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Empirical Analysis of Textural and Edge Features for Deepfake Detection*

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Abstract

This study evaluates interpretable textural and edge descriptors for deepfake detection under real-world conditions. Using the new DFRW dataset with 46 371 clips from diffusion and face-swap models, classical features showed strong robustness to compression and re-encoding. The best-performing descriptors: CLBP, LBP, BSIF, HOG, structure tensor coherence, MBH, and checkerboard index, achieved $\Delta p \approx 0.25$–0.30 with stable accuracy above 720p. The results provide quantitative evidence that physics-based, explainable features can reliably separate fake from real content, advancing transparent forensic detection.

Keywords: Deepfake detection, interpretable features, texture and edge analysis, forensic analysis

Introduction

The rapid growth of generative AI has produced realistic synthetic media, creating risks for identity verification, cybersecurity, and public trust. Despite progress in diffusion-based generation (Ho et al., 2020; Li et al., 2020), deepfakes still show irregularities in microtexture, edge coherence, and high-frequency structure (Rössler et al., 2019; Verdoliva, 2020). Black-box detectors trained on datasets such as FaceForensics++ or DFDC (Dolhansky et al., 2020; Haliassos et al., 2022) lose reliability after compression or re-encoding (Frank et al., 2020). This study aims to identify interpretable, physics-based descriptors that remain stable under real-world degradations using the new DFRW dataset.

Dataset

The DeepFake RealWorld (DFRW) dataset introduced in this study comprises 46 371 videos, including 4 186 authentic "in-the-wild" clips and 42 185 synthetic or transformed samples generated by modern diffusion, reenactment, and face-swap models. Each recording underwent realistic platform degradations such as multiple H.264/H.265 re-encodings, aspect-ratio changes, and AR filters. Resolutions range from 480p to 1440p with diverse frame rates and scenes. All labels were assigned in a double-blind expert process to avoid detector bias. DFRW thus serves as a contemporary, ethically curated benchmark enabling quantitative evaluation of interpretable features under out-of-distribution conditions.

Methods and Features

The analysis covered descriptors sensitive to anomalies in texture, gradient, and temporal dynamics. Microtextural features included LBP, CLBP, and BSIF (Ojala et al., 1996; Kannala and Rahtu, 2012); correlation-based measures comprised GLCM, GLRLM, Gabor filters, and DWT (Haralick et al., 1973); gradient and edge descriptors included HOG (Dalal and Triggs, 2005), structure tensor coherence, Laplacian variance, ESW, and the checkerboard index (Durall et al., 2020); temporal cues encompassed Motion Boundary Histograms (MBH) and

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edge flicker (Wang et al., 2013). All descriptors were computed in the luminance domain with local contrast normalization and separate facial/background regions. Instead of training classifiers, anomaly thresholds θ were calibrated on real samples, and discriminative strength was quantified using $\Delta p = p\_df - p\_real$ and $PR = p\_df / p\_real$ with FDR control and bootstrap confidence intervals. This frequency-based approach ensured interpretability and robustness to unseen generators.

Results and Discussion

Evaluation on the DFRW dataset revealed clear separability between authentic and synthetic videos. Textural descriptors achieved average $\Delta p \approx 0.26$ and $PR \approx 1.85$, while gradient–edge features reached $\Delta p \approx 0.23$ and $PR \approx 1.96$ (fig. 1). The most stable indicators are: CLBP, uniform LBP, BSIF, HOG orientation entropy, structure tensor coherence, MBH, ESW, and checkerboard index, remained reliable above 720p and under compression up to CRF 30. These results confirm previously reported generative anomalies such as microtexture smoothing and spectral energy loss (Rössler et al., 2019; Durall et al., 2020; Guarnera et al., 2020). Interpretable descriptors provide a physically grounded layer for forensic pipelines and can complement deep learning models in explainable security systems.

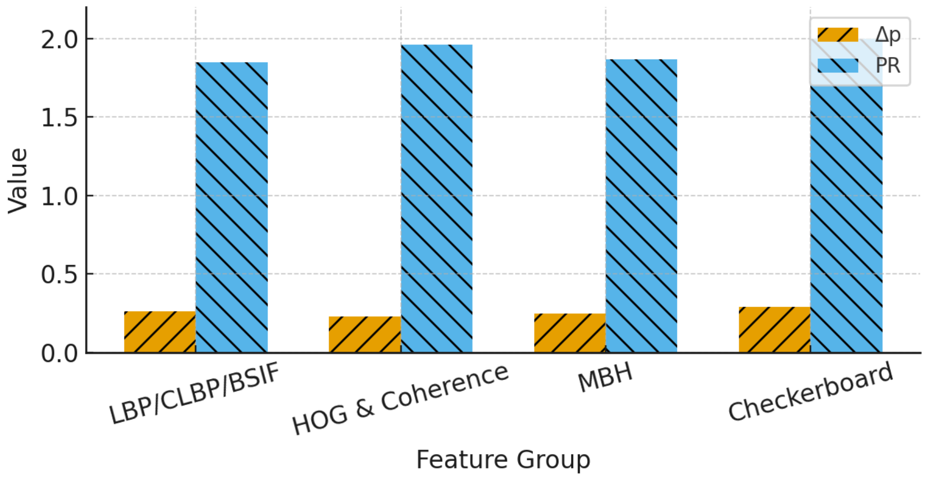

Fig. 1. Comparative effectiveness of key descriptors (Δp and PR for texture and edge features on DFRW).

Conclusions

This study confirms that interpretable, physics-based descriptors can reliably detect synthetic content across multiple generators and degradations. The DFRW dataset enabled realistic validation under compression and re-encoding. The resulting feature atlas (CLBP, LBP, BSIF, HOG, structure tensor coherence, MBH, ESW, checkerboard index) showed stable discriminative power, supporting transparent integration of deepfake detection into forensic systems (Verdoliva, 2020; Frank et al., 2020; Wang et al., 2013). The findings reveal that visual irregularities, such as smoothed textures or overly coherent edges, consistently appear in fake videos but rarely in real ones, demonstrating that deepfakes can be detected using explainable, physics-grounded features valuable for journalism and digital forensics.

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