

Image Restoration for Improving Facial Adversarial Robustness

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Abstract

With rapid advances and significant accomplishments in numerous applications, Machine Learning (ML) models in specific Deep Learning (DL) models are being used in many safety-critical contexts. However, these models have recently been discovered to be susceptible to adversarial attacks, which are well-crafted input images. Adversarial attacks are invisible to humans but are quite effective at tricking DL models during testing and deployment. We focus on a defense method based on deep image restoration networks that significantly improves facial adversarial robustness of various image-classification models. Adversarial images are created using Private Fast Gradient Sign Method (P-FGSM), StyleGAN and Fast Landmark Manipulation (FLM) methods. The adversarial images are then enhanced using deep image restoration networks to bring back them into the original space. The encoded weighted local magnitude patterns (WLMP) are extracted and provided to different types of classifiers to detect facial adversarial images from the clean images.

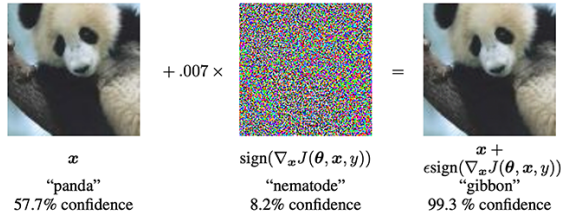


Fig. 1 Shows the adversarial image generation by FGSM.

The effectiveness of the proposed method has been demonstrated on two real-world datasets and experimental outcomes show that it significantly improves classification accuracy on all evaluating classifiers. It improves the highest classification accuracy from **98.75%** to **99.00%** on P-FGSM attacks, from **77.94%** to **85.25%** on adversarial attacks generated by StyleGAN and from **65.52%** to **69.50%** for FLM attacks.

Keywords: Machine Learning, Facial Images, Image Super Resolution, Adversarial Attacks, Adversarial Attacks Detection, Image Restoration.

1 Introduction

ML models in particularly DL models have made significant advancements and achieved remarkable results in several applications such as object detection [1], image classification [2], speech recognition [3], natural language processing [4], sentiment analysis [5] and multi-modal [6]. As a result, DL is increasingly being utilized in safety-critical domains. In spite of these advances and their success, perceptual systems of humans and machines are still vulnerable to certain malicious image attacks known as adversarial attacks [7, 8]. Adversarial attacks are carefully crafted by mixing small perturbations to inputs for misclassification by the classifier with high confidence. Multiple techniques have been introduced for generating adversarial attacks [8–14]. Fig. 1 shows an example for generating FGSM attack [8]. For instance, 2 depicts examples of original facial images and corresponding adversarial images generated by StyleGAN[15], FLM [16] and P-FGSM [14], respectively. Adversarial images are specifically designed to closely resemble the original images, leading to misclassification by the classifier. Thus, the existence of such adversarial attacks shows frailties in ML models.

The sensitivity of DL models to adversarial images can pose significant challenges and raise concerns, particularly in security and safety-critical applications. For instance, when adversarial attack is applied to the DL model, which is part of an autonomous vehicle, the model reads the present scene differently and a tragic accident may result. Despite several defense techniques have been proposed to avoid misclassification by the classifier [17–20], many



Fig. 2 Examples of original image, StyleGAN attack, FLM attack, and P-FGSM attack in column-wise.

of these defenses are not effective against various and more powerful adversarial attacks [7, 21]. Thus, improving adversarial robustness is essential for mitigating misclassification by the classifier.

Detection-based defense methods have recently gained significant attention as potential alternative solutions to counter adversarial attacks. In [22], ML models are enhanced with an additional class dedicated to classifying adversarial images. Metzen et al. [23] proposed a method to train neural networks (NN) specifically for recognizing and classifying adversarial attacks. Another technique [24] involves training an extra classifier to identify the presence of adversarial attacks. In [25], the input image dimensions are reduced and fed into a classifier, which is then trained using a small dataset and a fully-connected NN. Furthermore, in [26], a cascaded classifier is created, with each individual classifier implemented as a linear SVM on the Principal Component Analysis (PCA) for effective detection of adversarial examples among the original images. However, many defense methods face challenges when applied to real-world datasets, resulting in lower accuracy. As adversarial attacks can be highly sophisticated and adaptive, it becomes difficult to develop robust defense mechanisms that can consistently detect and mitigate these attacks.

In our work, we introduce a novel defense method that utilizes deep image restoration networks to enhance the robustness of facial recognition systems against adversarial attacks. This defense mechanism is an extension of our previous work [27]. First, we generate facial adversarial attacks by employing StyleGAN [15], FLM [16] and P-FGSM [14] techniques. Next, the crafted

adversarial images are enhanced using deep image restoration networks to bring back into the original space. We then extract the encoded WLMP features from the input image and utilize them as input for various classifiers, including different types of SVMs, RF, and k-NN. These classifiers are used to evaluate the performance of our proposed defense method. Through comprehensive experiments, we demonstrate the effectiveness of our defense approach in discriminating adversarial images from real ones. The experimental results show that our defense method significantly improves the performance of various classification models.

The key contributions of our paper can be summarized as follows:

- **Defense Method:** We propose a novel defense method based on deep image restoration networks to enhance the robustness of facial recognition systems against adversarial attacks. This defense mechanism effectively mitigates the impact of adversarial manipulations on facial images.
- **Adversarial Attacks Generation:** We craft facial adversarial attacks using techniques such as StyleGAN, FLM, and P-FGSM. These attack methods allow us to generate adversarial images that can deceive facial recognition systems.
- **Deep Image Restoration:** We utilize deep image restoration networks to restore the crafted adversarial images back to their original space. By leveraging advanced deep learning techniques, our networks effectively reverse the effects of adversarial attacks, ensuring that the images resemble their original counterparts.
- **Feature Extraction and Classification:** We extract encoded WLMP features from the input images and utilize them as input for various classifiers, including SVM, RF, and k-NN. This allows us to evaluate the performance of our defense method on different classifiers.
- **Experimental Evaluation:** We demonstrate the effectiveness of our proposed defense method through extensive experiments on real-world datasets. The experimental results show that our defense mechanism effectively discriminates adversarial images from real ones and significantly improves the performance of various classification models.

The remaining sections of the paper are organized as follows: Section II discusses related works to adversarial attacks and defense methods. Our proposed method is detailed in Section III. We present experimental results in Section IV and conclude the paper in Section V.

2 Literature Survey

In the field of face manipulation and detection, numerous approaches have been proposed over the years. However, it is observed that not all of these approaches for creating fake images or image attacks, as well as their detection methods, are suitable for effectively detecting facial adversarial attacks. We focus on presenting only state-of-the-art works that specifically address the generation

of adversarial images and its detection in order to provide a comprehensive understanding of the current advancements in the field and highlight the most relevant and effective approaches for detecting facial adversarial attacks.

2.1 Adversarial Attacks Generation

With the adversary's knowledge about the target classifier, the methods used to generate adversarial examples can be broadly classified into three categories: white-box, black-box, and semi white-box adversarial attacks.

In white-box attacks, the attackers have complete knowledge of the parameters, architecture, and gradients of the target classifier. This allows them to intentionally craft adversarial examples using all the available information. The initial works for generating adversarial examples on the MNIST dataset were proposed by Biggio et al. [28]. They targeted conventional machine learning classifiers like SVM and a fully-connected three-layer neural network. The first work to attack Deep Neural Networks (DNN) was presented by Szegedy et al. [7]. They formulated an optimized approach for generating minimal distorted adversarial examples. Goodfellow et al. [8] proposed a one-step method called the Fast Gradient Sign Method (FGSM) for fast generation of adversarial samples. Kurakin et al. [11] extended the FGSM to a basic iterative approach. In this approach, the FGSM is applied iteratively to generate adversarial examples. Moosavi et al. [29] examined the decision boundary of a classifier around a specific data point, aiming to find a path for that data point which leads to a different prediction by the classifier. This method, known as DeepFool, identifies the minimum perturbation required to cross the decision boundary. In [30], the authors proposed Jacobian-based Saliency Map Attack (JSMA). It iteratively manipulates the pixels of an image in a greedy manner to affect output of the model. In order to decide which pixels were most crucial for altering and creating adversarial images, it took into account the gradients of the model's output relative to the input.

When conducting black-box attacks, the attacker is unaware of the classifier's settings and training data. Only the model's input data and the accompanying outputs may be seen by the attacker. Adversaries can find flaws in the model and use them to launch attacks based on the input-output connection. The first successful method for taking down DNN classifiers in a black-box environment was developed by Papernot et al. [13]. The classifier's parameters or training dataset are unknown to the attacker. An optimization-based approach is proposed for black-box attacks in [31]. The attacker assumes no access to the prediction confidence of the classifier. Ilyas et al. [32] proposed a method to estimate gradient information and leveraged to generate adversarial examples in a black-box setting. A genetic algorithm to generate adversarial examples utilized by Alzantot et al. [33]. It evolves the input data to find perturbations that can deceive the target model.

In semi white-box attacks, a generative model is first trained in a white-box manner to create adversarial samples. Once the generative model is trained, the attacker can use it to generate adversarial samples in a black-box manner.

This approach allows the attacker to leverage the power of generative models to craft adversarial examples. The work by Xiao et al. [34] introduced a semi white-box adversarial attack model. The authors trained a Generative Adversarial Network (GAN) [35] to target a specific model. Adversarial samples are then generated directly from the trained generative model. Deng et al. [36] proposed the Additive Angular Margin Loss (ArcFace), a Convolutional Neural Network (CNN)-based method that maximizes face image classification accuracy. Advfaces [37] utilized GAN to craft adversarial face images with minimal perturbations in salient facial regions. SemanticAdv [38] proposed a method based on attribute-conditioned image editing to generate adversarial samples that appear semantically realistic. For a detailed review on adversarial attacks and defenses, Xu et al. [39] provide an extensive overview of various techniques and approaches in the field.

2.2 Adversarial Attacks Detection

One of the commonly used strategies to protect classifiers from misclassification is to detect adversarial attacks from the original inputs. Rather than directly predicting the class label for the input, these methods first determine whether the input is an original or an adversarial example. If the classifier detects that the input is adversarial, it refrains from making a class prediction. This approach aims to effectively distinguish between adversarial images and original ones, thereby reducing the chances of misclassification by the classifier. Adversarial attack detection algorithms play a crucial role in this process.

Many approaches have been proposed to distinguish between adversarial examples and original inputs. Here are some notable methods. Grosse et al. [22] proposed an auxiliary model to differentiate adversarial examples from original inputs. Gong et al. [24] trained a binary classifier to separate adversarial examples and then trained the classifier on the detected original examples. Metzen et al. [23] introduced an auxiliary neural network-based method for adversarial example detection. Hendrycks et al. [40] proposed a statistical method based on PCA, where original images tend to have higher weights on early principal components, while adversarial images have larger weights on latter principal components. Massoli et al. [41] presented a detection method that combines a deep learning model with k-NN classifier. Agarwal et al. [42] developed a method based on intensity values of pixels and PCA as features for detecting universal perturbations, using SVM classifier. Xie et al. [43] improved adversarial robustness by incorporating feature denoising blocks in neural networks. Mustafa et al. [44] proposed a defense method based on image super-resolution to enhance adversarial example detection. Recently, Sadu et al. [27] proposed a defense method that generates adversarial attacks using P-FGSM and provides the extracted features to different types of SVM classifiers for detection.

We propose a new defense method against facial adversarial attacks for improving adversarial robustness, which is based on deep restoration networks and feature denoising. Image restoration enhances adversarial images and improve their similarity to original images. Our method is different from

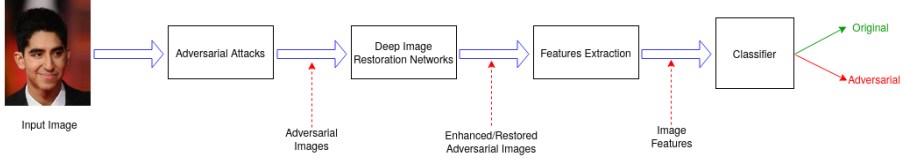


Fig. 3 The overall procedure of the proposed defense method.

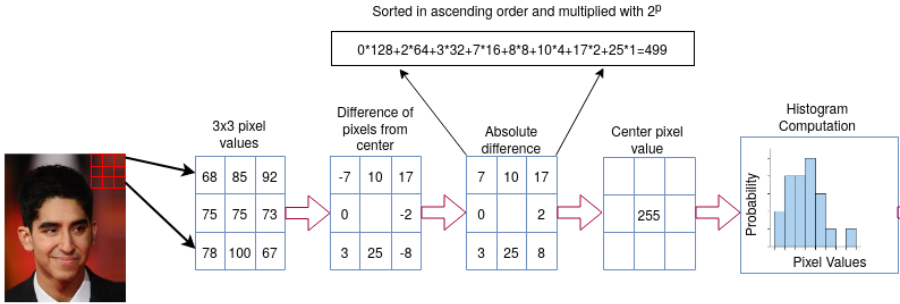


Fig. 4 The procedure for extraction of WLMP features

the state-of-the-art methods. First, adversarial images are generated based on P-FGSM, StyleGAN and FLM. These adversarial images are designed to protect the image scenes and effectively mislead classifiers into high-confidence misclassifications. To restore the adversarial images to their original form, we employ techniques such as image super resolution and feature denoising. This process aims to bring the adversarial images closer to the original images, thereby improving their robustness against adversarial attacks. The performance is evaluated on various types of SVM classifiers, RF and k-NN. The results show that our defense method significantly improves the adversarial robustness.

3 Proposed Method

We detail the procedure of the proposed defense method in this section and summarized as follows: 1) Adversarial images are generated based on P-FGSM, StyleGAN and FLM, 2) Image restoration is used to enhance adversarial images, 3) WLMP encoded features are extracted from the input facial images, 4) Trained and tested on different types of classifiers for demonstrating the detection performance. Workflow of the proposed defense method is as shown in Fig. 3.

3.1 Adversarial Attacks

The adversarial face images are generated based on attacks P-FGSM[14], StyleGAN [15] and FLM [16]. The attacks are briefly discussed as follows:

3.1.1 P-FGSM[14]

Let an image I and \hat{y}_i is its true class label of one of the scene types shown in I . Let a set of N scene classes of an image be $y_1, \dots, y_i, \dots, y_N$. Then, a multiclass classifier M is applied to image I to generate one-hot vector y of size N -dimensional, is given by:

$$y = M(I) \quad (1)$$

where $y = \{y_1, \dots, y_i, \dots, y_N\}$ is obtained from a selection on the probability vector $p = \{p_1, \dots, p_i, \dots, p_N\}$. Here, p_i is the probability of the scene class y_i of the image I .

$$p_i = p(y_i/I) \quad (2)$$

A transformation T is defined such that $\hat{I} = T(I)$ to induce M to classify the image I with a different scene label:

$$y \neq M(\hat{I}) \quad (3)$$

The transformation T aims to apply a minimal distortion to the image I in order to make it unnoticeable. Additionally, T should be designed to ensure that the true class label \hat{y}_i cannot be inferred from the predicted class $M(\hat{I})$ or from the probability distribution of the predicted classes. Thus, T is defined as follows:

$$\hat{I} = T(I) = I + \delta_I^* \quad (4)$$

where δ_I^* is an adversarial perturbation. It is generated as follows:

$$\delta_I^* = \arg_{\delta_I} \max J_M(\theta, I + \delta_I, y) \quad (5)$$

In the P-FGSM, adversarial images are generated by adaptively targeting a class label \hat{y} based on the classification probability vector p obtained from the classifier. To achieve a high misclassification rate, P-FGSM takes advantage of the fact that the true class labels are often among the class labels with the highest collective probabilities. It selects the target class label \hat{y} from a subset of classes based on a specified threshold $\sigma \in [0, 1]$. To determine the target class label \hat{y} , the elements of the probability vector p are sorted in non-increasing order and denoted as $p' = \{p'_1, \dots, p'_N\}$. The cumulative probability of each class label is calculated by summing the probabilities up to that class label.

$$\hat{y} = R(\{y_j : \sum_{i=1}^{j-1} p'_i > \sigma\}), \quad (6)$$

where R is a function that selects a class label arbitrarily from the input set and σ is a threshold to control the number of classes to select \hat{y} : a higher σ

denotes a smaller subset of target classes. P-FGSM generates the adversarial image $\hat{I} = \hat{I}_N$ iteratively, starting from $\hat{I}_0 = I$, as

$$\hat{I} = \hat{I}_{N-1} - \epsilon \times \text{sign}(\Delta_I J_M(\theta, \hat{I}_{N-1}, \hat{y})), \quad (7)$$

by increasing the prediction probability of class label \hat{y} until a desired classification probability or a threshold on maximum number of iterations is reached.

3.1.2 FLM [16]

FLM utilizes the gradient of the model's prediction with respect to the facial landmarks to determine the displacement field. By computing the gradient, FLM obtains the direction in which each landmark should be moved to generate the adversarial landmark locations. This iterative process aims to find the optimal displacement field f that manipulates the facial landmarks to create the desired adversarial effect. The adversarial landmark location x_i^{adv} can be obtained by adding the displacement vector f_i to the original landmark x_i .

Let ϕ be a function for landmarks detection that maps the input face image into a set of n 2D landmark locations $X = \{x_1, x_2, \dots, x_n\}$, where $x_i = (u_i, v_i)$. Let $x_i^{adv} = (u_i^{adv}, v_i^{adv})$ is the obtained after transformation of x_i , and defines the i -th landmark location of the corresponding adversarial face image x^{adv} . FLM defines flow or displacement field f per landmark to produce the location of the corresponding adversarial landmarks for manipulating the input face image based on X . It optimizes the spatial displacement vector $f_i = (\Delta u_i, \Delta v_i)$ for the i -th landmark $x_i^{adv} = (u_i^{adv}, v_i^{adv})$. It uses the direction of the gradient of the prediction same as FGSM [8] to find the landmark displacement field f in an iterative manner. The adversarial landmark x_i^{adv} can be obtained from the original landmark x_i and the displacement vector f_i as:

$$x_i^{adv} = x_i + f_i, (u_i^{adv}, v_i^{adv}) = (u_i + \Delta u_i, v_i + \Delta v_i) \quad (8)$$

3.2 Feature Denoising and Deep Image Restoration Networks

An effective denoising technique can help to mitigate the effect of added perturbations if not eliminated because all adversarial attacks add noise to an input image in the form of well-crafted small perturbations. Image denoising either in the spatial or frequency domain causes a loss of textural information, which is counterproductive to our goal of producing clean image-like performance on denoised images. We denoise adversarial images using bilateral (BL) filter [45], which is the mostly used edge-preserving denoising technique. It combines both range and domain filtering to smooth images and preserves edges in a way similar to human performance. It averages only perceptually similar colors and preserves only perceptually visible edges.

Algorithm 1 A Robust Defense against Adversarial Facial Images with Image Restoration (BL + SR)

/* Image de-noising Input */

Input: Adversarial image x^{adv}

Output: Denoised Image $x_D = D(x^{adv})$

1. Convert the RGB image into gray color image using the transformation $0.299 * R + 0.587 * G + 0.114 * B$.
2. Denoise noisy patterns in the image using BL Filter.
3. Revert the denoised image back to RGB.

/* Image Super-Resolution (SR) */

Input: Denoised image $x_D = D(x^{adv})$

Output: Super Resolved Image $x_{SR} = N(x_D)$

4. Transform adversarial images back to normal image space using deep image restoration networks: $N(\cdot)$.

/* Adversarial Images Detection */

5. Extract encoded features for the recovered or super resolved images.
 6. Forward the extracted features to the classifier model for correct prediction.
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Fig. 5 Examples of original images, adversarial images generated using FLM, Restored adversarial images by BL Filter, Restored adversarial images by BL+SR.



Fig. 6 Examples of original images, adversarial images generated using P-FGSM, Restored adversarial images by Bilateral Filter, Restored adversarial images by BL+SR.

Image super-resolution (SR) reconstructs a high-resolution image I^{SR} from a low-resolution image I^{LR} . Depending on the situation, the relationship between I^{LR} and the original high-resolution image I^{HR} can change. Recently, DNNs [46, 47] have shown to significantly enhance peak signal-to-noise ratio (PSNR) in the SR problem. We reconstruct high-resolution images for denoised images based on an enhanced deep super-resolution network (EDSR) [48]. It consists of residual blocks and ResNet architecture and produced significantly improved performance in the single image SR problem.

3.3 Facial Adversarial Attacks Detection

Once the adversarial images restored into the original space, we extract WLMP features [49] from each facial image. It is observed that the use of smoothing and blending techniques in digital image editing is common for removing abnormalities in fake or altered face images. These techniques aim to create a more visually consistent appearance by reducing or eliminating noticeable artifacts or inconsistencies. As a result, the texture surfaces in these edited images can often appear mostly unaltered, making it challenging to detect the alterations visually. To handle this issue, the proposed defense method leverages WLMP features to highlight the most altered regions of the face images when they are being attacked or altered. The WLMP features encode the differences between a center pixel and its adjacent pixels, giving more weight to the nearest pixels compared to the ones farther away. By doing so, these features can effectively capture and emphasize the local changes in the image,

even if the overall texture surfaces appear largely unaltered. The procedure for extracting the WLMP features for each facial image is described as shown in Fig. 4. These extracted features are then provided as input to various types of classifiers to discriminate between the face adversarial images and the original ones.

The process of extracting WLMP features for each facial image involves the following steps:

1. Divide the input face image into multiple blocks of size 3×3 . Each block represents a local region of the image.
2. Compute the differences between the center pixel of each block and its adjacent pixels. These differences are calculated as the absolute values of the pixel intensity differences.
3. To give higher weightage to the pixels that are closer to the center pixel, sort the obtained differences in increasing order. Then, multiply each absolute difference value by a weight factor of 2^p , where $p = 0, 1, 2, \dots, 7$. This weight factor increases with the proximity of the adjacent pixel to the center pixel. Adjust the resulting value of the center pixel to ensure it falls within the range of 0 to 255. For example, if the computed value exceeds 255, set it to 255.
4. Compute the histogram feature vector based on the modified center pixel values across all the blocks in the image. The histogram represents the distribution of the modified pixel values.
5. Finally, the extracted feature vectors obtained from the training dataset are provided as input to different types of classifiers. These classifiers learn the presence of adversarial attacks based on the extracted WLMP features and can be used to classify facial images as either original or adversarial.

3.4 Algorithm Description

An algorithm of the proposed defense method is provided in Algorithm 1. First, we denoise the adversarial face image using BL filter. It smooths the effect of adversarial noise. After that, SR is performed as a mapping function to enhance the visual quality of images, which brings the images in the adversarial space into the original space in high-resolution. Then, encoded WLMP features are extracted for each facial image and trained with different types of SVM classifiers, Random Forest and k-NN in adversarial training fashion. Our defense method minimizes the effect of adversarial perturbations in the image domain and significantly improves the overall performance of the classifier.

4 Experimental Results

The performance of the proposed defense method is trained and tested on two real-world image datasets. Its performance is demonstrated with different types of classifiers.

Table 1 The overall results of the proposed defense method on CeleA Dataset

S.No	Dataset	Adversarial Attack	Image Restoration Networks	Classifier	Precision	Recall	F1-score	Accuracy(%)
1	CelebA	P-FGSM	No	Linear SVM	1.0	0.98	0.99	98.75
				Polynomial SVM	1.0	0.97	0.98	98.5
				Sigmoid SVM	0.72	0.73	0.72	72
				Gaussian SVM	1.0	0.96	0.98	98
				Random Forest	1.0	0.97	0.97	98.5
				k-NN	0.98	0.97	0.98	97.5
			BL+SR	Linear SVM	0.99	1.0	1.0	99
				Polynomial SVM	0.98	1.0	0.99	98
				Sigmoid SVM	0.93	1.0	0.96	93
				Gaussian SVM	0.99	1.0	0.99	99
				Random Forest	0.99	1.0	0.99	99
				k-NN	0.98	1.0	0.99	98

Table 2 The overall results of the proposed defense method on FFHQ Dataset

Dataset	Adversarial Attack	Classifier	No Image Restoration Networks				BL				BL+SR			
			Precision	Recall	F1-score	Accuracy(%)	Precision	Recall	F1-score	Accuracy(%)	Precision	Recall	F1-score	Accuracy(%)
FFHQ	StyleGAN	Linear SVM	0.71	0.7	0.7	70.1	0.85	0.85	0.85	80.07	0.85	0.85	0.85	80.07
		Polynomial SVM	0.78	0.78	0.78	77.94	0.89	0.89	0.89	85.29	0.89	0.89	0.89	85.29
		Sigmoid SVM	0.66	0.65	0.65	65.69	0.83	0.82	0.82	77.12	0.83	0.81	0.82	76.47
		Gaussian SVM	0.62	0.56	0.59	60.29	0.8	0.71	0.75	68.63	0.8	0.71	0.75	68.95
		Random Forest	0.66	0.67	0.66	66.18	0.83	0.82	0.82	76.47	0.83	0.81	0.82	75.82
		k-NN	0.71	0.48	0.57	63.73	0.88	0.73	0.8	75.16	0.88	0.71	0.79	74.18
	FLM	Linear SVM	0.67	0.58	0.62	64.66	0.78	0.66	0.72	68.09	0.78	0.67	0.72	68.45
		Polynomial SVM	0.65	0.43	0.52	60.21	0.77	0.53	0.63	62.29	0.77	0.53	0.63	62.49
		Sigmoid SVM	0.56	0.58	0.57	55.86	0.65	0.56	0.6	55.24	0.65	0.57	0.61	55.68
		Gaussian SVM	0.57	0.6	0.58	57.66	0.71	0.71	0.71	64.81	0.71	0.71	0.71	64.65
		Random Forest	0.59	0.62	0.6	59.26	0.71	0.72	0.71	66.01	0.71	0.72	0.71	65.77
		k-NN	0.59	1	0.74	65.52	0.67	0.95	0.79	69.5	0.67	0.94	0.78	68.65

4.1 Dataset

Our defense method is evaluated on two real-world datasets **CelebFaces Attributes Dataset (CelebA)**[50] and **Flickr-Faces-HQ, (FFHQ)**[15].

4.1.1 CelebA

It is a large-scale face attributes dataset consists of a total of 202,599 celebrity face images. Each face image in the dataset is annotated with 40 different attribute labels, providing additional information about various facial characteristics. It also includes face images captured in diverse conditions, such as different poses, background clutter and other variations. Moreover, it also exhibits a high level of diversity, containing a total of 10,177 unique identities.

4.1.2 FFHQ

It consists of a total of 70,000 real faces sourced from Flickr and an equal number of 70,000 fake faces generated using the StyleGAN technique [15]. It

encompasses a significant level of variation in terms of age, ethnicity and image backgrounds. It also includes a wide range of accessories such as eyeglasses, sunglasses, hats and more.

Fig. 5 shows examples of restored adversarial images for FLM attacks. The first row shows the original facial images and their corresponding FLM attacks are shown in the second row. In the third and forth rows, the restored adversarial images after BL and BL+SR are shown respectively. Similarly, Fig. 6 shows examples of original face images, their adversarial images generated by P-FGSM, the restored adversarial images after BL and BL+SR are shown in row-wise respectively.

4.2 Performance of the Proposed Defense Method

The proposed defense method is trained and tested on two real-world datasets. Its performance is demonstrated with various types of classifiers. The overall statistics of the proposed defense method on CeleA dataset is presented in Table 1. The results show that before employing image restoration, the classifiers Linear SVM, Polynomial SVM, Sigmoid SVM, Gaussian SVM, Random Forest and k-NN classifier detect with an accuracy of 98.75%, 98.5%, 72%, 98%, 98.5% and 97.5% respectively. Among the classifiers, Linear SVM shows its effectiveness in detecting facial adversarial images from the original with the highest accuracy of 98.75%. After employing image restoration such as BL followed by SR (BL+SR) to the adversarial images, the classification accuracy improves from 98.75% to 99% for Linear SVM, from 72% to 93% for Sigmoid SVM, from 98% to 99% for Gaussian SVM, from 98.5% to 99% for Random Forest and from 97.5% to 98% for k-NN on CelebA dataset with P-FGSM adversarial attack.

On FFHQ dataset with both adversarial attacks StyleGAN and FLM, our method achieves 5 – 10% improvement in the classification accuracy in almost all classification models even if it achieves low classification accuracy before applying image restoration. The results on FFHQ dataset before and after applying image restoration (BL+SR) with adversarial attacks StyleGAN and FLM are shown in Table 2. Our experimental results show that BL alone is sufficient sometimes to bring back the adversarial images into the original space, leading the classifier towards correct prediction. Thus, the results show that significant improvement in the detection accuracy after employing the image restoration BL+SR on the adversarial images.

5 Evaluating Robustness of Intensity-based and Geometric-based Adversarial Attacks

Almost all intensity-based attacks augment the input samples with high-frequency components and employ a l_p - norm constraint to regulate the distortion. The adversarial samples may not necessarily sit on the same manifold as the natural samples since the l_p - norm is not a perfect similarity metric. On the other hand, geometric-based adversarial attacks are extremely

robust against adversarial training compared to intensity-based adversarial attacks because they are targeting the most important locations in the images using geometric perturbations. We use P-FGSM [14] and FLM [16] for intensity-based and geometric-based adversarial attacks, respectively. We evaluate the robustness of intensity-based and geometric-based adversarial attacks by extracting the encoded WLMP features with various classifiers on CelebA dataset. Geometric-based adversarial attacks are much more resistant against all evaluating classifiers except Sigmoid SVM. The overall statistics for evaluating the robustness of both adversarial attacks are presented in Table 3.

Table 3 Robustness comparison of intensity-based and geometric-based adversarial attacks on CelebA dataset

S.No	Classifier	Intensity-based Adversarial Attack (P-FGSM)				Geometric-based Adversarial Attack (FLM)			
		Precision	Recall	F1-score	Accuracy(%)	Precision	Recall	F1-score	Accuracy(%)
1	Linear SVM	0.96	0.97	0.96	96.4	0.77	0.75	0.76	76.16
2	Polynomial SVM	0.89	0.96	0.92	91.89	0.75	0.79	0.77	76.16
3	Random Forest	0.91	0.98	0.94	94.14	0.74	0.8	0.77	75.99
4	Sigmoid SVM	0.52	0.54	0.53	51.35	0.58	0.63	0.6	58.77
5	Gaussian SVM	0.91	0.94	0.92	92.34	0.7	0.79	0.74	72.35
6	k-NN	0.87	0.99	0.93	91.89	0.74	0.49	0.59	65.73

6 Conclusions

A new defense method for improving robustness against facial adversarial attacks is proposed based on deep image restoration networks. We generate a well-protected version of adversarial face images based on P-FGSM, FLM and StyleGAN and have proved that these images can mislead the classifier to misclassification with high confidence. Image restorations such BL followed by SR are performed on adversarial images to enhance the visual quality of images, which brings back the low resolution adversarial images into the high resolution original space. The encoded features are extracted for the recovered images and trained on various types of classifiers. The results are demonstrated on two real-world datasets for different adversarial attacks. The experimental results show that there is a significant improvement in the classification accuracy after employing the image restoration in the classification models and also geometric-based adversarial attacks are more robust to defend than intensity-based adversarial facial adversarial attacks.

We will focus on various denoising filters and deep image super resolution networks to improve adversarial robustness further for different adversarial attacks in future work. We will also investigate whether SR or denoising alone is sufficient for all types of DL-based adversarial attacks.

Conflict of Interest:

The authors have no conflicts of interest to declare.

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