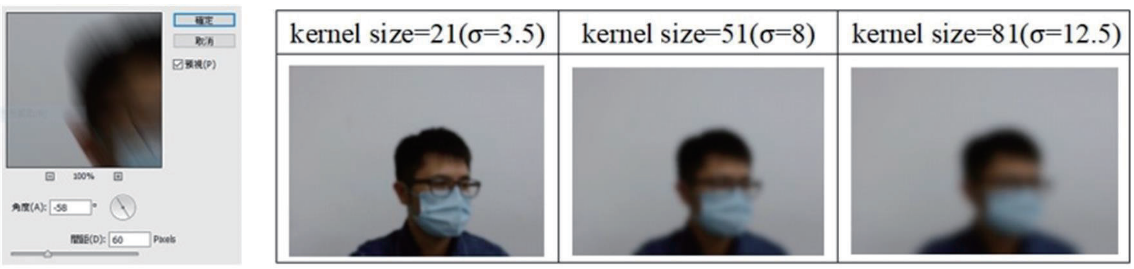
The Gaussian blurring process on images, as mentioned, can be used to reduce the level of detail of an image to provide an unsharp, blurred image, which is much more acceptable in surveillance applications requiring personal privacy protection (blurred facial pixels for identity recognition in this study). After performing Gaussian blurring on an image, the value of each pixel in the image is the weighted average of the surrounding pixel values, and therefore, the processed image contains no apparent boundaries (also known as Gaussian smoothing). The rationale behind Gaussian blurring is to perform convolution calculations between the original clean image and a given low-pass filter governed by the two-dimensional (2D) Gaussian distribution function, which is shown as follows:[7]

$$G(u,v) = \frac{1}{2\pi\sigma^2} e^{-\left(u^2+v^2\right)/2\sigma^2}, \tag{3}$$

where u and v are used to construct a blurred radius r ($r^2 = u^2 + v^2$); σ is the standard deviation, which is viewed as a tunable parameter to control the blur level of the blur kernel in the overall Gaussian blurring procedure. Note that different σ values will generate various corresponding sizes of blur kernels:[7]

$$\sigma = 0.3 \times \left(\left(kernel\ size - 1\right) \times 0.5 - 1\right) + 0.8. \tag{4}$$

Note that in Eq. (4), a large σ value will yield a corresponding large blur kernel size. The clean image convolved with such a Gaussian distribution function with a large blur kernel will correspondingly hybridize with large degrees of blur. Similar to the task of preparing motion-blurred face image datasets, in this work, to construct a database of Gaussian-blurred face images for evaluating the performance of CNN identity classification with DeblurGAN, two



(a) (b)

Fig. 1. (Color online) (a) Motion blur created using the Photoshop tool. (b) Gaussian blur created with different blur levels (different sizes of blur kernels).

types of Gaussian-blurred images are also created, namely, I_B(*Gaussian*, σ = 8) with a blur kernel size of 51 and I_B(*Gaussian*, σ = 12.5) with a blur kernel size of 81, which indicate small and large degrees of smoothness (blur levels) on a Gaussian distribution process, respectively (also see Fig. 1).

3.2 Substandard face images with different degrees of motion or Gaussian blur improved by DeblurGAN for performance evaluations of VGGNet identity recognition

Figure 2 depicts the performance evaluation procedure for substandard face images with different degrees of motion or Gaussian blur (mentioned in the previous section) improved by DeblurGAN. As can be seen in Fig. 2, the designed procedure for blur reduction by DeblurGAN is to use the restored images, I_R(*Motion*) and I_R(*Gaussian*), each of which has two different settings of low and high levels of blur before blur reduction, to perform CNN-based identity classification for further comparison of identity recognition accuracy among the various blurred face images. For further improvement of the recognition accuracy of identity classifications using DeblurGAN-restored face images, the original clean image (the sharp image with no blur), I_C, and the two different types of blurred face images before performing DeblurGAN, I_B(*Motion*) and I_B(*Gaussian*), are also input to the calculation procedure for CNN-based identity classifications.

As illustrated in Fig. 2, a blur detection process was also constructed and incorporated into the overall identity recognition procedure. When using an RGB camera to capture a face image for identity recognition in an online inference test, the blur condition of the obtained image will first be checked by blur detection. The blur detection adopted in this work is one of the focus measure threshold methods.[13] If the captured image is blurred with an estimated focus measure value lower than the threshold set in the system, this face image will be considered to be substandard and will undergo DeblurGAN processing before identity classification. Otherwise,

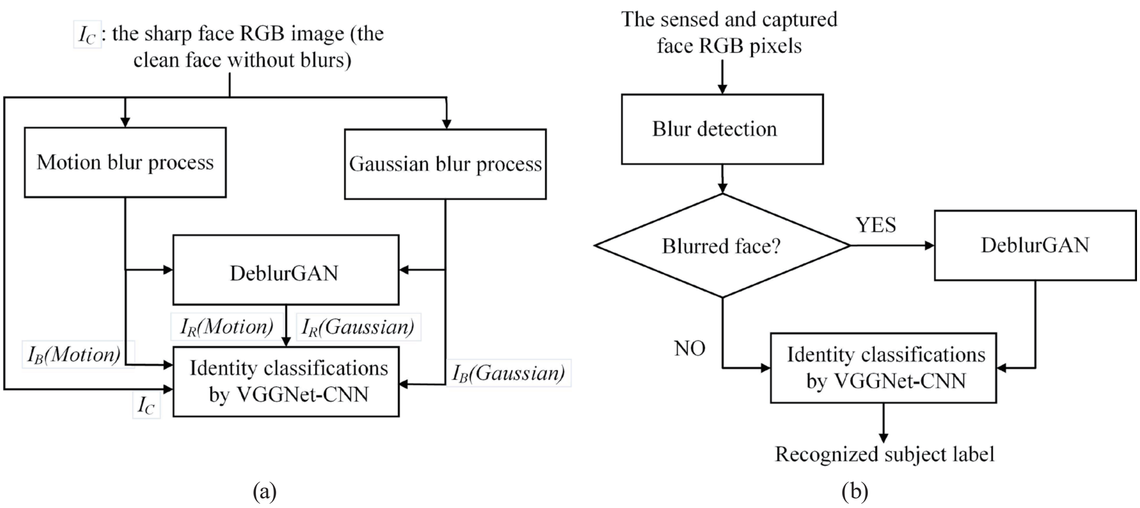


Fig. 2. (a) Flowchart of VGGNet-CNN identity classification performance evaluation of improperly blurred face images with motion or Gaussian blur improved by DeblurGAN. (b) Online test of VGGNet-CNN identity classification with DeblurGAN.

an apparently high focus measure value that exceeds the threshold implies that the acquired face image is sharp and acceptable for identity classification computations where no DeblurGAN processing is required. The focus measure threshold method of detecting the blur of an image is essentially an edge detection approach with an appropriate Laplacian operator. A negative Laplacian kernel with a 5 × 5 matrix is adopted herein for supporting blur detection:

$$Laplacian\,kernel = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & 4 & -1 & -1 \\ -1 & 4 & 4 & 4 & -1 \\ -1 & -1 & 4 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 \end{bmatrix}. \tag{5}$$

This 5 × 5 matrix of the Laplacian kernel [Eq. (5)] will then be convolved with a test RGB image (mainly the grayscale form) to verify blurring. After such convolution computations, the 'variance' of the new pixel values of the transformed image will be viewed as the focus measure to judge whether the test image can be concluded to be blurred (variance ≤ threshold) or nonblurred (variance > threshold). Finally, in identity recognition, the face classification model employed in this work belongs to the VGGNet type (mainly the classical VGG16-CNN), which has a standard model structure containing a series of calculations of the convolution, max-pooling, and fully connected (FC) classification processes.(10,11) The model of the VGG16 convolution neural network contains a total of sixteen calculation layers: thirteen convolution layers comprising five pooling layers for the feature learning and extraction of the input facial RGB-sensing pixel data and three FC layers that are appended at the final stage of the process for classification computations of extracted facial feature parameters of ten indicated subjects. In this work of identity recognition, the acquired facial RGB image from the camera will be further resized to 224 × 224 pixels (VGG16-compatible input type) and finally be classified as one of the ten subjects with the highest classification possibility value among ten neural nodes of the final FC layer (each subject to be classified is specifically denoted by one of the ten configured nodes).

4. Experiments

The experiments of recognition performance evaluations of CNN-based identity classifications using substandard facial pixels with the typical image noise of motion or Gaussian blur improved by the generative deep learning of DeblurGAN are conducted in a laboratory environment. A total of ten subjects (10 males) were recruited to capture face images and establish the required image database. The Kinect camera produced by Microsoft is used in this work for the acquisition of facial RGB pixels images.(14) Note that two different types of image sensors are simultaneously equipped with the Kinect camera: the CMOS RGB image sensor and the depth IR image sensor (also known as the time-of-flight sensor).(15) Only the RGB image sensor is employed in this work. The frame rate of facial image capture is set to 30. A PC with Intel® Xeon® W-2235 CPU, 32G RAM, GeForce GTX3080Ti GPU, and Windows10 (64-bit) is utilized to perform all required calculation tasks in this work. The experiments are divided into two operation phases: the training phase to establish the DeblurGAN model and the recognition performance evaluation phase of CNN-based identity recognition using various types of face images (sharp, motion-blurred, Gaussian-blurred, and DeblurGAN-restored). In the conducted experiment, we mainly observe the increase condition of the recognition accuracy of DeblurGAN-restored images estimated from the motion-blurred or Gaussian-blurred face images with different levels of blur. In the phase of DeblurGAN training, 800 sharp faces are obtained, where each of the ten objects is captured in 80 continuous-time face images. These collected 800 sharp faces are then transformed into the corresponding blurred images using the motion- and Gaussian-blurring processes, as described in Sect. 3.1. The face image database of 800 image pairs, each pair containing a sharp image and the corresponding blurred image, is then used as the training data for establishing the DeblurGAN model, as mentioned in Sect. 2. The DeblurGAN model trained in this work has satisfactory performance indexes of a total training loss of 0.0646 (see Fig. 3), a *PSNR* of 30.0397dB (see Fig. 4), and an SSIM close to 0.889 (see Fig. 5). The well-trained DeblurGAN model with the various fine performance index curves

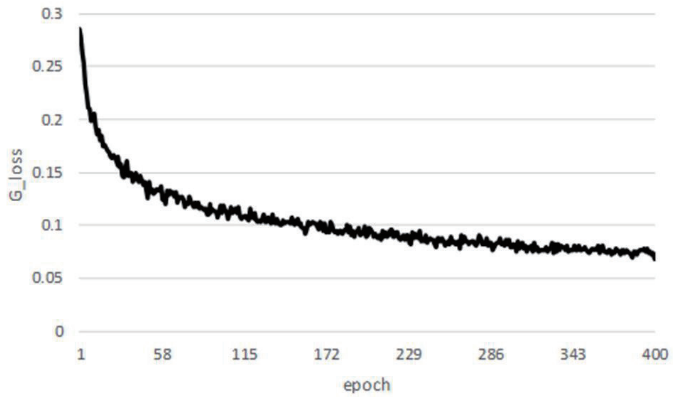


Fig. 3. Training loss in the training phase of the DeblurGAN model.

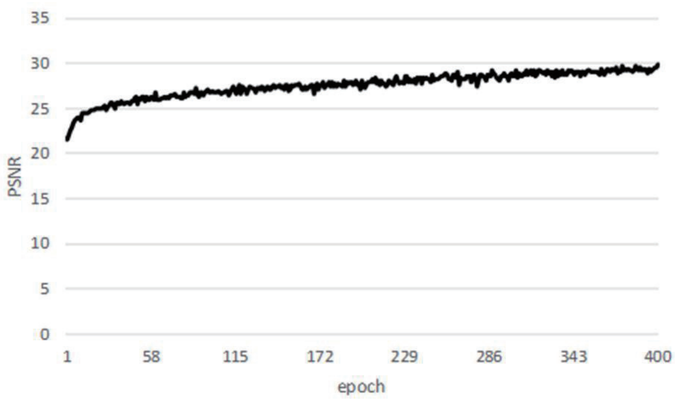


Fig. 4. *PSNR* in the training phase of the DeblurGAN model.

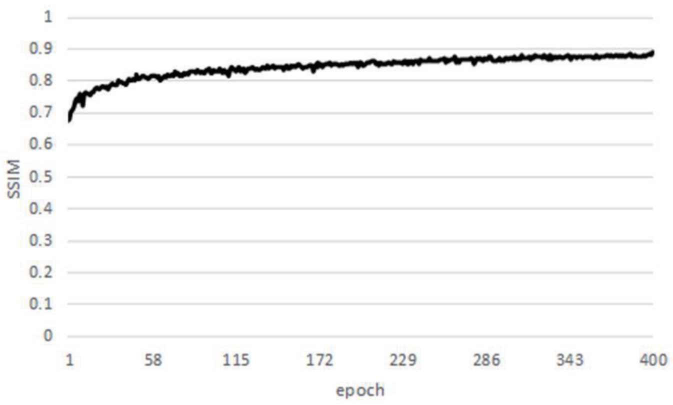


Fig. 5. *SSIM* in the training phase of the DeblurGAN model.

shown in Figs. 3–5 is then applied to improve substandard face images with motion or Gaussian blur in the phase of CNN-based identity classification.

The same ten subjects as recruited for the DeblurGAN training procedure are requested again to record face image data in the CNN-based identity classification phase for evaluating the effectiveness of DeblurGAN in improving the quality of the blurred face image. The dataset of sharp faces without blur disturbances contains 10000 clean face images, 1000 images captured from each of the ten subjects (i.e., the set of I_C). These 10000 sharp face images then undergo two blurring processes, motion blurring and Gaussian blurring, to transform them into blurred face image sets. Two motion-blurred face image datasets are established: one set of 10000 motion-blurred images with low blur levels [i.e., the set of $I_B(Motion, pixel = 60)$, 60 image pixels averaged along the same motion direction, as mentioned in Sect. 3.1] and another set of 10000 motion-blurred images with high blur levels [i.e., the set of $I_B(Motion, pixel = 80)$, 80 image pixels averaged]. For Gaussian blurring, similar to the motion-blurring task, two Gaussian-blurred face image datasets are created: a dataset containing 10000 Gaussian-blurred images with small amounts of blur [i.e., the set of $I_B(Gaussian, \sigma = 8)$, the small blur kernel size of 51, as mentioned in Sect. 3.1] and a dataset composed of 10000 Gaussian-blurred images with large amounts of blur [i.e., the set of $I_B(Gaussian, \sigma = 12.5)$ with a large blur kernel size of 81]. These four blurred face image datasets, $I_B(Motion, pixel = 60)$, $I_B(Motion, pixel = 80)$, $I_B(Gaussian, \sigma = 8)$, and $I_B(Gaussian, \sigma = 12.5)$, are then subjected to blur-removal operations by the trained DeblurGAN model. The model performances are indicated in Figs. 3–5. These various face image datasets containing sharp, blurred or recovery images are finally sent to the CNN identity classification process for evaluating and comparing recognition accuracies (see Fig. 2 in Sect. 3.2).

Tables 1–4 show the recognition performances of VGGNet identity classifications (mainly using the VGG16-CNN framework) using the created face image datasets. Note that the set of sharp face images without blur results in the highest recognition accuracy of VGG16-CNN identity classifications, achieving 95.8%. In the VGG16-CNN identity classifications with the support of image blur alleviations by DeblurGAN, the effects of DeblurGAN to restore the

Table 1
Recognition performances of two face image datasets—motion-blurred (low levels) images and their DeblurGAN-restored images—in the VGGNet (VGG16-CNN) identity classification task (*PSNR* index provided only for the reference of motion-blurred images recovered by DeblurGAN).

	$I_B(Motion, pixel = 60)$	$I_R(Motion, pixel = 60)$
Recognition accuracy	92.35	94.95
PSNR	24.49	23.37

Baseline for recognition performance comparisons (I_C): 95.8%

Table 2
Recognition performances of two face image datasets—motion-blurred (high levels) images and their DeblurGAN-restored images—in the VGGNet (VGG16-CNN) identity classification task (PSNR index provided only for the reference of motion-blurred images recovered by DeblurGAN).

	$I_B(Motion, pixel = 80)$	$I_R(Motion, pixel = 80)$
Recognition accuracy (%)	90.92	93.98
PSNR (dB)	23.22	26.65

Baseline for recognition performance comparisons (I_C): 95.8%

Table 3
Recognition performances of two face image datasets—Gaussian-blurred (low levels) images and their DeblurGAN-restored images—in the VGGNet (VGG16-CNN) identity classification task (PSNR index provided only for the reference of Gaussian-blurred images recovered by DeblurGAN).

	$I_B(Gaussian, \sigma = 8)$	$I_R(Gaussian, \sigma = 8)$
Recognition accuracy (%)	91.99	94
PSNR (dB)	26.93	29.11

Baseline for recognition performance comparisons (I_C): 95.8%

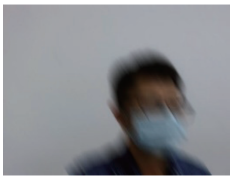
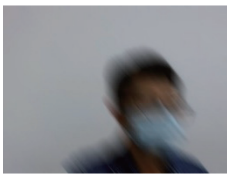
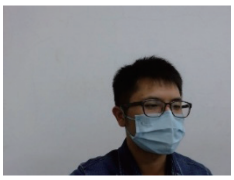
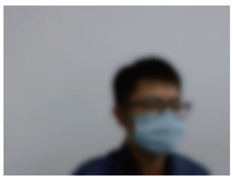
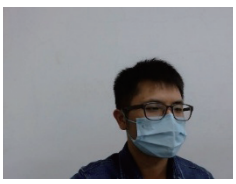
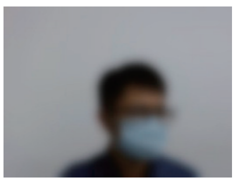
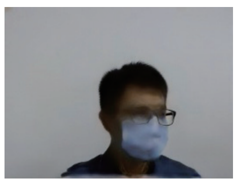
Table 4
Recognition performances of two face image datasets—Gaussian-blurred (high levels) images and their DeblurGAN-restored images—in the VGGNet (VGG16-CNN) identity classification task (PSNR index provided only for the reference of Gaussian-blurred images recovered by DeblurGAN).

	$I_B(Gaussian, \sigma = 12.5)$	$I_R(Gaussian, \sigma = 12.5)$
Recognition accuracy (%)	62.33	91.86
PSNR (dB)	21.09	27

Baseline for recognition performance comparisons (I_C): 95.8%

blurred faces in the aspect of recognition rate improvements are significant: an increase of 2.6% for the low motion-blurred image set of $I_B(Motion, pixel = 60)$, an improvement of 3.06% for the high motion-blurred image set of $I_B(Motion, pixel = 80)$, an increase of 2.01% for the low Gaussian-blurred image set of $I_B(Gaussian, \sigma = 8)$, and an increase of 29.53% for the high Gaussian-blurred image set of $I_B(Gaussian, \sigma = 12.5)$. From these performance results of VGG16-CNN identity recognition in Tables 1–4, the following points can be made:(1) DeblurGAN effects the greatest improvement for face images with large amounts of Gaussian blur;(2) a substandard face image with a high degree of Gaussian blurring results in extremely poor CNN identity recognition, but with the assistance of DeblurGAN, the restored face image or the recognition result becomes more reliable;(3) DeblurGAN shows a higher recognition performance increase for both Gaussian- and motion-blurred face images with large amounts of blur;[4] in online test applications of VGG16-CNN identity recognition with blurred face images made by Gaussian blurring (such as surveillance requiring high privacy protection, as previously mentioned), the threshold of the focus measure (when using the Laplacian kernel convolution approach for blur detection) is recommended to be set at a relatively large value so that most of the Gaussian-blurred images that are unsuited to VGG16-CNN identity recognition can be improved, and for applications of identity recognition frequently accompanied by motion-blurred face images, the focus measure threshold can be set to a relatively small value where only images with extremely severe motion blurring undergo blur-removal calculations of DeblurGAN before identity recognition (also see Fig. 2 in Sect. 3.2). Finally, image recovery conditions of all Gaussian- and motion-blurred face images with different degrees of blur created after the DeblurGAN process are also provided in Table 5. It is clearly observed in Table 5 that DeblurGAN can have a significant effect on the recovery of blurred face images, especially those with only a small degree of blur [the low motion-blurred image set of I_B(*Motion*, *pixel* = 60) and the low Gaussian-blurred image set of I_B(*Gaussian*, σ = 8)].

Table 5
(Color online) Recovery conditions of Gaussian- and motion-blurred face images with different degrees of blur after DeblurGAN.

	Clean face	Blurred face	Restored face
Low levels of motion blurring (*pixel* = 60)			
High levels of motion blurring (*pixel* = 80)			
Low levels of Gaussian blurring (σ = 8)			
High levels of Gaussian blurring (σ = 12.5)			

5. Conclusions

In this work, the generative deep learning of DeblurGAN was used to alleviate the blur of blurred face images created by motion or Gaussian blurring for the evaluation of the recognition accuracy of VGGNet identity classifications using substandard facial pixels with blur noise. Various face image datasets containing different degrees of motion or Gaussian blur were designed and established for performance comparisons of the VGG16-CNN identity recognition task. A series of performance analysis and comparisons were carried out on the observed experiment results of identity recognition using the sharp, motion- or Gaussian-blurred, and DeblurGAN-restored face images. Various points were revealed by this study, which will provide a reference for the development of practical application systems in real life using VGGNet identity classifications integrated with the online blur detection and DeblurGAN processing of blurred face images.

References

1 L. Li, X. Mu, S. Li and H. Peng: IEEE Access **8** (2020) 139110. https://doi.org/10.1109/ACCESS.2020.3011028
2 G. Sumanth, K. V. Kanimozhi, and Murugesan: Proc. 2022 IEEE 14th Int. Conf. Mathematics, Actuarial Science, Computer Science and Statistics (IEEE, 2022) 1–4. https://doi.org/10.1109/MACS56771.2022.10023060
3 S. A. Grosz and A. K. Jain: IEEE T-BIOM **6** (2024) 30. https://doi.org/10.1109/TBIOM.2023.3317303
4 J. Wei, Y. Wang, H. Huang, R. He, Z. Sun, and X. Gao: IEEE Trans. Inf. Forensics Secur. **18** (2023) 57. https://doi.org/10.1109/TIFS.2022.3221897
5 M. M. Kabir, M. F. Mridha, J. Shin, I. Jahan, and A. Q. Ohi: IEEE Access **9** (2021) 79236. https://doi.org/10.1109/ACCESS.2021.3084299.
6 T. Brooks and J. T. Barron: Proc. 2019 IEEE/CVF Conf. Computer Vision and Pattern Recognition (IEEE, 2019) 6833–6841. https://doi.org/10.1109/CVPR.2019.00700
7 P. Singhal, A. Verma, and A. Garg: Proc. 2017 4th Int. Conf. Advanced Computing and Communication Systems (IEEE, 2017) 1–6. https://doi.org/10.1109/ICACCS.2017.8014612
8 O. Kupyn, V. Budzan, M. Mykhailych, D. Mishkin, and J. Matas: Proc. 2018 IEEE/CVF Conf. Computer Vision and Pattern Recognition (IEEE, 2018) 8183–8192. https://doi.org/10.1109/CVPR.2018.00854
9 J. Gui, Z. Sun, Y. Wen, D. Tao, and J. Ye: IEEE Trans. Knowl. Data Eng. **35** (2023) 4. https://doi.org/10.1109/TKDE.2021.3130191
10 Y. Zhiqi: Proc. 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conf. (IEEE, 2021) 2530–2533. https://doi.org/10.1109/IAEAC50856.2021.9390856
11 U. Muhammad, W. Wang, S. P. Chattha, and S. Ali: Proc. 2018 24th Int. Conf. Pattern Recognition (IEEE, 2018) 1622–1627. https://doi.org/10.1109/ICPR.2018.8545591
12 J. Redmon, S. Divvala, R. Girshick, and A. Farhadi: Proc. 2016 IEEE Conf. Computer Vision and Pattern Recognition (IEEE, 2016) 779–788. https://doi.org/10.1109/CVPR.2016.91
13 A. N. Almustofa, Y. Nugraha, A. Sulasikin, I. D. Bhaswara, and J. I. Kanggrawan: Proc. 2022 10th Int. Conf. Information and Communication Technology (IEEE, 2022) 275–280. https://doi.org/10.1109/ICoICT55009.2022.9914850
14 I. J. Ding and N. W. Zheng: Sens. Mater. **32** (2020) 2329. https://doi.org/10.18494/SAM.2020.2881
15 I. J. Ding and N. W. Zheng: Sens. Mater. **34** (2022) 203. https://doi.org/10.18494/SAM3557