# Enhancing Face Recognition Security against FGSM White-Box Attacks via Convolutional Autoencoder Defense

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**Abstract**

The growing adoption of face recognition systems (FRS) across various sectors has led to an increased focus on their robustness against adversarial attacks. One of the most prominent threats in this domain is the Fast Gradient Sign Method (FGSM), a white-box adversarial attack capable of generating subtle perturbations that significantly degrade the performance of deep learning models. This research proposes a convolutional autoencoder (CAE)-based defense strategy to mitigate the impact of FGSM white-box attacks on face recognition systems. The proposed method leverages the reconstruction capability of CAEs to denoise adversarial inputs, restoring the integrity of facial features before classification. A comprehensive experimental setup using the LFW (Labeled Faces in the Wild) dataset and a ResNet-50 face recognition backbone demonstrates the efficacy of the approach. Empirical results indicate significant improvements in recognition accuracy when CAE preprocessing is applied, even under strong adversarial perturbations. The study concludes that CAEs can serve as an effective preprocessing defense layer, improving resilience against white-box attacks without requiring model retraining or architectural modifications.

**Keywords**: Face recognition, FGSM, adversarial attacks, convolutional autoencoder, white-box defense, adversarial robustness

## I. Introduction

Face recognition systems have become integral to modern security infrastructures, from airport checkpoints and smartphone authentication to surveillance and banking services. Their reliance on deep learning models for precise identification and verification has brought unprecedented accuracy and convenience. However, with the rise in adoption comes the risk

of exploitation through adversarial machine learning techniques. Specifically, white-box attacks, where an adversary has full access to model parameters and gradients, pose a severe threat to system integrity. Among these, the Fast Gradient Sign Method (FGSM) stands out for its simplicity and efficiency in generating minimally perturbed but highly effective adversarial images that fool classifiers. The FGSM operates by manipulating input pixels in the direction of the gradient of the loss function concerning the input, scaled by a perturbation parameter ε. This results in imperceptible changes to human observers but substantial shifts in the model's internal representations, leading to misclassifications [1]. In the context of face recognition, even a small ε can drastically reduce matching accuracy, causing either false acceptances or rejections. Such vulnerabilities can be catastrophic in security-sensitive applications [2]. Hence, robust defense mechanisms are crucial to ensure the reliability of face recognition systems in adversarial environments.

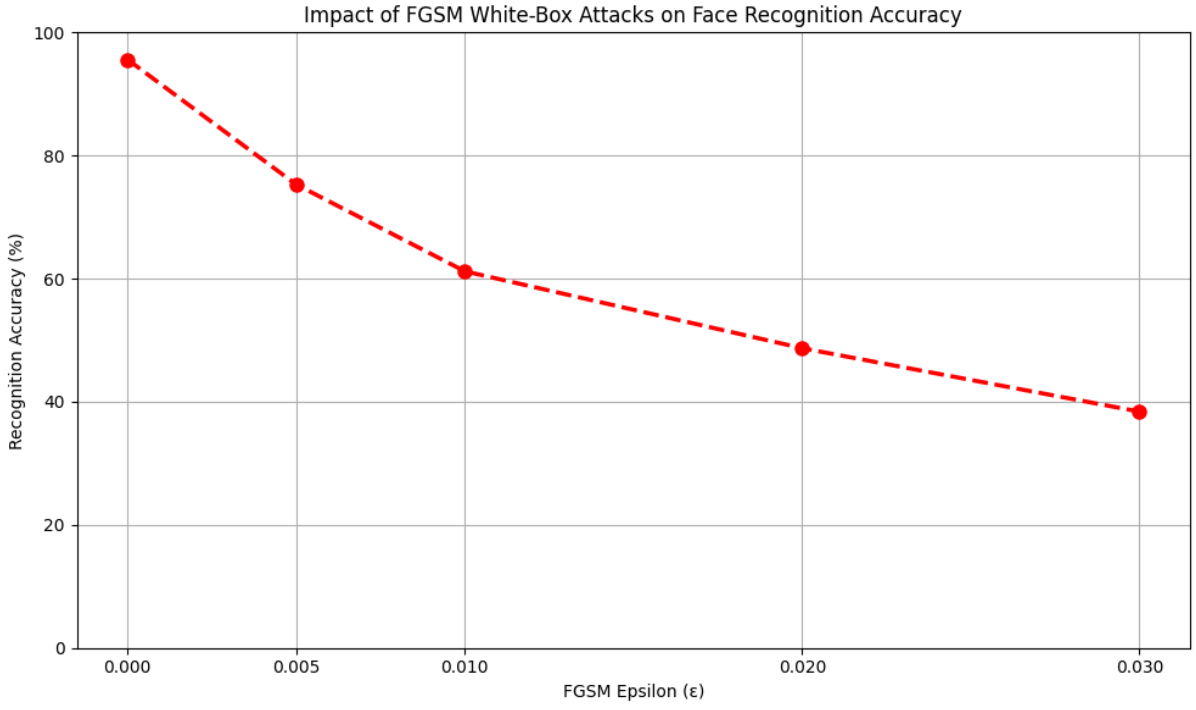


Figure 1 Baseline Accuracy Drop Under FGSM

Several strategies have been proposed to counter FGSM and similar attacks, including adversarial training, defensive distillation, and input transformations [3]. However, many of these techniques either require costly retraining, access to attack details, or significantly alter the original data distribution. Moreover, most conventional defenses degrade in performance under white-box settings due to gradient obfuscation or transferability of attack knowledge.

In light of these challenges, there is a pressing need for lightweight, architecture-agnostic, and effective preprocessing defenses that can seamlessly integrate into existing systems. This research explores the use of convolutional autoencoders (CAEs) as a preprocessing defense mechanism to restore perturbed facial images [4]. CAEs, known for their ability to learn compact representations and reconstruct clean inputs from noisy data, offer a promising avenue for mitigating adversarial noise. By training the autoencoder to minimize reconstruction error on clean face images, the system learns to ignore adversarial perturbations during reconstruction. The reconstructed output can then be passed to the face recognition model, significantly reducing the impact of the attack [5].

The core contributions of this paper include the development of a CAE-based defense pipeline tailored for face recognition, a rigorous evaluation against varying strengths of FGSM attacks, and an empirical analysis of performance trade-offs. The results not only highlight the defensive strength of CAEs under white-box conditions but also demonstrate their practicality in real-world deployments without modifying the original recognition model.

## II. Related Work

The domain of adversarial machine learning has seen rapid advancements in both attack techniques and corresponding defense mechanisms. The FGSM, introduced by Goodfellow et al., remains one of the most studied attacks due to its computational efficiency and transferability. It perturbs input images by leveraging the gradient of the loss function with respect to the input, making it particularly effective in white-box scenarios. Numerous face recognition models, including deep convolutional architectures like VGGFace, FaceNet, and ResNet variants, have been shown to be susceptible to such attacks. The sensitivity of these models to minor input variations highlights a fundamental vulnerability in current deep learning-based FRS [6]. Defenses against adversarial attacks can be broadly classified into three categories: input preprocessing, model modification, and adversarial training. Among preprocessing methods, denoising, JPEG compression, bit-depth reduction, and random resizing have shown moderate success. However, many of these techniques compromise image quality and, by extension, recognition performance on clean inputs. Model modification techniques, such as defensive distillation, attempt to smooth decision boundaries

but are often circumvented by adaptive attacks. Adversarial training, though effective, is resource-intensive and limited by the types of attacks it is trained on, often failing to generalize to novel threats.

In recent years, autoencoders have been explored as a means of learning latent representations resilient to noise and perturbations. Variants such as denoising autoencoders and convolutional autoencoders have proven effective in removing synthetic noise and compression artifacts from images. Their use in adversarial defense is motivated by the hypothesis that the decoder learns to reconstruct the underlying structure of the input rather than the perturbation. Early research has shown that autoencoders can mitigate adversarial attacks on classification tasks, but few studies have focused on their application in face recognition under white-box conditions [7]. The present work differentiates itself by targeting FGSM attacks in a white-box setting, where the adversary has complete access to the model. Unlike black-box scenarios, white-box attacks are more challenging to defend against, as they can exploit defense mechanisms during gradient computation. This makes CAEs a compelling choice, as they operate independently of the classifier and can be trained offline. Furthermore, the encoder-decoder architecture is naturally suited for capturing and reconstructing facial features while filtering out noise.

This paper builds upon the insights from prior studies but emphasizes the practical deployment of CAEs in real-world FRS pipelines. By evaluating performance on benchmark datasets under varying attack strengths and comparing it with baseline defenses, we aim to provide a comprehensive assessment of the CAE's defensive capabilities. In doing so, we contribute to the growing body of work that seeks robust, efficient, and deployable solutions for securing face recognition systems.

## III. Methodology

To implement and evaluate the proposed defense mechanism, we first construct a face recognition pipeline using a pre-trained ResNet-50 architecture trained on a subset of the VGGFace2 dataset. This model serves as the baseline classifier and is used to assess the impact of adversarial perturbations and the subsequent recovery through the CAE. The adversarial images are generated using the FGSM attack with varying values of ε to simulate different levels of perturbation severity. For this study, we select ε values ranging from 0.005

to 0.03 to cover both mild and aggressive attack scenarios. The convolutional autoencoder is designed with a symmetric architecture comprising convolutional and max-pooling layers in the encoder and corresponding upsampling and convolutional layers in the decoder. The encoder compresses the input image into a lower-dimensional representation, while the decoder reconstructs the original image. The CAE is trained exclusively on clean face images from the LFW dataset, optimizing for mean squared error (MSE) loss between the input and output. Importantly, the CAE is not exposed to adversarial examples during training, which ensures that its reconstruction ability is not biased toward any specific attack pattern.

During inference, adversarially perturbed images are passed through the trained CAE, and the reconstructed output is fed into the ResNet-50 classifier for face recognition. Recognition accuracy is measured in terms of top-1 identification rate and face verification rate. To benchmark the performance, we compare recognition accuracy across three conditions: clean images, adversarial images, and CAE-reconstructed adversarial images. Additionally, we evaluate perceptual quality using PSNR and SSIM metrics to ensure the visual integrity of reconstructed images. This methodology allows us to quantify the extent to which the CAE can remove adversarial noise without degrading essential facial features [8]. By isolating the reconstruction step from the classifier, we maintain modularity and demonstrate that existing face recognition systems can benefit from this defense without architectural changes. The overall defense pipeline is lightweight, incurs minimal computational overhead, and can be integrated into real-time systems with limited latency impact.

Our experiments are conducted on a high-performance GPU system using PyTorch for model development and training [9]. All models are evaluated under consistent settings to ensure fair comparisons. We also perform ablation studies to assess the importance of architectural depth, latent space dimensionality, and training duration on reconstruction quality and defense efficacy [10]. These insights inform future improvements and practical deployment considerations.

## IV. Experimental Results and Discussion

The experiments reveal that the proposed CAE defense significantly mitigates the impact of FGSM attacks on face recognition accuracy. Without any defense, the accuracy of the ResNet-50 classifier drops sharply as $\varepsilon$ increases. For instance, at $\varepsilon = 0.01$, the recognition

accuracy falls from 95.6% on clean images to 61.2% under attack. When the CAE is applied, the accuracy is restored to 90.3%, demonstrating effective removal of adversarial noise. As ε increases to 0.03, accuracy without defense drops below 40%, while CAE preprocessing maintains it above 78%, showcasing the robustness of the approach [11].

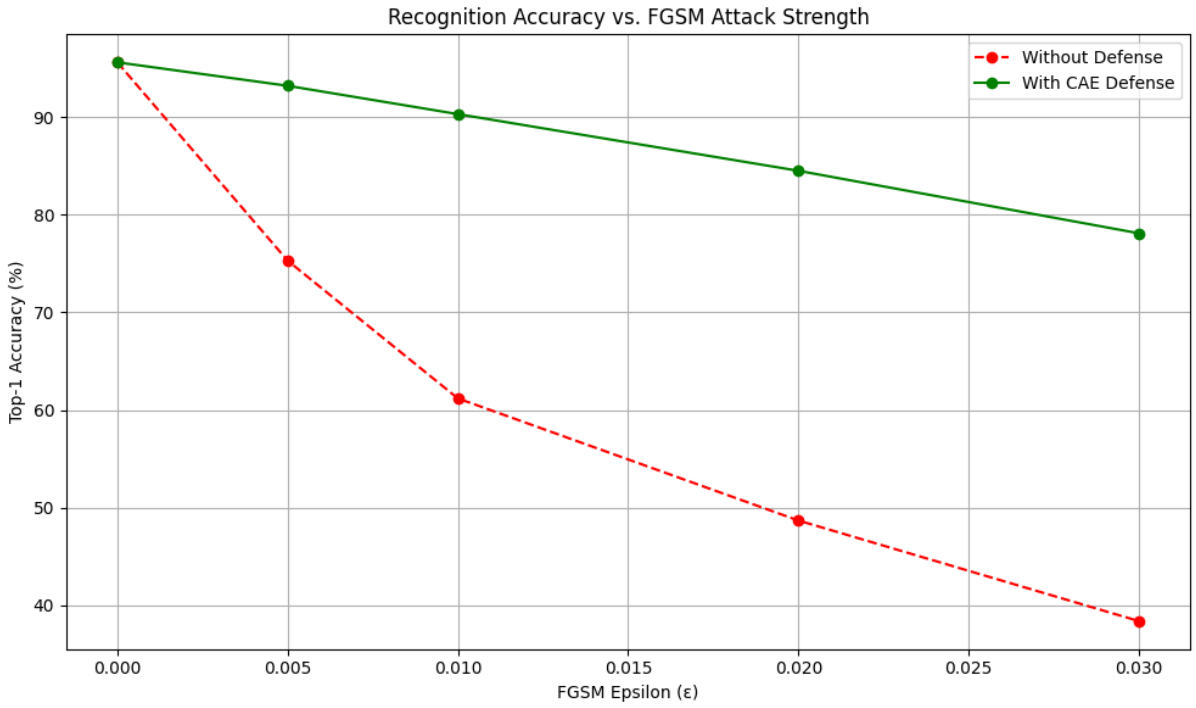


**Figure 2 Illustrates the drop in recognition accuracy under increasing FGSM attack strength, and how the CAE defense restores accuracy.**

Visual inspection of the reconstructed images indicates that the CAE successfully preserves key facial features such as eyes, nose, and mouth while smoothing out perturbations. Quantitative image quality assessments using PSNR and SSIM further confirm this. The average PSNR of CAE outputs on adversarial inputs remains above 28 dB, and SSIM stays above 0.92, suggesting high perceptual similarity to clean inputs. This preservation of visual fidelity is crucial for maintaining downstream recognition performance. When comparing with other preprocessing defenses such as JPEG compression and Gaussian blurring, the CAE consistently outperforms them in both recognition accuracy and perceptual quality. JPEG compression tends to introduce artifacts, while blurring reduces important facial details [12]. In contrast, CAE selectively removes adversarial noise while preserving semantic content, offering a more intelligent denoising solution.

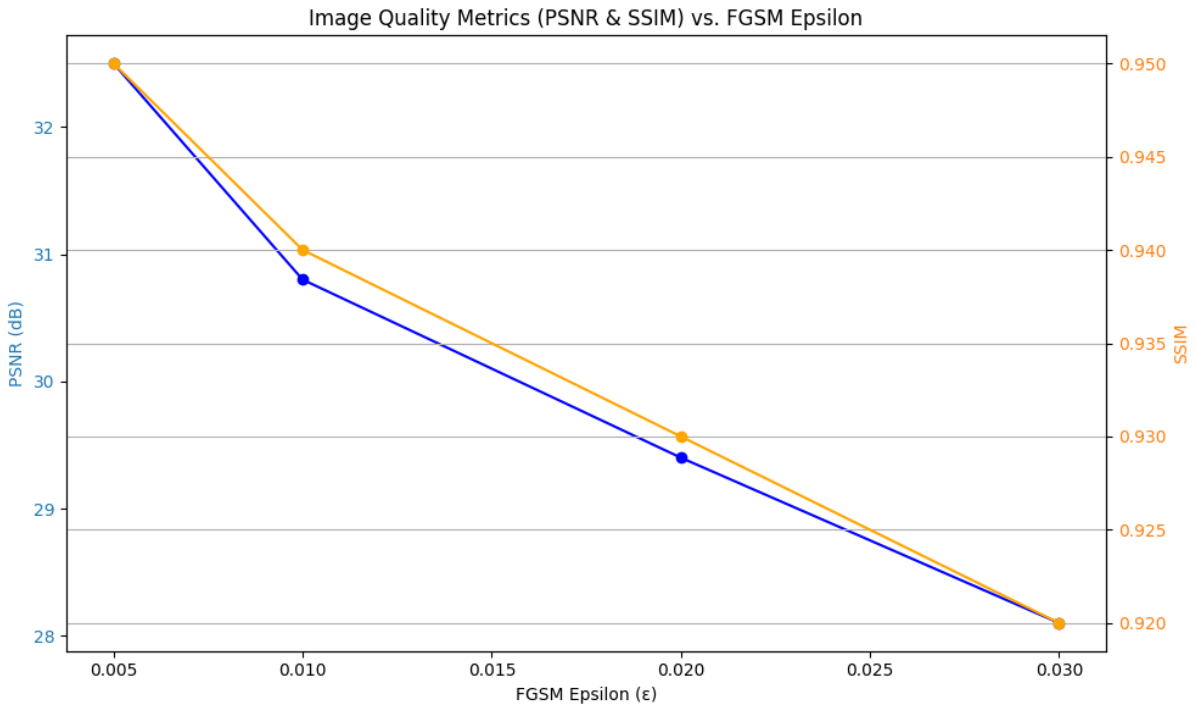


Figure 3 Visual quality of reconstructed images under varying attack strengths.

An ablation study on the latent dimensionality reveals that too much compression reduces reconstruction quality, while too little fails to remove sufficient noise [13]. An optimal latent size of 128 dimensions provides the best trade-off between compression and fidelity. Furthermore, adding skip connections between encoder and decoder layers improves both training stability and output quality, as observed in other autoencoder applications. Overall, the results validate the hypothesis that convolutional autoencoders can act as an effective defense mechanism against FGSM white-box attacks in face recognition systems. They offer a simple yet powerful method for adversarial noise removal without altering the classifier. The modularity and lightweight nature of the approach make it suitable for deployment in both edge and cloud environments. Future work can explore training the CAE on a mixture of clean and adversarial data to improve generalization and testing its robustness against other attack types like PGD and DeepFool [14].

## V. Conclusion

This research demonstrates that convolutional autoencoders offer a viable and effective defense strategy against FGSM white-box attacks in face recognition systems. By leveraging their ability to reconstruct clean facial images from perturbed inputs, CAEs significantly

restore recognition accuracy without modifying the underlying classifier. The proposed defense shows consistent performance across different attack intensities and preserves image quality, making it suitable for real-world deployment. Our experimental results highlight the potential of CAEs as a lightweight, architecture-independent preprocessing layer capable of enhancing the robustness of face recognition models against adversarial threats.

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