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Adversarial Attacks and Defences in Deepfake Detection: A Comprehensive Threat Model and Mitigation Framework

Robust Detection Under Adversarial Conditions

Rakhi Rathi, Aditya Shinde, Ishwar Shirole, Zaki Shaikh
Co-Authors: Dr. V.C Bagal, Prof A.L. Rane
K. K Wagh Institute Of Engineering Education and Research, Nashik

Abstract - Deepfake detection systems have demonstrated impressive accuracy on standard benchmarks, yet remain vulnerable to adversarial attacks deliberately crafted to evade detection. This paper presents the first comprehensive evaluation of adversarial robustness in deepfake detection, testing 32 state-of-the-art detectors against 156 attack variants ($L\infty$, L2, L0 constrained perturbations; targeted and untargeted; audio, video, and multimodal). We demonstrate that even robust classifiers achieve 100% attack success rates with imperceptible perturbations ($L\infty=4/255 \approx 0.016$ in normalized audio amplitude), and that ensemble methods provide false security by accepting evasion through simple transferability. We propose ROBUST-DETECT, a certified defense combining randomized preprocessing, prediction hardening, and dynamic threshold adjustment, achieving ε-robustness (ε=0.01) with 96.1% clean accuracy on deepfake detection tasks. Our work establishes adversarial robustness as a critical evaluation dimension for deployment-ready deepfake detectors, provides practitioners with threat models, and offers practical defenses suitable for production systems.

Keywords - deepfake detection, adversarial robustness, evasion attacks, certified defenses, robust machine learning.

I. INTRODUCTION

A. Motivation

Deepfake detection faces a fundamental challenge: as detection systems improve, motivated adversaries will invest in attacks to evade them. This adversarial dynamic—well-established in spam detection [1], intrusion detection [2], and malware analysis [3]—has been largely neglected in deepfake literature.

Consider a criminal distributing non-consensual deepfake content: detection systems flag the content within seconds, but what if the attacker could add imperceptible noise to bypass detection while remaining visually/aurally identical? This is not theoretical—adversarial examples are well-established in computer vision [4][5], speech processing [6], and natural language processing [7].

Critical Question: Are current deepfake detectors robust to adversarial perturbations? Our evaluation reveals a troubling answer: no, with 100% attack success rates using imperceptible perturbations.

B. Threat Model

We consider three attack scenarios:

Scenario 1 – Evasion: Adversary modifies a deepfake file to evade detection (confidence < 0.5) subject to imperceptibility constraints.

Scenario 2 – Poisoning: Adversary injects a backdoor into training data; poisoned model predicts "authentic" on trigger inputs while maintaining clean accuracy.

Scenario 3 – Model Extraction: Adversary queries detector API to extract the model through query-efficient extraction. This paper focuses on Scenario 1 (evasion), the most immediate threat.

C. Contributions

1) First comprehensive adversarial robustness evaluation of 32 deepfake detectors against 156 attack variants, establishing baseline vulnerability.
2) Adversarial attack taxonomy for deepfake domain: frequency-domain perturbations, adversarial synthesis, codec-based attacks, GAN-based perturbations.
3) Transferability analysis demonstrating adversarial deepfakes transfer across models (66–92% attack success), enabling black-box attacks.
4) ROBUST-DETECT framework combining randomized preprocessing, prediction hardening, and certified robustness guarantees (ε=0.01 robustness with 96.1% clean accuracy).
5) Practical defenses suitable for deployment without retraining, including detection-time hardening and post-hoc robustification.

II. RELATED WORK

A. Adversarial ML Background

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Adversarial examples were discovered in image recognition [4] and have since spread to speech [6], NLP [7], and malware detection [8]. Key findings from other domains:

- Image recognition: L∞ perturbations with ε=8/255 can achieve 100% attack success [9]
- Speech recognition: L2 perturbations of ~0.001 amplitude can force misclassification [10]
- Transferability: 60–90% of adversarial examples transfer to different models [11][12]

B. Defense Strategies

Defense strategies include [13][14]: adversarial training (re-train model on perturbed examples [15]); certified defenses (randomized smoothing [16], IBP [17]); preprocessing (JPEG compression [18], median filtering [19]); detection-based adversarial example detectors [20][21]; and ensemble voting [22].

C. Deepfake Detection Robustness (Prior Work)

Adversarial robustness in deepfake detection is largely unexplored. A single prior work [23] tested one detector against simple perturbations, finding 100% success rates. Our work extends [23] by: 32× more models; 156 attack variants vs. 1; multiple attack methods beyond Lp perturbations; defense algorithms with theoretical guarantees; and analysis of transfer attacks and ensemble vulnerabilities.

III. ATTACK METHODS

A. Lp-Norm Constrained Perturbations

Given deepfake audio x, we find perturbation δ such that ||δ||_p is minimized subject to: f(x+δ) < 0.5 (evasion goal) and x+δ remains valid audio. Implementations include L∞ attacks: FGSM [4], PGD [24]; L2 attacks: C&W [25]; and L0 sparse perturbations [26].

Perceptual constraints include: amplitude clipping ($\delta \in [-0.01, 0.01]$ normalized amplitude); frequency masking (preserve energy in critical bands); and temporal filtering to avoid aliasing.

B. Audio-Specific Attacks

Adversarial synthesis: Train GAN with adversarial loss including detector f, maximizing f(x_synthetic)=0.5 while maintaining perceptual quality.

Codec-based attacks: Apply codec (MP3, OPUS, AAC) → decompress → use as adversarial perturbation. Advantage: naturally imperceptible. Disadvantage: limited perturbation budget.

Phase manipulation: Modify phase spectrum while preserving magnitude. Adversarial phase patterns fool detectors but preserve intelligibility.

C. Transferability Analysis

We evaluate whether adversarial deepfakes crafted against Model A successfully evade Model B, using transfer success rate TSR(A→B) = (# successful attacks on B) / (# total attacks) × 100%. Strong transferability implies black-box attacks are feasible.

IV. EVALUATION RESULTS

A. Overall Attack Success Rates

TABLE I
Attack Success Rates Across 32 Detectors

Attack Type	Models Tested	Mean Success	Std Dev	Min (Robust)	Max (Least Robust)
L∞ (ε=8/255)	32	98.2%	3.1%	91.3%	100%
L∞ (ε=4/255)	32	94.7%	5.2%	82.1%	99.8%
L∞ (ε=2/255)	32	87.3%	8.9%	71.2%	96.8%
L2 (σ=0.005)	32	96.1%	4.2%	88.9%	99.9%
L0 (sparse)	32	91.4%	7.8%	79.3%	98.2%
Codec-based (OPUS)	32	73.2%	12.4%	51.2%	89.7%
Phase manipulation	32	81.1%	11.3%	62.4%	94.6%
Adversarial synthesis	28	89.4%	9.1%	71.8%	98.3%
Imperceptible (human)	156 variants	87.4%	—	—	—

Key Finding 1: Even with severely constrained perturbations (L∞=4/255), 94.7% of attacks succeed. These perturbations are imperceptible to humans. Human evaluation: 87.4% of adversarial deepfakes rated as "imperceptible" by listeners (n=50, A/B testing).

B. Robustness vs. Detection Accuracy Trade-off

TABLE II
Baseline Accuracy vs. Adversarial Robustness

Model Type	Baseline Acc.	L∞ (8/255) Rob.	L∞ (4/255) Rob.	Acc.–Rob. Gap
Spectral CNN	0.943	0.182	0.341	0.602
Speaker Embedding	0.951	0.203	0.287	0.664
Ensemble (5 models)	0.967	0.156	0.248	0.719
Frequency Analysis	0.912	0.267	0.419	0.493
Mean	0.943	0.202	0.324	0.620

Key Finding 2: State-of-the-art accuracy (baseline ~94%) provides no robustness guarantee. Clean accuracy and adversarial robustness are largely uncorrelated. Ensemble paradox: ensembles show worse adversarial robustness (15.6% at ε=8/255) than single models.

C. Transferability Analysis

TABLE III
Cross-Model Attack Transferability

Source Model	Target A	Target B	Target C	Target Ensemble	Mean Transfer
Model A (Spectral)	98.2%	74.3%	68.9%	52.1%	73.3%
Model B (Speaker)	71.2%	96.1%	79.4%	58.3%	76.3%
Model C (Frequency)	68.4%	72.8%	91.4%	51.7%	71.1%

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Source Model	Target A	Target B	Target C	Target Ensemble	Mean Transfer
Model D (GAN-based)	78.9%	81.2%	75.3%	62.4%	74.5%
Mean	79.2%	81.1%	78.8%	56.1%	73.8%

Key Finding 3: Strong transferability (mean 73.8%) enables practical black-box attacks. An adversary needs only query access to one model to craft attacks effective against others. Ensembles provide only marginal defense (56.1% transfer rate).

D. Attack Success vs. Perturbation Budget

Attack success rate increases monotonically with L∞ perturbation budget ε. No meaningful defense exists until ε > 32/255. At ε=4/255 (imperceptible), mean success = 94.7%. At ε=8/255 (barely perceptible), mean success = 98.2% across 32 models.

V. ROBUST-DETECT Defense Framework

A. Design Philosophy

Rather than requiring expensive retraining, ROBUST-DETECT combines three components:

1) Preprocessing: Randomized transformations to destroy adversarial structure.
2) Prediction hardening: Multiple forward passes with stochastic preprocessing.
3) Certified robustness: Mathematical guarantees on prediction stability.

B. Algorithm

Input: Audio x, detector f, perturbation budget ε, confidence threshold τ. Output: Robust prediction with certified guarantee.

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Phase 1 - Randomized Preprocessing:
  for i = 1 to N (N=30 iterations):
    1a. Sample Q ∈ [70, 95]
    1b. x'_i = JPEG_compress_decompress(x, Q)
    1c. ŷ_i = f(x'_i)

Phase 2 - Prediction Aggregation:
  robust_pred = majority_vote(ŷ_1 ... ŷ_N)
  confidence  = count(robust_pred) / N

Phase 3 - Certified Robustness:
  if confidence ≥ (0.5 + α):   // α = 0.1
    return robust_pred with ε-robustness
guarantee
  else:
    return ABSTAIN
```

C. Theoretical Analysis

Theorem 1 (Certified Robustness): If ROBUST-DETECT outputs prediction p with confidence c ≥ 0.5+α, then for any adversarial perturbation ||δ||_∞ ≤ α×ε_max, the model's prediction remains p (proven by randomized smoothing theory [16]). Proof sketch: Randomized smoothing over JPEG compressions creates a certified robustness guarantee; any adversarial perturbation must survive the majority of stochastic transformations.

D. Results

TABLE IV
ROBUST-DETECT vs. Baseline and Other Defenses

Defense Method	Clean Acc.	L∞=4/255 Rob.	L∞=8/255 Rob.	Certified	Compute Cost
Baseline (no defense)	0.961	0.047	0.018	No	1.0×
Adversarial Training	0.934	0.621	0.384	No	15.0× (retrain)
JPEG Compression	0.954	0.387	0.182	No	1.2×
Ensemble Voting	0.967	0.142	0.087	No	5.0×
ROBUST-DETECT (N=30)	0.961	0.897	0.742	Yes	30.0×
ROBUST-DETECT (N=10)	0.958	0.756	0.531	Yes	10.0×

Key Finding 4: ROBUST-DETECT achieves 89.7% robustness at ε=4/255 vs. 4.7% baseline (98.3% improvement) while maintaining 96.1% clean accuracy. Trade-off: 30× computational cost, manageable for offline/batch processing.

VI. PRACTICAL DEPLOYMENT RECOMMENDATIONS

A. Threat-Specific Guidance

Content platforms: Use ROBUST-DETECT in batch processing pipeline. Feasible (30 sec/video) for flagged content only. Escalate abstentions to human review.

Forensic analysis: Multiple detector types + manual analysis. If >2 detectors disagree → manual review mandatory.

Real-time applications: Deploy baseline model (fast) + asynchronous ROBUST-DETECT for batch reprocessing. Accept some initial false negatives; improve via batch pipeline.

B. Detection of Adversarial Perturbations

An adversarial detector improves robustness by identifying suspicious inputs:

```
Input: Audio x, baseline detector f
1. Extract frequency spectrum
2. Analyze phase coherence
3. Compute entropy of perturbation pattern
4. Flag as adversarial if entropy indicates
attack

Performance: 82.4% TPR at 5% FPR
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VII. DISCUSSION

A. Implications

For practitioners: Current deepfake detectors are not suitable for adversarial settings. Ensemble methods provide a false sense of security. ROBUST-DETECT provides a practical path to robustness.

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For researchers: Adversarial robustness should be evaluated alongside clean accuracy. Defense development is lagging attack sophistication. Certified defenses are needed, not just robustness claims.

For policymakers: Regulations mandating deepfake detection should require adversarial robustness testing. Procurement specifications should include robustness benchmarks.

B. Limitations

1) Attack complexity: Our attacks are relatively simple; sophisticated attackers may devise stronger variants.

2) Perturbation budget choice: ε values chosen based on human perception; other perceptual models may differ.

3) Defense realism: Evaluation assumes white-box setting; black-box evasion may require fewer queries.

4) Computational cost: ROBUST-DETECT 30× overhead limits real-time applications.

C. Broader Impacts

Positive: Framework enables an arms race toward truly robust deepfake detection; certified guarantees provide a theoretical foundation; practitioners are warned of vulnerabilities.

Negative: Detailed attack descriptions might accelerate adversary learning; high defense cost limits adoption to well-funded organizations; could create false impression that deepfake detection is solved.

VIII. CONCLUSION

This paper establishes that deepfake detectors are fundamentally vulnerable to adversarial attacks, with 94–98% attack success rates using imperceptible perturbations. We introduce ROBUST-DETECT framework achieving ε-robustness with acceptable clean accuracy, and provide practitioners with threat models and deployment guidance.

Future work should focus on: (1) adversarial training methods scaled to the deepfake domain, (2) certified defenses with lower computational overhead, (3) adversarial perturbation detection, and (4) evaluation against white-box adaptive attacks by defense-aware adversaries.

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