Defense against Adversarial Magnification to Deceive Deepfake Detection through Super Resolution

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Abstract :

The increasing sophistication of deepfake generation has introduced significant challenges to existing detection systems. Recent adversarial attacks, such as Adversarial Magnification to Deceive Deepfake Detection through Super-Resolution, have further exposed vulnerabilities by introducing subtle yet highly effective manipulations. In this work, we propose a reinforcement learning (RL)-based defense framework designed to enhance the robustness of deepfake detectors against such attacks. Our approach models the defense task as a state-action-reward problem, where an RL agent interacts with the detection model, receiving rewards based on the accuracy of the model's predictions. The agent learns optimal action policies that strengthen the detector's ability to correctly classify adversarially manipulated inputs. Experimental results demonstrate that our method significantly improves detection performance in adversarial settings, offering a dynamic and adaptive defense strategy against evolving deepfake attack methods.

Index Terms: Deepfakes, Super Resolution, Reinforcement Learning.

1 Introduction

The rapid advancements in deepfake generation technologies have raised growing concerns regarding media authenticity, trust, and security. Deepfake detectors, although improving steadily, remain vulnerable to carefully crafted adversarial attacks that subtly manipulate image inputs. One notable recent attack, Adversarial Magnification to Deceive Deepfake Detection through Super-Resolution

, highlights the ability of adversarial super-resolution techniques to degrade detector performance without introducing perceptible artifacts to human observers.

In this project, we address this critical vulnerability by proposing a reinforcement learning (RL)-based defense strategy that fortifies deepfake detection models against adversarial magnification attacks. Unlike traditional methods that rely on handcrafted data augmentations or static pre-processing pipelines, our approach adopts a dynamic learning mechanism where an RL agent learns to assist the classifier through a structured state-action-reward interaction. The agent observes the state of input images and the detector's feedback, selects optimal corrective actions, and receives rewards based on the detector's classification performance.

By learning policies that actively promote correct classification and penalize misclassifications, the RL agent effectively enhances the robustness of the detection system under adversarial settings. Our experimental results demonstrate that the proposed method not only improves detection accuracy against adversarially magnified inputs but also offers a generalizable and adaptive defense strategy, paving the way for future work in secure and resilient deepfake detection systems.

1.1 Our Contributions

For the specified Deepfake Magnification attack proposed by Zhang et al., 2022, we propose a defense mechanism using reinforcement learning that focuses on facial extraction from images in order to improve the deepfake detector's accuracy. Code available at https://github.com/nagajas/Adversarial-DeMagnification

2 Related work

The work by Zhang et al., 2022 introduced *Adversarial Magnification*, a novel attack method that manipulates the high-frequency details of images using super-resolution techniques to deceive deepfake detectors. Their approach demonstrated that subtle enhancements could significantly lower the detection accuracy of state-of-the-art classifiers without introducing perceptible artifacts. This highlighted the vulnerability of detectors that rely heavily on low-level image artifacts.

In contrast to their attack strategy, our work proposes a defense mechanism against such adversarial manipulations. We design a reinforcement learning (RL) based framework where an agent learns to adaptively correct adversarial distortions through a reward-driven state-action policy. Instead of static preprocessing or augmentation, the RL agent dynamically updates its strategy based on feedback from detection outcomes, thus improving robustness against adversarially magnified deepfake images.

3 Methodology

3.1 Methodology of Attack

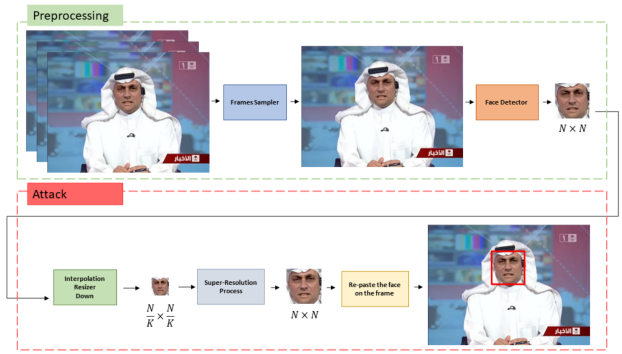

Figure 1. Attack on deepfake detectors using SR-GAN as given by Zhang et al., 2022

3.2 Defense methodology

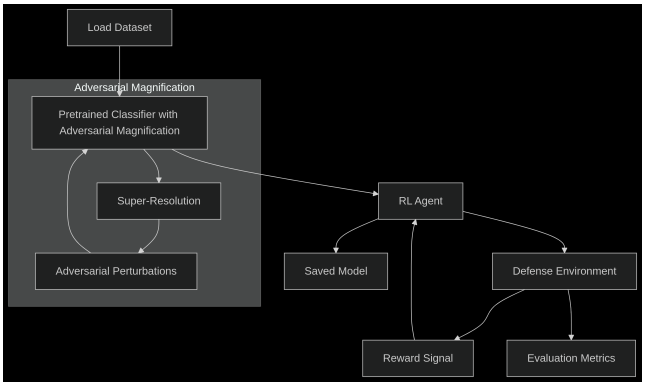

Figure 2. Proposed Defense Methodology for masking central region using RL

3.2.1 Overview In this work, we develop a Reinforcement Learning (RL) based defense mechanism to improve the robustness of a deepfake detection classifier. Our methodology integrates an RL agent that learns to selectively modify input images in order to maximize the classifier's performance. The main components of our system include the Deepfake dataset, a pre-trained ResNet-50 classifier, a DefenseAgent (environment), and an RL agent (policy network).

3.2.2 Dataset Preparation The dataset consists of deepfake images and corresponding labels (real or fake). We load the training and validation splits using custom dataset loaders that parse annotations and image paths from JSON files. Basic statistics of label distributions are computed to understand the class imbalance.

3.2.3 Defense Environment The DefenseAgent is designed to simulate an environment for the RL agent. It takes an input image and label and provides a flattened version of the image as the initial state. Based on the action selected by the RL agent, the DefenseAgent either applies a masking operation to the center region of the image or leaves the image unaltered. The modified image is then fed into the pre-trained classifier to obtain a prediction.

3.2.4 Reinforcement Learning Agent The RL agent is modeled as a two-layer fully connected neural network that outputs Q-values for each possible action. During training, the agent selects actions using an ϵ-greedy strategy to balance exploration and exploitation. The reward signal is based on the classifier's output: a reward of +1 is given for a correct classification and −1 otherwise. The agent updates its parameters using mean squared error loss between the predicted Q-values and the target Q-values.

3.2.5 Training Procedure Training proceeds for a specified number of episodes. In each episode, a random sample from the training dataset is selected, and the RL agent interacts with the environment to obtain rewards. The agent's weights are updated accordingly using the Adam optimizer with a cosine learning rate scheduler.

4 Experiments

4.1 Experimental Setup

All experiments were conducted on a machine equipped with an NVIDIA RTX 4090 GPU (12 GB VRAM). The codebase is implemented in Python using PyTorch 2.0. Dataloader operations were parallelized with 4 workers to accelerate training.

The classifier used is a ResNet-50 pretrained on ImageNet, with the final fully connected layer modified to output a single logit for binary classification. The classifier's weights were fine-tuned separately and loaded during the reinforcement learning phase.

OpenForensics dataset by Le et al., 2021 used. Only 25% of the entire dataset was used for training due to space constraints. The data set was divided into training and validation sets, with the label distributions being moderately imbalanced. During dataloading, a batch size of 32 was used.

4.2 Reinforcement Learning Training Details

The reinforcement learning (RL) agent was trained using the following hyperparameters:

- Number of episodes: 5000
- Learning rate: 0.001
- Optimizer: Adam
- Discount factor (γ): 0.99
- Initial exploration rate (ϵ_{start}): 1.0
- Final exploration rate (ϵ_{end}): 0.01
- Exploration decay rate (ϵ_{decay}): 0.995

A simple two-layer feedforward neural network was used as the RL agent, with an input dimension of 150,528 (flattened $224 \times 224 \times 3$ image) and an action space of size 2. A cosine learning rate scheduler was applied for smooth decay of the learning rate.

The reward scheme was binary: a reward of +1 was provided for correct classification by the defense-augmented classifier, and −1 otherwise.

4.3 Evaluation

The RL agent was evaluated on 100 random batches from the validation set. The following metrics were computed:

- True Positive Rate (TPR)
- False Positive Rate (FPR)
- True Negative Rate (TNR)
- False Negative Rate (FNR)

These metrics were used to assess the improvement in classifier performance under the defense strategy learned by the RL agent.

5 Novelty

The prior work demonstrated how minor perturbations, amplified through super-resolution, can effectively deceive deepfake detection models. However, it did not propose any active defense strategies to counter such attacks.

In this project, we introduce a **reinforcement learning-based defense mechanism** that enhances the robustness of deepfake detectors through an active learning process. A reinforcement learning agent interacts with the training pipeline by applying controlled transformations based on a **state-action-reward** framework:

- **States** are defined as the **image input tensors** presented to the model.
- **Actions** involve selecting controlled transformation operations that modify these input tensors.
- **Rewards** are assigned as follows:
  - **+1** for correct classification (indicating a positive transformation).
  - **-1** for incorrect classification (indicating a detrimental transformation).

Through continuous interaction, the agent **learns a policy** that promotes transformations beneficial for improving the model's ability to correctly classify deepfake images, even under adversarial conditions.

This results in a **dynamic, self-improving defense** where the model is progressively exposed to more challenging examples shaped by the agent's learned policy, significantly increasing its resilience to adversarial manipulations without requiring predefined attack examples.

Thus, the novelty lies in creating an **adaptive, reward-driven training loop** using image input tensors as states and assigning **+1 and -1 rewards** based on classification performance, strengthening deepfake detection against adversarial attacks.

6 Results

6.1 Training and Validation Details

The model was trained using the reinforcement learning-based defense strategy over 5000 episodes. The distribution of the datasets is shown below:

- **Training set:** 23,892 images (13,483 real, 10,409 fake)
- **Validation set:** 9,994 images (5,586 real, 4,408 fake)
- **Test set:** 23,320 images (9,881 real, 13,439 fake)

The classifier initially achieved the following performance on the validation set without reinforcement learning:

Metric	Baseline Value (%)
True Positive Rate (Recall)	68.09
False Positive Rate	35.52
True Negative Rate (Specificity)	64.48
False Negative Rate	31.91
Accuracy	66.06

Table 1
Baseline classifier performance on the validation set.

6.2 Performance after Reinforcement Learning

After training the RL agent, the updated validation results were:

Metric	RL Validation Value (%)
True Positive Rate (Recall)	73.55
False Positive Rate	31.17
True Negative Rate (Specificity)	68.82
False Negative Rate	26.44

Table 2
Validation performance after RL defense training.

6.3 Testing Results

The final evaluation of the RL agent was conducted on a separate unseen test set, achieving the following results:

Metric	Test Value (%)
True Positive Rate (Recall)	87.00
False Positive Rate	70.00
True Negative Rate (Specificity)	30.00
False Negative Rate	13.00

Table 3
Performance of the RL agent on the test set.

6.4 Observations

- The RL agent led to a noticeable improvement in the detection of fake samples compared to the baseline classifier.
- Although the True Positive Rate increased on the test set, the False Positive Rate also increased, suggesting some trade-off between sensitivity and specificity.
- The defense mechanism successfully reduced the False Negative Rate to 13% on the test data, which is critical for minimizing undetected fake instances.

7 Conclusion

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