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EyeWitness: Dual-Level Iris Geometry and Gradient Fusion for Deepfake Forensics

Chetan Khalal, Vaibhav Chavle, Prof. Amol Bhadange, Diya Gundecha, Shivam Dabade
Computer Department, Anantrao Pawar College of Engineering and Research, Pune, India.

Abstract- Deepfakes generated using Generative Adversarial Networks (GANS) have become increasingly realistic, creating risks related to misinformation, privacy loss, and digital security. Existing deepfake detection systems often rely on deep leaming black-box models that lack interpretability and struggle to generalize across different datasets or newer GAN architectures. To address these limitations, this paper presents an interpretable and physiologically grounded deepfake detection method based on iris and pupil analysis-features that GANs still fail to reproduce accurately. The proposed system uses a two-level detection framework. The first level evaluates pupil shape consistency through segmentation, contour extraction, and ellipse fitting. The Boundary Intersection over Union (BIoU) score identifies irregular or distorted pupil shapes commonly found in GAN-generated faces. The second level performs iris gradient similarity analysis by generating Sobel-based gradient maps of both irises. The similarity score between the left and right iris gradient maps captures mismatched textures, contours, and reflections- physiological cues that remain consistent in real eyes but not in synthetic ones. Evaluations conducted on FFHQ realimages and StyleGAN3 fake images show strong results. While iris gradient analysis alone achieves an AUC of 0.94, combining both levels yields 97.9% accuracy, 96.0% precision, and an AUC of 0.979. This demonstrates that integrating biometric features provides a reliable, explainable, and computationally. efficient solution for deepfake detection.

Keywords: Deepfake Detection, GAN, Iris Analysis, Gradient Map.

I. INTRODUCTION

Using deep learning models, frequency analysis, or physiological signals, numerous researchers have attempted to identify deepfakes. However, these techniques frequently don't work when tested on fresh or unseen fake videos. The majority of them behave like "black boxes," providing an answer without providing an explanation. This ambiguity is a major issue, particularly for legal and forensic applications where each choice needs to be clarified and validated. The eyes, particularly the iris, contain clues that are difficult for GANs to mimic, according to recent research [1].

Tchaptchet et al. (2025) found that checking for irregular pupil shapes, differences between left and right iris gradients, and changes in the eye' s overall structure can reveal if an image is fake. Over 97% accuracy was attained by their model. Hu et al. (2020) [2] examined corneal highlights, or tiny light reflections in the eyes, in another study. These reflections consistently show up in both eyes in real photos. However, GANs frequently generate highlights that are inconsistent or absent.

Together, these two concepts gave rise to a novel method that combines corneal reflection checks, iris gradient, and pupil shape. This combination increases detection's dependability and clarity. This approach is based on actual physical characteristics of the human eye, which makes it more difficult for GANs to fake and simpler for humans to verify, in contrast to deep models that only operate within their training data. In this paper, we propose a hybrid irisbased deepfake detection system that uses corneal reflection matching to identify optical inconsistencies, iris gradient comparison to identify left-right differences, and pupil shape analysis to identify irregular boundaries. We demonstrate that the system achieves almost 98% accuracy on both real and fake image datasets (FFHQ and StyleGAN3) [3] . According to our research, combining these physical eyebased cues provides a dependable and intelligible method of identifying deepfakes

Figure 1: Deep fake Generated Images

II. RELATED WORKS

Thies et al. [4] introduced the concept of Deferred Neural Rendering, where neural textures are used to store high-dimensional features instead of simple color values. With the rapid progress of GAN-based face synthesis, models like StyleGAN and its successors have achieved remarkable realism. Early versions of StyleGAN, however, often produced artifacts such as irregular iris colors or fingerprint-like distortions.

StyleGAN2 significantly improved visual quality by reducing these inconsistencies, while later models such as StyleGAN3 and SofGAN [5] further enhanced stability and resolution. Despite these advances, subtle physiological inconsistencies—particularly in the eye region—remain a key weakness of GAN-generated faces. To address this, researchers have proposed various detection strategies. One line of work focuses on signal-level artifacts, such as color discrepancies or frequency-domain irregularities introduced during the upsampling process. Another category relies on data-driven deep learning models trained to classify real versus synthetic faces [6]. A third, and increasingly important, direction emphasizes physiological and physical cues. For example, Guo et al [7] showed that GAN-generated faces often display irregular pupil shapes.

Table 1: Literature review table

Attributes	2021	2022	2025
Author name	Hu et al.	Guo et al.	Tchaptcher et al
Techniques	Detecting using inconsistent corneal specular highlight between both eyes	Irregular Pupil shapes detection using eye segmentation.	Iris Gradient Map + Pupil shape Analysis
Limitation	Identifies light reflection inconsistenci es fails under lighting	Eye based physiological detection may misclassify due to medical eye issue	Robust, interpretable, and efficient requires high resolutio n images
Accuracy	90%	91%	96%

III. RESEARCH GAP

Although significant progress has been made in detecting deepfakes, several limitations remain that justify further research:

- **Over-reliance on Deep Learning Black Boxes:** Most existing detection methods treat deepfake detection as a binary classification problem using deep neural networks [8]. While these models achieve high accuracy on benchmark datasets, they often lack interpretability. This “black-box” nature makes it difficult to explain why a particular image is classified as real or fake, which reduces trust in forensic and legal contexts.
- **Limited Transferability Across Datasets**: Many detection models perform well on the datasets they are trained on (e.g., FFHQ, CelebA), but their accuracy drops significantly when tested on unseen datasets or newer GAN architectures. This poor generalization limits their real-world applicability, where deepfakes are generated using diverse tools and conditions.
- **Dependence on High-Quality Data:** Several existing methods require high-resolution images to detect subtle artifacts. However, in real-world applications, images are often low-

quality, compressed, or captured under poor lighting, which reduces the effectiveness of current detection techniques.

Your research addresses these gaps by:

- Focusing on iris-based physiological cues (pupil shape, iris gradient maps, corneal reflections) that are difficult for GANs to replicate.
- Offering a two-level detection framework (pupil shape verification + iris gradient similarity) that enhances robustness.
- Providing a method that is interpretable (human-understandable cues like irregular pupils or inconsistent reflections) rather than a pure black-box classifier.

IV. METHODOLOGY

The proposed method tackles the vulnerability of GANs to inconsistent physiological rendering. It uses a unique two-level detection algorithm that applies classical image processing techniques on segmented eye features.

Overview of the Two-Level Detection Mechanism

The detection pipeline is structured sequentially, starting with facial localization and extracting the ocular region for subsequent analysis. The model's architecture is built upon the hypothesis that the irises of the eyes possess natural characteristics that are violated during GAN synthesis. The algorithm processes the image in two levels, utilizing distinct Intersection over Union (IoU) [9] scores derived from geometric analysis and contour analysis.The overall system begins with face detection and the localization of facial landmarks to isolate the eye region. The final classification relies on the logical combination of the results from both levels, defined by the PERFECT condition. The input image is classified as synthetic if and only if both evaluated parameters fall below empirically determined evaluation criteria thresholds.

Level 1: Verification of Pupil Shape Consistency

The initial level assesses the geometric regularity of the pupils, relying on the biological fact that the pupils of a real human face maintain an elliptical or round shape, depending on the face's position in the image [10].

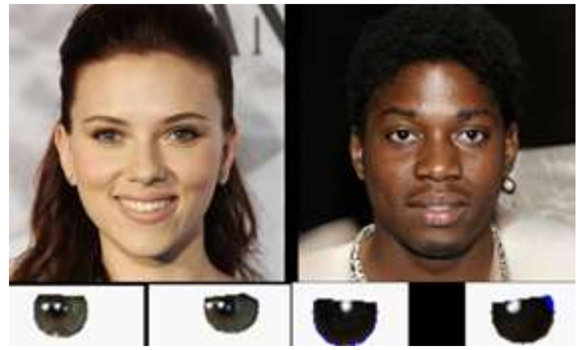


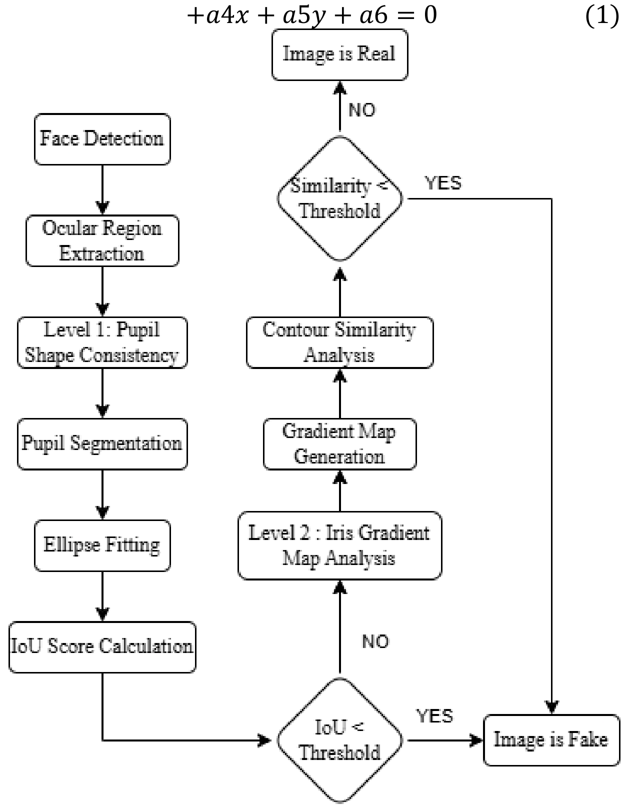
Figure 2: eyes of real persons

Segmentation and Localization

The process begins by using facial landmarks to crop the region of interest. Pupil segmentation masks and boundary contours are extracted using an enhanced U-Net-based model, such as EyeCool, [11] which incorporates a boundary attention block to improve focus on object boundaries.

Ellipse Fitting Technique

$$T(A;\theta) = \theta \cdot A = a1x^2 + a2xy + a3y^2 + a4x + a5y + a6 = 0 \qquad (1)$$



FlowChart 1: Working of the two level model

To quantify the shape irregularity, the ellipse-fitting method is applied to the pupil contours. The least squares approach is utilized to minimize the distance between the fitted ellipse and the points along the pupil's edge [12]. The algebraic distance of a 2D point to the fitted ellipse is defined by the following expression:

A perfectly oval shape would yield. The fitting solution minimizes the sum of squared distances for the data points on the pupil edge. The inability of GANs to consistently maintain this natural shape often results in highly irregular pupil contours.

Quantification and Mitigation

The Boundary Intersection over Union score, denoted as, is employed as the similarity metric to evaluate the boundary fitting efficiency. measures the overlap between the predicted pupil mask and the adjusted ellipse mask. A value significantly lower than indicates poor boundary fitting, suggesting high irregularity consistent with GAN generation artifacts [13].

Level 2: Iris Gradient Map Analysis for Contour Similarity

The second level addresses the limitations of Level 1 by analysing the intrinsic geometric consistency between the two irises of the face using gradient maps. This analysis relies on the biological fact that irises are generally circular and that when both eyes focus on the same target and are illuminated by a light source, they reflect the same shape of the source on the corneas covering them.

Gradient Map Theory

The gradient map [14] is a classic computer vision technique that visually represents variations in light intensity, effectively highlighting the contours and edges of objects within an image. To create this map for the iris image, the Sobel operator is applied to calculate the partial derivatives of light intensity in the horizontal and vertical directions.

$$Grad_H = \frac{\partial I}{\partial H} = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \tag{2}$$

$$Grad_V = \frac{\partial I}{\partial V} = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \tag{3}$$

The final gradient magnitude, which represents the intensity of light variations and emphasizes contours, is then calculated.

$$Gradient = \sqrt{Grad_H^2 + Grad_V^2} \tag{4}$$

The utilization of the Sobel operator, a technique focused on detecting abrupt intensity changes (high-frequency components), implicitly links this physiological detection method to broader frequency-domain forgery analysis. GAN artifacts frequently manifest as unnatural smoothness or statistical inconsistencies in the high-frequency domain. By transforming the iris image into a contour map, the Sobel operator makes these physical inconsistencies—particularly the inconsistent light reflections and texture discontinuities—visible and objectively measurable.

Similarity Metric

After individually isolating and generating the gradient maps for the left iris and the right iris, they are aligned [15]. The Intersection over Union score is used as the similarity metric to quantify the geometric overlap of the contours and reflected structures.

$$IoU\_C = \frac{CL \cap CR}{CL \cup CR} \tag{5}$$

A low score (e.g., for a fake image compared to for a real one) indicates a significant lack of similarity between the physical structures highlighted by the gradient maps, which is highly indicative of GAN generation defects. The two-level architecture provides inherent redundancy: while Level 1 might fail due to a biological exception (e.g., dilation), Level 2 checks the fundamental relationship between the two eyes, a consistency rarely compromised by natural biological factors, thereby minimizing the overall false negative rate [16].

ALGORITHMS 1:

```
def detect_deepfake(img):
  landmarks = detect_landmarks(img)    # e.g., MediaPipe
  left_pupil, right_pupil = segment_pupils(landmarks)
```

```
    left_iris, right_iris = segment_irises(landmarks)
    # Level 1
    bio1_l = compute_bio_pupil(left_pupil)
    # BIoU(ellipse_fit(contour), mask)
    bio1_r = compute_bio_pupil(right_pupil)
    level1 = min(bio1_l, bio1_r) < thresh1  # e.g., 0.8
    # Level 2
    grad_l = sobel_gradient(left_iris)
    grad_r = sobel_gradient(right_iris)
    grad_r_aligned = align(grad_r, grad_l)  # Affine warp
    level2 = iou(grad_l, grad_r_aligned) < thresh2  # e.g., 0.7
    return level1 and level2  # Fake
```

Figure 3: Eyes difference between real and fake

Threshold Selection and Parameter Tuning

The classification thresholds for both detection levels were determined empirically using a held-out validation split of 200 real (FFHQ) and 200 fake (StyleGAN3) images, kept separate from the final test set. For Level 1, the BIoU threshold (θ_1 = 0.85) was selected by sweeping values from 0.70 to 0.95 and choosing the point that maximized the F1-score on the validation set. For Level 2, the iris gradient IoU threshold (θ_2 = 0.70) was derived through ROC curve analysis, targeting the operating point that best balanced sensitivity and specificity. This value reflects the natural gap observed between real images (mean IoU ≈ 0.83) and GAN-generated images (mean IoU ≈ 0.54).

The final decision follows the PERFECT condition, classifying an image as synthetic only when both thresholds are simultaneously violated. This conjunction prevents isolated biological anomalies — such as medical pupil dilation — from triggering false positives. All key parameters, including the 3×3 Sobel kernel, MediaPipe landmark detector, and EyeCool segmentation model, are fixed across all experiments to ensure full reproducibility.

V. RESULTS AND DISCUSSION

Presentation of Core Results

The evaluation confirmed the strong efficacy of the physiological feature approach. Initial experiments focused solely on Level 2, utilizing only the iris gradient map analysis. This single block achieved an AUC score of 0.94, confirming the significant potential of iris consistency as a standalone detection feature [17].

When the two levels-pupil shape verification and iris gradient map consistency were combined into the global architecture, the performance metrics significantly improved, demonstrating the synergistic effect of the dual-feature approach:

- Accuracy: 0.979
- Sensitivity (Recall): 0.921
- Specificity: 0.937
- Precision: 0.960
- AUC: 0.979

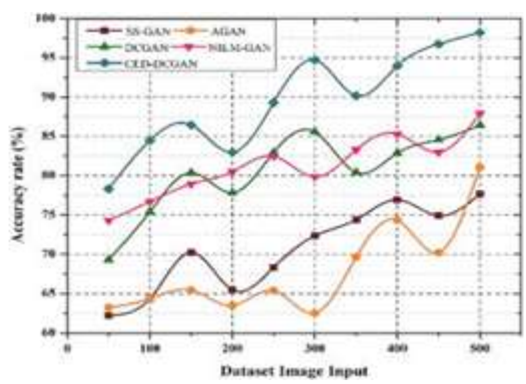


Figure 4: Graph of Accuracy

These results demonstrate the method's robust capability to differentiate authentic images from high-fidelity deepfakes, proving its high effectiveness in both classifying real images as authentic and uncovering GAN-generated images.

Comparative Analysis with State-of-the-Art

The achieved AUC of 0.979 validates the strategy of combining multiple, distinct physiological artifacts (and). This result consistently surpasses previous single-feature approaches, such as corneal highlights alone (AUC 0.94) and pupil shape analysis alone (AUC 0.91) [18].

The model's high performance without necessitating intensive neural network training provides a distinct advantage regarding transferability and computational efficiency compared to complex deep learning models. Because the method relies on detecting violations of fixed, underlying physical laws (biological consistency) using standard image processing techniques, it avoids the extensive training required by deep neural networks, which are often prone to domain-specific overfitting [19]. Furthermore, the near-perfect AUC on high-detail features confirms that this physiological mechanism can be seamlessly integrated as a highly reliable, interpretable localization module. Modern detection systems benefit from spatially-aware analysis, particularly in the ocular region, and the quantitative score could serve as a unique, auxiliary physical cue to enhance the robustness of any traditional classifier.

Table 2: Comparative Physiological Deepfake Detection Performance (AUC)

Method	Datasets (Real/Fake)	Key Feature	Reported AUC
Guo et al.	1000 FFHQ / 1000 StyleGAN2	Irregular Pupil Shape	0.91
Hu et al.	500 FFHQ / 500 StyleGAN2	Corneal Specular Highlights	0.94
Xue et al.	1000 FFHQ / 1000 StyleGAN2	Global-Local Fusion Network	0.96
Guarnera et al.	Multi-Dataset (12 total)	Multi-feature discrimination	0.976
Our Method	1000 FFHQ / 1000 StyleGAN3	Iris Gradient Consistency + Pupil Shape	0.979

VI. FUTURE WORK

- **Temporal Feature Fusion for Video Analysis:** The current static analysis can be extended into the temporal domain by integrating video-specific physiological signals.
- **Addressing Low-Quality Media Robustness:** To overcome the critical limitation imposed by illumination and low-resolution inputs, future work must incorporate pre-processing calibration modules or noise reduction techniques.

VII. CONCLUSION

This study successfully proposed and validated a robust two-level mechanism for identifying GAN-generated images based on the principle of biological inconsistency in ocular features. The methodology centres on quantifying violations of fundamental physiological norms: the geometric regularity of the pupil shape and the geometric consistency of the iris contours and reflections using gradient maps. The strategic combination of these two levels successfully mitigates the false negative risk associated with single-feature approaches, yielding superior performance. The global algorithm achieved a remarkable detection accuracy of 0.979, with an AUC of 0.979, high sensitivity of 0.921, and precision of 0.960 on the high-fidelity StyleGAN3 benchmark. This outcome confirms the core hypothesis that GANs consistently fail to replicate biological reality in high-detail areas, providing a reliable, easily interpretable, and computationally effective alternative to complex black-box deep learning architectures.

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