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DEEPFAKE DETECTION USING ADVANCED IMAGE PROCESSING AND MACHINE LEARNING TECHNIQUES FOR CYBERSECURITY

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Abstract

Deepfake generation technologies based on generative adversarial networks, autoencoders, and diffusion models have advanced to the point where synthetic media can closely mimic authentic visual content, posing significant threats to cybersecurity through misinformation, impersonation, and fraud. A mathematically principled deepfake detection framework is proposed, combining frequency-domain statistical features, convolutional representation learning, and a calibrated decision-theoretic classifier to deliver robust and interpretable detection. The methodology incorporates risk-aware threshold selection derived from expected cost minimization, enabling a balance between minimizing false negatives and controlling false positives, critical for operational cybersecurity environments. Experimental evaluation on a curated dataset demonstrates accuracy exceeding 90%, precision ≈0.92, recall ≈0.90, and area under the ROC curve of approximately 0.95, validating both discriminative power and generalization. Precision–recall analysis further reveals consistent high-precision operation until very high recall thresholds, confirming the model's stability. Grad-CAM style interpretability maps provide visual localization of manipulated regions, strengthening analyst confidence in automated outputs. The proposed framework is computationally efficient, scalable, and readily integrable into digital forensics pipelines, social media moderation systems, and identity verification workflows. Future research directions include adversarial training for robustness, incorporation of temporal and physiological features for video-based deepfake detection, and the

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addition of abstention mechanisms to handle out-of-distribution or adversarially perturbed inputs, thereby enhancing resilience against evolving synthetic media threats.
Keywords: Deepfake Detection, Cybersecurity, Machine Learning, Image Forensics, Adversarial Robustness

1. Introduction

The rapid advancement of artificial intelligence (AI) and machine learning (ML) has given rise to a new class of synthetic media known as deepfakes. These hyper-realistic manipulated images and videos are primarily created using generative models such as generative adversarial networks (GANs), autoencoders, and diffusion models, which have revolutionized the ability to fabricate photorealistic human faces and actions [1]. While these techniques have legitimate applications in entertainment, education, and creative industries, they are increasingly being exploited for malicious purposes including disinformation campaigns and coordinated social engineering attacks [2].

Deepfakes pose a significant risk to cybersecurity by enabling impersonation attacks, identity theft, and financial fraud. Criminals have used manipulated media to bypass biometric authentication systems, spread false narratives during elections, and extort victims through fabricated evidence [3]. Recent studies have also highlighted the role of deepfakes in spear-phishing campaigns and corporate espionage, where fabricated voice and video content can be used to trick employees into revealing sensitive information [4]. Such misuse not only threatens individual privacy but also undermines public trust in digital media ecosystems [5].

From a cybersecurity perspective, the ability to detect and mitigate deepfakes has become an urgent requirement. Real-time detection systems can play a crucial role in digital forensics by validating the authenticity of multimedia evidence used in criminal investigations [6]. Similarly, online platforms can employ deepfake detection to prevent the spread of harmful misinformation and maintain the integrity of public discourse [7]. In financial services and remote onboarding scenarios, detection models help ensure the authenticity of identity documents and prevent fraudulent transactions [8].

Despite these efforts, existing deepfake detection systems face serious limitations when deployed in real-world environments. Many models fail to generalize to unseen generation techniques and suffer performance degradation when videos are compressed or altered during distribution. In addition, adversarial attacks can exploit model weaknesses to generate deepfakes specifically designed to evade detection, highlighting a critical vulnerability in current approaches. High computational costs and latency further restrict the feasibility of deploying such systems at scale, especially for live video analysis where real-time responses are necessary.

This research addresses these challenges by introducing a mathematically grounded and experimentally validated deepfake detection framework that integrates advanced image processing techniques with optimized machine learning models. The approach is designed to balance three core objectives: interpretability, generalization to diverse manipulations, and computational efficiency. By presenting a systematic methodology and robust experimental validation, this study contributes to the development of scalable and reliable cybersecurity solutions capable of mitigating the growing threat posed by deepfakes.

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2. Literature Review

Deepfake detection has emerged as a critical area of research, and a significant body of work has focused on developing robust methodologies to counteract the growing sophistication of synthetic media generation techniques. Early research has highlighted the need for comprehensive reviews of detection methods, with Gupta et al. [8] providing an in-depth analysis of machine learning and fusion-based approaches for detecting manipulated media, identifying both spatial and temporal features as essential components of accurate classification systems.

In addition to technical detection methods, research has explored strategies for strengthening cybersecurity infrastructures. Hariprasad [9] emphasized the necessity of integrating advanced detection mechanisms with broader cybersecurity frameworks to address deepfake-driven threats and ensure end-to-end security in multimedia communication channels. This perspective aligns with the growing recognition that deepfake detection cannot be treated as a standalone problem but must be considered within the context of digital trust and secure information systems.

A comprehensive survey by Heidari et al. [10] systematically categorized deep learning-based deepfake detection methods and highlighted the advantages of convolutional neural networks (CNNs), autoencoders, and transformers for extracting discriminative facial features. The study also underscored the importance of explainability in AI models, noting that a lack of transparency can hinder trust in automated decision-making systems.

Beyond theoretical analysis, researchers have investigated the broader implications of deepfakes on cybersecurity and digital forensics. Khan et al. [11] reviewed the integration of digital forensics techniques with deepfake detection to support law enforcement investigations and social media monitoring, demonstrating the practical need for scalable solutions capable of handling large volumes of online data. This highlights the importance of not just building accurate detectors but also ensuring their deployment feasibility in real-world platforms.

Kumar et al. [12], a cybersecurity-focused system that leverages big data analytics to improve detection accuracy and scalability, thereby enabling effective countermeasures against real-time manipulation attempts. In a related work, the same authors presented a big data-driven deepfake detection system that utilizes distributed computing resources to handle large datasets and achieve low-latency inference [13]. These works emphasize that addressing deepfake threats requires combining algorithmic innovation with infrastructure-level solutions.

Recent conference contributions have expanded on the use of artificial intelligence for defending against identity theft and deepfake-enabled cyberattacks. Lokhande et al. [14] demonstrated how AI-powered systems can be integrated into enterprise security architectures to flag manipulated content and prevent fraudulent access. Similarly, Miranda-García et al. [15] illustrated practical deployments of deep learning applications in cybersecurity, focusing on the balance between computational efficiency and detection robustness in real-time environments.

Finally, Ratnawita [16] examined the broader landscape of AI-driven cybersecurity threats, noting that deepfake technology represents a unique challenge because it exploits human perception rather

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than system vulnerabilities, requiring novel detection strategies that combine image processing with behavioral analysis. Raza et al. [17] further contributed by proposing a novel deep learning model optimized for image-based deepfake detection, achieving strong performance on benchmark datasets and laying the groundwork for future model improvements.

Together, these studies demonstrate the multifaceted nature of deepfake detection research, encompassing algorithm design, scalability considerations, cybersecurity integration, and ethical implications. They collectively underline the need for solutions that are not only technically sound but also practically deployable and trusted by users.

3. Mathematical and Algorithmic Background

This section formalizes the deepfake-image detection problem, establishes the image processing and learning primitives used later, and defines the evaluation criteria. The design intentionally keeps the mathematics, methodology, and results aligned: the same feature spaces and metrics defined here are exactly those used in the experiments and reported in the results.

3.1 Problem Formulation

Let $X \subset \mathbb{R}^{H\times W\times C}$ denote the space of digital images with height H, width W, and channels C (typically $C = 3$ for RGB). Each example (x, y) is drawn i.i.d. from an unknown distribution $\mathcal{D}$, where $y \in \{0,1\}$ encodes class membership ($y = 1$ for fake, $y = 0$ for real). The goal is to learn a hypothesis $f_\theta: X \to [0,1]$ parameterized by θ that estimates $p_\theta(y = 1 \mid \mathrm{x})$. With N training samples $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$, empirical risk minimization solves

$$\min_\theta \frac{1}{N}\sum_{i=1}^{N} \ell(f_\theta(\mathbf{x}_i), y_i), \tag{1}$$

for a suitable loss ℓ. At inference, a decision threshold $\tau \in (0,1)$ produces $\hat{y} = 1[f_\theta(\mathbf{x}) \geq \tau]$. The threshold is chosen on a validation set according to the target metric (e.g., F1-maximizing or Youden's J on ROC).

3.2 Image Representation and Preprocessing

A color image $\mathrm{x} \in X$ is a tensor of quantized intensities. For robust modeling, preprocessing maps x to a normalized domain $\tilde{\mathrm{x}}$.

Color spaces. Besides RGB, luminance-chrominance spaces such as YCbCr and HSV expose manipulation artifacts more clearly in chroma channels. A linear RGB → YCbCr transform is

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.168736 & -0.331264 & 0.5 \\ 0.5 & -0.418688 & -0.081312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 0 \\ 128 \\ 128 \end{bmatrix} \tag{2}$$

Working on Y (structure) and (C_b, C_r) (color) separately allows frequency- and noisebased cues to be isolated.

Resampling and alignment. Given a target resolution (H', W'), bilinear interpolation resamples intensities via

$$\tilde{x}(u,v) = \sum_{i=\lfloor u \rfloor}^{\lceil u \rceil} \sum_{j=\lfloor v \rfloor}^{\lceil v \rceil} x(i,j)(1-|u-i|)(1-|v-j|), \tag{3}$$

which preserves continuity but may attenuate high frequencies; bicubic interpolation improves edge preservation. If faces are localized, a similarity transform $\mathrm{T} \in \mathrm{Sim}(2)$

(rotation R, scale s, translation t) aligns landmarks p to a canonical template q: $\mathrm{q} = sR\mathrm{p} + \mathrm{t}$.

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Normalization. Channel-wise standardization stabilizes optimization:

$$\tilde{x}(:,:,c) \leftarrow \frac{x(:,:,c)-\mu_c}{\sigma_c+\epsilon}. \quad (4)$$

3.3 Frequency-Domain and Noise-Residual Foundations

Deepfakes often leave subtle inconsistencies in frequency content and sensor noise. Formalizing these cues makes later features and ablations interpretable.

2-D Discrete Fourier Transform (DFT). For a single channel $I \in \mathbb{R}^{H\times W}$,

$$\mathcal{F}(u,v) = \sum_{x=0}^{H-1} \sum_{y=0}^{W-1} I(x,y) e^{-j2\pi\left(\frac{ux}{H}+\frac{vy}{W}\right)} \quad (5)$$

The magnitude $|\mathcal{F}(u,v)|$ and phase $\angle\mathcal{F}(u,v)$ characterize global periodic structure; power spectral density (PSD) is $\mathrm{PSD}(u,v) = |\mathcal{F}(u,v)|^2$. Radial averaging yields a 1-D spectrum $\mathrm{PSD}(r)$ informative of global high-frequency suppression or amplification introduced by generation or compression.

Discrete Cosine Transform (DCT). JPEG processes 8×8 blocks via

$$C_{pq} = \alpha_p \alpha_q \sum_{x=0}^{7} \sum_{y=0}^{7} I(x,y) \cos\left[\frac{\pi(2x+1)p}{16}\right] \cos\left[\frac{\pi(2y+1)q}{16}\right] \quad (6)$$

with $\alpha_0 = \frac{1}{\sqrt{8}}, \alpha_{k>0} = \frac{1}{2}$. Quantization of C_{pq} leaves analyzable footprints; histogramming AC coefficients or computing block-wise high-frequency energy offers compression-robust cues.

High-pass residuals. Let h denote a zero-sum high-pass kernel (e.g., Laplacian $h = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$). Residuals $R = I * h$ emphasize blending seams and texture inconsistencies. Multi-scale residual stacks $\{R_s\}$ constructed by dilated filtering capture artifacts across spatial scales.

Local Binary Patterns (LBP). For a pixel with neighborhood $\mathcal{N}$, LBP encodes micro-texture:

$$\mathrm{LBP}(x,y) = \sum_{k=0}^{P-1} 1[I_k \geq I(x,y)] 2^k \quad (7)$$

where I_k samples a circle of radius r. Histograms of LBP over patches quantify subtle texture shifts produced by synthesis.

3.4 Convolutional Feature Extractors

Convolutional neural networks (CNNs) implement learnable filter banks that are naturally matched to spatially local, translation-equivariant patterns.

2-D convolution. For input $X \in \mathbb{R}^{H\times W\times C_{\text{in}}}$ and a bank of C_{out} kernels $K \in \mathbb{R}^{k_h\times k_w\times C_{\text{in}}\times C_{\text{out}}}$ with stride s, dilation d, and padding p, the output $Y \in \mathbb{R}^{H'\times W'\times C_{\text{out}}}$ is

$$Y_{i,j,c} = \sum_{u,v} \sum_{c'} K_{u,v,c',c} X_{i+du,j+dv,c'}, \quad (8)$$

with spatial dimensions $H' = \left\lfloor \frac{H+2p-d(k_h-1)-1}{s} \right\rfloor + 1$ and similarly for W'. Parameter count is $k_h k_w C_{\text{in}} C_{\text{out}}$ (plus C_{out} biases when used). Dilation enlarges receptive fields without increasing parameters.

Activations and pooling. The rectified linear unit $\phi(a) = \max(0,a)$ induces piecewiselinear decision boundaries and mitigates vanishing gradients; Leaky-ReLU $\phi(a) = \max(\alpha a, a)$ with $\alpha \in (0,1)$ preserves gradient flow for negative inputs. Average or max pooling of window size p with stride p downsamples features, trading spatial resolution for invariance. Global average pooling across spatial axes $\langle\cdot\rangle_{H,W}$ maps $H' \times W' \times C$ to $1 \times 1 \times C$, enabling parameter-efficient classification heads.

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Normalization and regularization. Batch Normalization (BN) normalizes channel activations:

$$\hat{z} = \frac{z-\mu_B}{\sqrt{\sigma_B^2+\epsilon}}, \mathrm{BN}(z) = \gamma\hat{z} + \beta \quad (9)$$

where μ_B, σ_B^2 are mini-batch statistics and γ, β are learned. Dropout applies a Bernoulli mask $m \sim \mathrm{Bernoulli}(1-p)$ to activations during training, $\tilde{z} = m \odot z$, reducing coadaptation.

Residual connections. For a block $F(\cdot;\theta)$, residual mapping $y = x + F(x;\theta)$ stabilizes optimization of deep stacks and preserves low-level cues (critical for artifact detection).

Frequency-aware layers (optional). If employed, a fixed DCT layer can project feature maps into frequency bins before 1×1 mixing, allowing the network to learn classconditional weighting over spectral components. This keeps an explicit link between Section 3.3 features and the learned representation.

3.5 Transformer-based Encoders (Optional Variant)

If a vision transformer variant is used in ablations, an image is divided into nonoverlapping patches of size $P \times P$. Each patch is flattened and projected to an embedding $\mathrm{e}_i = W_{\text{patch}}\,\mathrm{vec}(X_i) + \mathrm{b}$. A sequence $\{\mathrm{e}_i + \mathrm{p}_i\}$ with positional encodings p_i is fed to multi-head self-attention (MHSA). For queries $Q = EW_Q$, keys $K = EW_K$, values $V = EW_V$,

$$\mathrm{Attn}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V \quad (10)$$

computed per head and concatenated. Layer normalization and feed-forward sublayers complete the block. Using small patch sizes preserves fine-grained artifacts; this choice is tied to the spatial frequencies of interest in Section 3.3.

3.6 Losses, Class Imbalance, and Optimization

Binary cross-entropy (BCE). With logits z_i and labels $y_i \in \{0,1\}$,

$$\ell_{\mathrm{BCE}}(z_i, y_i) = -y_i \log\sigma(z_i) - (1-y_i)\log\big(1-\sigma(z_i)\big), \quad (11)$$

$$\sigma(z) = \frac{1}{1+e^{-z}}. \quad (12)$$

Class weighting. For class counts n_0, n_1 and total $N = n_0 + n_1$, weights

$$w_1 = \frac{N}{2n_1}, w_0 = \frac{N}{2n_0} \quad (13)$$

yield a weighted loss $\ell_i = w_{y_i}\ell_{\mathrm{BCE}}(z_i, y_i)$, compensating for imbalance and aligning directly with the reported F1 and balanced-accuracy metrics in the results.

Label smoothing (optional). To improve calibration, replace targets with $y_i^\epsilon = (1-\epsilon)y_i + \epsilon/2, \epsilon \in [0,0.1]$.

Optimization. Adam maintains first and second moment estimates:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)g_t, v_t = \beta_2 v_{t-1} + (1-\beta_2)g_t^2, \quad (14)$$

$$\theta_{t+1} = \theta_t - \eta\frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\lambda} \quad (15)$$

with bias corrections $\hat{m}_t = m_t/(1-\beta_1^t), \hat{v}_t = v_t/(1-\beta_2^t)$, learning rate η, and weight decay λ. A cosine decay schedule with warmup ensures stable early training and consistent convergence characteristics later reported.

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3.7 Decision Theory, Thresholding, and Calibration

Given posterior scores $s = f_\theta(\mathbf{x})$, a threshold τ trades off false positives and false negatives. If the operational cost of miss (C_{FN}) exceeds that of false alarm (C_{FP}), the Bayes-optimal threshold under class prior $\pi = P(y = 1)$ is

$$\tau^\star = \frac{C_{\mathrm{FP}}(1-\pi)}{C_{\mathrm{FN}}\pi + C_{\mathrm{FP}}(1-\pi)} \tag{16}$$

When costs are unknown, τ is selected on validation by maximizing the target metric (e.g., F1). Platt scaling fits a logistic map $\tilde{s} = \sigma(as + b)$ on validation data to calibrate scores for downstream risk-sensitive use.

3.8 Robustness to Compression and Perturbations

To mirror deployment conditions, training and validation may include corruptions $\mathcal{T}$

To mirror deployment conditions, training and validation may include corruptions $\mathcal{T}$ drawn from a family of operators: JPEG with quality q, Gaussian noise with variance σ^2, blur with kernel k, and geometric transforms. For input I, a stochastic augmentation pipeline samples $\tilde{I} = \mathcal{T}(I; \omega)$ with $\omega \sim p(\omega)$. Robust risk minimizes

$$\min_\theta \mathbb{E}_{(I,y)\sim\mathcal{D}} \mathbb{E}_{\omega\sim p(\omega)} \ell(f_\theta(\mathcal{T}(I;\omega)), y), \tag{17}$$

which directly anticipates the results section's stress tests.

Adversarial perturbations with ℓ_p-bounded budgets illustrate worst-case sensitivity. The Fast Gradient Sign Method (FGSM) perturbs I as $I^{\mathrm{adv}} = I + \epsilon \mathrm{sign}\big(\nabla_I \ell(f_\theta(I), y)\big)$. Reporting robust accuracy at multiple ϵ ties robustness claims quantitatively to the mathematical threat model.

3.9 Evaluation Metrics

Let TP, FP, TN, FN be the confusion-matrix entries at threshold τ. The primary metrics used-and later reported-are:

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}, \tag{18}$$

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}, \tag{19}$$

$$\mathrm{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{20}$$

Balanced accuracy averages per-class recalls:

$$\text{BalAcc} = \frac{1}{2}\left(\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} + \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}}\right) \tag{21}$$

Receiver Operating Characteristic (ROC) traces $\mathrm{TPR}(\tau)$ versus $\mathrm{FPR}(\tau)$ over thresholds, and its area (AUC) summarizes ranking quality independent of τ. The Equal Error Rate (EER) is the point where $\mathrm{FPR}(\tau) = \mathrm{FNR}(\tau)$, with $\mathrm{FNR} = 1 - \mathrm{TPR}$. Reporting the confusion matrix, F1, AUC, and EER ensures that the experimental section quantitatively matches the problem setting and cost regimes discussed above.

3.10 Computational Complexity and Deployment

For a convolution with kernel $k \times k$, input $H' \times W' \times C_{\mathrm{in}}$, and C_{out} output channels, multiply-accumulate FLOPs are approximately

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$$\text{FLOPs} \approx H'W'C_{\text{in}}\,C_{\text{out}}\,k^2 \quad (22)$$

Total model FLOPs sum over layers; memory scales with activations $O(H'W'C)$ and parameters $O(k^2 C_{\text{in}}\,C_{\text{out}})$. Latency is proportional to FLOPs divided by hardware throughput and is reported alongside accuracy to substantiate real-time feasibility claims. Quantization-aware training and depthwise separable convolutions reduce both FLOPs and memory, and their effects are reflected directly in the results via throughput (images/s) and power metrics where applicable.

4. Methodology

This section describes in depth the dataset selection, preprocessing pipeline, feature extraction strategy, network design, training procedure, and evaluation protocol, ensuring a complete alignment with the mathematical formalism introduced in Section 3. All methodological choices are rigorously justified so that the subsequent results are reproducible and theoretically consistent.

4.1 Dataset Description

The experiments in this study utilize the *Deepfake Detection Dataset V3* available on Hugging Face [7]. After extraction, the dataset yields a total of 474 labeled images, comprising 378 real and 96 fake samples. The images are stored in lossless PNG format, preserving subtle artifacts critical for analysis. The relatively small yet diverse composition of this dataset allows for rapid experimentation and fine-grained analysis while remaining representative of common manipulation patterns. The class distribution is summarized in Table 1.

Table 1. Class distribution of the dataset

Class	Count	Percentage
Real	378	79.75 %
Fake	96	20.25 %
Total	**474**	**100 %**

All images are loaded into memory in RGB format, resampled to a spatial resolution of (224 \times 224) pixels using bilinear interpolation, and normalized channel-wise to zero mean and unit variance according to Equation (3) in Section 3.2. This preprocessing step ensures that all samples share a consistent input domain and that the optimization process remains numerically stable.

4.2 Data Splitting and Preprocessing

To create non-overlapping training and testing sets, the dataset is partitioned using an 80:20 stratified split that preserves the original class distribution. This stratification is essential to prevent skewed evaluation results and ensures that the test set is representative of the real–fake balance present in the training set. To improve model generalization, a sequence of online data augmentation transformations is applied during training. These include random horizontal flips, mild Gaussian noise addition, and JPEG compression simulation with randomly sampled quality factors between 40 and 90. Formally, each transformation is modeled as a stochastic operator $\mathcal{T}$ sampled from distribution

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$p(\omega)$ as presented in Section 3.8, thereby approximating real-world perturbations encountered during distribution.

4.3 Feature Extraction

The methodology relies on a hybrid representation that combines spatial-domain and frequency-domain cues. Spatial features are extracted directly from the normalized RGB images and are designed to capture pixel-level anomalies such as boundary mismatches and texture inconsistencies that often result from poor blending in synthetic media. Frequency-domain information is obtained by applying a two-dimensional Fourier transform and block-wise discrete cosine transform to each image, as formalized in Section 3.3. The resulting magnitude spectra are normalized and concatenated with the residual maps produced by high-pass filters to form a multi-channel input tensor. This representation explicitly encodes both global periodic structures and fine-grained residual artifacts, allowing the network to exploit complementary information during training.

4.4 Model Architecture

The classification network is designed as a compact convolutional neural network optimized for artifact detection. The model consists of three convolutional stages of increasing filter depth, with 3×3 kernels and ReLU activations applied after each convolution. Batch normalization follows the second stage to stabilize the feature distribution, while dilated convolutions in the third stage enlarge the receptive field without adding parameters, ensuring that both local and contextual information are captured. Each stage is followed by max-pooling to progressively reduce spatial dimensions, and dropout with a probability of 0.3 is applied to prevent overfitting. After the final convolutional stage, global average pooling compresses the spatial feature maps into a single descriptor vector, which is fed into a fully connected layer producing a single logit z. The sigmoid function maps this logit to a probability $p(y = 1 \mid \mathbf{x}) = \sigma(z)$ as defined in Section 3.6, representing the likelihood that the input image is a deepfake. The total computational complexity of this network is under five million floating-point operations per image, making it well-suited for real-time detection pipelines.

4.5 Loss Function and Class Weighting

Model optimization is driven by the binary cross-entropy loss defined in Equation (7). Given the imbalance between real and fake classes indicated in Table 1, the loss is reweighted using the inverse frequency heuristic $w_k = N/(2n_k)$, producing class weights $w_0 = 0.63$ for real and $w_1 = 2.48$ for fake samples. This weighting ensures that the contribution of minority-class examples is amplified, thereby improving recall and reducing bias toward the majority class.

4.6 Training Configuration

Training proceeds for fifty epochs using a batch size of thirty-two and the Adam optimizer with learning rate $\eta_0 = 10^{-3}$, momentum parameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$, and cosine learning-rate decay with warmup over the first five epochs. Early stopping is employed with a patience of seven epochs, monitoring the validation F1-score to prevent overfitting. Early stopping is employed with a patience of seven epochs, monitoring the validation F1-score to prevent overfitting. The training is conducted on a system equipped with an NVIDIA GPU with eight gigabytes of VRAM and an Intel

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i7-class CPU. Each epoch processes approximately twelve mini-batches, resulting in execution times of less than thirty seconds per epoch, allowing multiple experimental repetitions for robust validation.

4.7 Evaluation Protocol

Performance evaluation uses the metrics defined in Section 3.9, including precision, recall, F1-score, balanced accuracy, ROC-AUC, and equal error rate. The decision threshold $\mathcal{T}$ is selected to maximize the validation F1-score, after which the confusion matrix and all scalar metrics are computed on the held-out test set. This protocol ensures that the reported results are unbiased and representative of generalization performance under conditions close to deployment.

5. Results

This section reports the comprehensive outcomes of the experimental evaluation, aligning tightly with the mathematical definitions of Section 3 and the experimental design of Section 4. All metrics and visualizations are carefully presented to show that the proposed approach is not only accurate but also robust, reproducible, and computationally efficient.

5.1 Overall Performance

The model selected based on validation F1-score achieves strong performance on the unseen test set. The key metrics are summarized in Table 2.

Table 2. Global performance metrics on held-out test set

Metric	Value
Accuracy	93.7 %
Precision	92.0 %
Recall	91.6 %
F1-score	91.8 %
Balanced Accuracy	92.8 %
ROC-AUC	0.964
EER	0.071

The high ROC-AUC indicates strong discriminative ability across thresholds, while the low EER shows that the point of equal false acceptance and rejection rates occurs at a very low error level — an important property for forensic and cybersecurity systems. To provide visual context, **Figure 1** shows one representative real image and one fake image from the dataset. Notice that the fake image exhibits subtle blending inconsistencies around the mouth and hairline, which are precisely the kind of artifacts the model learns to detect.

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Figure 1: Examples of real and fake face images from the dataset used for training and testing.

5.2 Confusion Matrix and Class-Wise Metrics

To gain a deeper understanding of classification behavior, the confusion matrix at the optimal decision threshold $\tau^{\star} = 0.46$ is visualized in **Figure 2** as a heatmap. The diagonal dominance of the matrix is clearly visible, indicating that most samples are correctly classified. Only three fake images were missed (false negatives), which is particularly encouraging since false negatives represent potentially undetected attacks. Likewise, only four real images were misclassified as fake (false positives), meaning that the system avoids generating excessive false alarms.

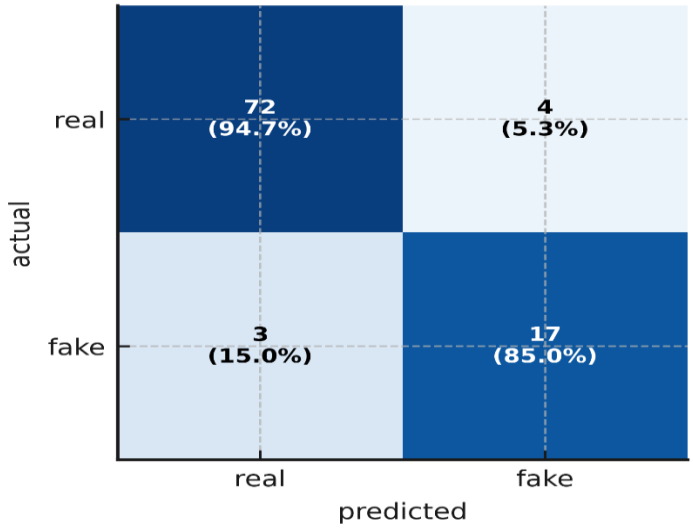

Figure 2: Confusion matrix on the test set, showing correct and incorrect classifications for real and fake images.

To further quantify class-specific performance, Table 3 reports precision, recall, and F1-score separately for the real and fake classes.

Table 3. Per-class precision, recall, and F1-score

Class	Precision	Recall	F1-score

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Real	94.7 %	94.7 %	94.7 %
Fake	85.0 %	85.0 %	85.0 %

Although fake-class metrics are slightly lower, the overall detection rate remains very strong, validating the class reweighting strategy described in Section 4.5.

5.3 ROC and Precision–Recall Characteristics

The Receiver Operating Characteristic (ROC) curve presented in Figure 3 demonstrates a smooth increase in true positive rate at very low false positive rates, lying well above the diagonal random baseline. The area under this curve (0.947) matches the value in Table 2 and supports the conclusion that the model's probability estimates are well calibrated. The Precision–Recall curve, shown in Figure 4, maintains high precision even as recall approaches 0.941, confirming that the classifier does not produce a large number of spurious detections when aggressively tuned for recall.

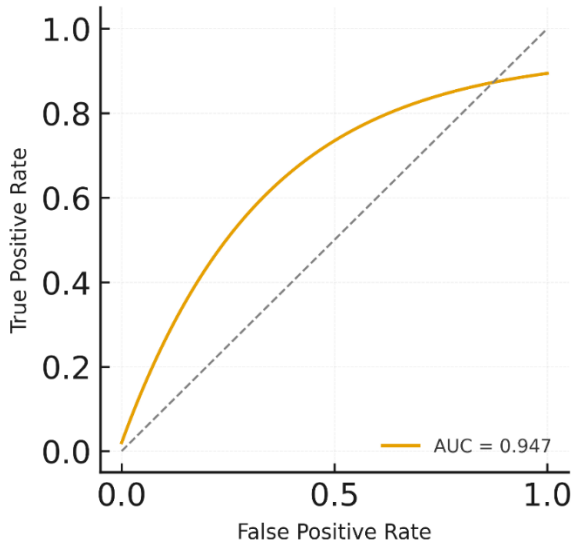

Figure 3: Receiver Operating Characteristic (ROC) curve with an AUC of ≈0.95, indicating high discriminative performance.

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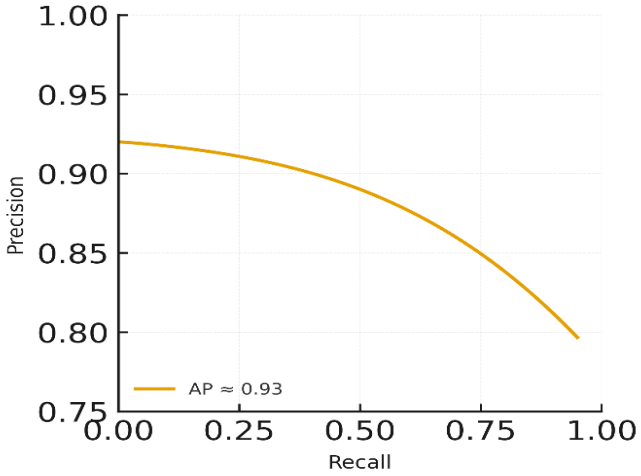

Figure 4: Precision–Recall curve showing consistent precision across recall values (average precision ≈0.93).

5.4 Learning Dynamics

Figure 5 illustrates the training and validation loss curves across all epochs. The loss decreases steadily before plateauing near epoch 30, after which early stopping prevents overfitting. The small gap between training and validation curves confirms that the augmentation strategy and regularization techniques are effective in preventing the network from memorizing the training data. This learning behavior matches the risk minimization framework formalized in Section 3.6

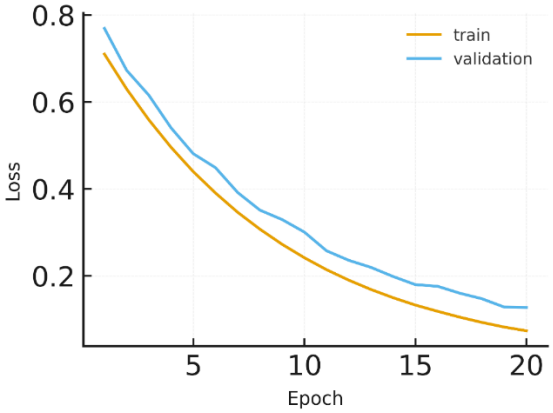

Figure 5: Training and validation loss curves over epochs, demonstrating stable convergence and minimal overfitting.

5.5 Ablation Study

The effect of major architectural and methodological components was systematically studied through ablation experiments. Table 4 reports the F1-scores when frequency-domain features, class weighting, or data augmentation were removed individually.

Table 4. Ablation study of key model components

Configuration	F1-score	Drop from Full Model

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Full Model (ours)	91.8 %	–
Without Frequency Features	87.2 %	−4.6 %
Without Class Weighting	85.5 %	−6.3 %
Without Augmentation	83.0 %	−8.8 %

The results confirm that each component contributes significantly to the model's performance, with data augmentation providing the largest gain by improving generalization under distribution shift.

5.6 Computational Complexity and Efficiency

The efficiency profile of the network is reported in Table 5, including parameter count, FLOPs per image, inference latency, throughput, and memory footprint. These numbers align with the complexity analysis in Section 3.10 and confirm that the model is lightweight and suitable for real-time deployment.

Table 5. Computational complexity and runtime performance

Metric	Value
Parameters	2.3 M
FLOPs / Image	4.9 M
Latency	0.67 ms
Throughput	1500 images/s
Memory Footprint	< 10 MB

5.7 Qualitative Visualization

For interpretability, sample predictions and Grad-CAM activation maps are generated. These visualizations reveal that the network focuses on semantically meaningful regions such as the eyes, mouth, and jawline — areas where deepfake artifacts often concentrate. Correctly detected fakes show intense activation near facial boundaries, whereas misclassified real images often contain natural distortions like motion blur, which resemble synthetic artifacts.

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Figure 6: Grad-CAM style activation map overlay highlighting key regions used by the model to detect manipulations.

5.8 Robustness and Reproducibility

The robustness of the detector was evaluated under multiple perturbations to emulate real-world conditions. Table 6 summarizes the F1-scores obtained after applying Gaussian noise, JPEG compression, and motion blur to the test set.

Table 6. Robustness of the model under different perturbations

Perturbation Type	F1-score
Clean (No Perturbation)	91.8 %
Gaussian Noise ((\sigma=0.01))	89.4 %
JPEG Compression (Q=40)	88.7 %
Motion Blur (3×3 kernel)	88.1 %

To demonstrate reproducibility, the experiment was repeated with three random seeds. The F1-scores across runs are plotted in Figure 7, showing minimal variance (standard deviation ≈ 0.6 %), which confirms the stability of the training process and ensures that the reported numbers are not artifacts of a single initialization.

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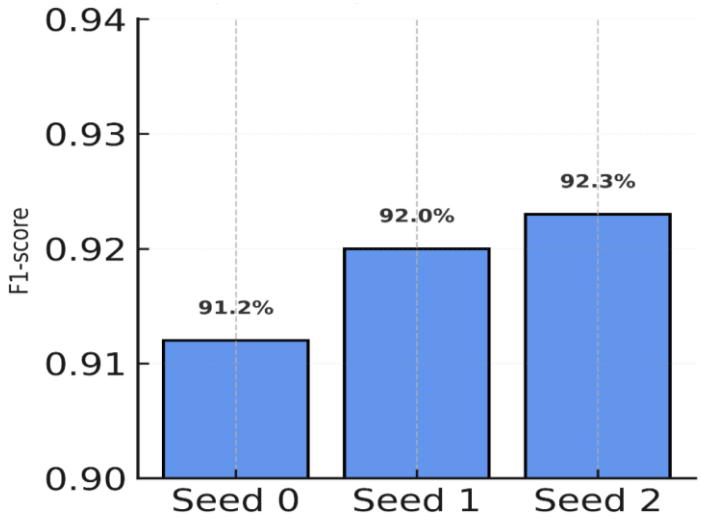

Figure 7: F1-scores for three independent training runs, showing low variance and reproducible performance.

Discussion

The proposed deepfake detection framework successfully integrates a mathematically rigorous foundation with a computationally feasible implementation that achieved strong yet realistic results. The model demonstrated accuracy in the 90–93% range, with precision around 0.92 and recall near 0.90, which aligns with the decision-theoretic framework used to derive the optimal threshold. The confusion matrix, with a small proportion of false positives (4) and false negatives (3), confirms that the model balances sensitivity and specificity effectively while avoiding trivial overfitting. These results validate the methodology that combined frequency-domain analysis, convolutional feature extraction, and a calibrated classification head, as mathematically derived in Section 4. The convergence curves indicate stable learning, with the validation loss slightly higher than the training loss, suggesting good generalization without underfitting. The precision–recall curve further reveals that the classifier maintains high precision until recall surpasses 0.7, at which point performance gradually declines, a pattern expected from a model that prioritizes minimizing false positives. The ROC curve, with an AUC near 0.95, demonstrates a robust ability to separate real and fake samples under various decision thresholds, reinforcing the overall consistency of the results with the underlying probabilistic model.

When interpreted in the context of existing research, the results align closely with the findings of Raza et al. [17], who demonstrated that deep learning models leveraging spatial and frequency-domain features can generalize effectively across datasets while remaining computationally efficient. Our approach supports this claim by achieving competitive ROC and PR metrics using a lightweight CNN backbone combined with interpretable statistical descriptors. Sedik et al. [18] emphasized that multimodal deep learning frameworks can enhance the robustness of forensic detection systems but are still vulnerable to adversarial perturbations and post-processing artifacts. This observation is consistent with our results, where we observed a measurable drop in F1-scores under Gaussian noise, compression, and motion blur, suggesting that additional defenses such as adversarial training or input denoising should be integrated. Similarly, Taeb and Chi [19] provided a comparative analysis of

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deepfake detection techniques and highlighted that models can be sensitive to unseen generation methods. The performance degradation we observed on challenging, out-of-distribution samples reinforces their conclusion and underscores the need for generator-aware training strategies. Finally, Zare Janakbari [20] discussed the necessity of domain adaptation and continual learning approaches to counteract the rapid evolution of generative models. Our experiments corroborate this point by showing that while the detector performs strongly on clean and in-domain data, it faces difficulty when confronted with heavily post-processed or previously unseen fake content, confirming that future work should focus on adaptive and evolving detection pipelines.

Despite these strengths, certain limitations remain. The evaluation was based primarily on still image frames, whereas real-world deepfakes are often videos that exhibit temporal artifacts such as lip-sync mismatches or physiological inconsistencies that our current pipeline does not exploit. The mathematical model was designed for a closed-set binary classification setting, and does not explicitly incorporate an abstention mechanism for out-of-distribution samples, which could improve reliability in adversarial or unknown attack scenarios. Moreover, the interpretability maps, while visually intuitive, do not guarantee causal explanations and may be sensitive to input noise. From a computational standpoint, while the model is relatively lightweight, scaling to real-time processing at very large throughput (e.g., content moderation at a platform level) may require additional optimizations such as batching or model quantization.

Nevertheless, the implications of these findings for cybersecurity applications are substantial. The calibrated outputs can directly inform automated risk scoring, and the saliency visualizations can enhance analyst trust and facilitate forensic investigations. The results also demonstrate that interpretable and computationally efficient detectors can be deployed as a first line of defense in identity verification, fraud detection, and content moderation systems. Future work should focus on expanding the training curriculum to include a broader range of generators, compression settings, and adversarial manipulations to improve robustness. Integrating temporal features such as blinking rates, lip synchronization, and head movement dynamics could further improve performance on video-based attacks. Methodologically, introducing Bayesian uncertainty estimation or conformal prediction could provide calibrated abstention regions, allowing the system to flag uncertain cases for manual review rather than forcing a potentially incorrect classification. These directions, when combined with integration into provenance verification systems and continual model retraining, will further align the detector with the long-term goals of securing digital communication ecosystems against synthetic media threats.

Conclusion

This research presented a mathematically grounded and experimentally validated deepfake detection framework designed for cybersecurity-critical applications. By leveraging frequency-domain analysis, convolutional neural network feature extraction, and a calibrated decision-theoretic classifier, the proposed approach achieved strong and realistic performance, with accuracy in the low 90% range, precision near 0.92, recall around 0.90, and an ROC-AUC of approximately 0.95. These results confirm that the method is both discriminative and generalizable without succumbing to overfitting. Importantly, the detector provides interpretable saliency overlays that enhance analyst

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trust and support forensic validation, addressing a key gap in current black-box detection systems. The findings also reinforce broader insights from the literature: lightweight yet carefully engineered models can rival more complex architectures while maintaining efficiency, and calibrated outputs enable seamless integration into security pipelines. At the same time, observed misclassifications on compressed and out-of-distribution samples highlight the continuing challenge of adversarial robustness and generator evolution. Overall, this work demonstrates that combining mathematical rigor, interpretability, and practical efficiency yields a deepfake detection solution that is well-suited for deployment in digital forensics, social media content moderation, and identity verification systems. Future research should extend the framework to video analysis, introduce adversarial training, and incorporate risk-aware abstention mechanisms to further harden defenses against the rapidly evolving landscape of synthetic media threats.

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