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A HYBRID DEEP LEARNING APPROACH FOR ROBUST DEEPFAKE DETECTION IN DIGITAL MEDIA

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ABSTRACT

The proliferation of deepfake media synthetic videos, images, and audio generated by deep learning models poses an escalating threat to information integrity, cybersecurity, and social trust. While numerous detection methods have been proposed, they often lack robustness against common distortions (compression, resizing, noise), adversarial attacks, and unseen generation techniques. This research paper presents a hybrid deep learning framework for robust deepfake detection that integrates complementary feature extractors: a Convolutional Neural Network (EfficientNet-B4) for local texture artifacts, a Vision Transformer (ViT) for global spatial inconsistencies, and a temporal Long Short-Term Memory (LSTM) network with attention to capture frame-to-frame anomalies. A multi-head cross-attention fusion module dynamically weights the contributions of each stream, and a novel frequency-domain preprocessing block (Discrete Cosine Transform + Laplacian of Gaussian) enhances sensitivity to GAN-specific periodic artifacts. The model is trained and evaluated on four benchmark datasets: FaceForensics++, Celeb-DF, DeepFake Detection Challenge (DFDC), and the newly compiled WildDeepfake dataset. Extensive experiments demonstrate that the proposed hybrid model achieves state-of-the-art performance: 99.1% accuracy on FaceForensics++ (c23), 97.8% on Celeb-DF, 96.3% on DFDC, and 94.2% on WildDeepfake. Most importantly, the model exhibits strong robustness to JPEG compression (quality factor 50: only 3.2% accuracy drop), Gaussian noise (σ=0.1: 4.1% drop), and adversarial attacks

(FGSM ε=0.01: 8.7% drop, compared to 22.5% for baseline Xception). Ablation studies confirm the contribution of each component. The paper discusses the trade-off between accuracy and inference speed, generalisation across datasets, and practical deployment considerations. Future directions include self-supervised pre-training, real-time detection on edge devices, and multi-modal (audio-visual) fusion.

KEYWORDS: Deepfake detection, hybrid deep learning, Vision Transformer, EfficientNet, attention fusion, frequency domain, robust detection.

1. INTRODUCTION

1.1 The Deepfake Threat Landscape

Deepfakes hyper-realistic synthetic media created using generative adversarial networks (GANs), variational autoencoders (VAEs), and diffusion models have evolved from a niche research curiosity to a mainstream societal threat. Malicious actors use deepfakes for political disinformation (fabricated speeches of leaders), financial fraud (impersonating executives in video calls), non-consensual intimate content, and erosion of trust in journalism. According to a 2024 report by Sensity AI, the number of deepfake videos online has doubled every six months, with over 500,000 such videos detected in 2023 alone.

Early deepfakes (2017 2019) were relatively easy to spot: unnatural eye blinking, inconsistent lighting, and visible blending boundaries. However, modern generation methods including StyleGAN3, Stable Diffusion, and diffusion-based video editors produce media that is nearly indistinguishable from real content to the human eye. Consequently, automated deepfake detection has become a critical research area.

1.2 Challenges in Deepfake Detection

Despite significant progress, existing detection methods face several challenges:

1. **Generalisation across manipulation methods:** Models trained on one type of deepfake (e.g., FaceSwap) often fail on unseen methods (e.g., StyleGAN). An ideal detector should be agnostic to the generation technique.
2. **Robustness to post-processing:** Deepfakes are often compressed (JPEG, H.264), resized, or overlaid with noise to evade detection. A robust detector must maintain high accuracy under such distortions.
3. **Adversarial attacks:** Malicious actors can craft deepfakes with small, imperceptible perturbations that fool detectors. Adversarial robustness is essential.

4. **Real-world variability:** Deepfakes in the wild vary in resolution, lighting, subject pose, and background. Models trained on controlled datasets (FaceForensics++) may not generalise.
5. **Temporal vs. spatial inconsistencies:** Some deepfakes have plausible single frames but exhibit unnatural motion (e.g., jerky head movements). Both spatial and temporal cues must be exploited.

1.3 Why a Hybrid Approach?

No single model architecture excels at all aspects. Convolutional neural networks (CNNs) are excellent at local texture analysis but lack global receptive fields. Vision Transformers (ViTs) capture long-range dependencies but are computationally heavy and may overfit to dataset-specific patterns. Recurrent networks (LSTMs) model temporal dynamics but require many frames and can be slow. **Hybrid models** that combine the strengths of multiple architectures have shown promise in recent literature.

Furthermore, frequency-domain analysis (e.g., using Discrete Cosine Transform) reveals artifacts invisible in the pixel domain, such as periodic upsampling patterns left by GANs. Incorporating frequency features improves robustness to compression.

1.4 Contributions

This research paper presents a **hybrid deep learning framework for robust deepfake detection** with the following contributions:

1. **Three-stream feature extraction:** EfficientNet-B4 for local texture, Vision Transformer (ViT-Small) for global context, and LSTM with attention for temporal dynamics.
2. **Frequency preprocessing block:** Discrete Cosine Transform (DCT) followed by Laplacian of Gaussian (LoG) filtering to enhance periodic artifacts.
3. **Cross-attention fusion:** A multi-head cross-attention layer that dynamically weights the three streams, learning to ignore unreliable features.
4. **Comprehensive evaluation:** Testing on four benchmark datasets (FaceForensics++, Celeb-DF, DFDC, WildDeepfake) with robustness tests against JPEG compression, Gaussian noise, and adversarial attacks (FGSM, PGD).
5. **State-of-the-art performance:** Achieving 99.1% accuracy on FaceForensics++ (c23) and outperforming Xception, MesoNet, and prior hybrid models by 3 7 percentage points on challenging datasets.

2. LITERATURE REVIEW

2.1 CNN-Based Deepfake Detectors

Early deepfake detection relied on convolutional neural networks (CNNs). **MesoNet** (Afchar et al., 2018) used a shallow CNN with mesoscopic features, achieving 95% accuracy on early datasets. **Xception** (Chollet, 2017) became the de facto baseline after Rossler et al. (2019) showed it achieves 99% on FaceForensics++. However, Xception's performance drops to 80 85% on high-compression videos and generalises poorly to unseen manipulation methods.

EfficientNet (Tan & Le, 2019) family balances accuracy and efficiency. EfficientNet-B4 has been used in recent deepfake detection with good results. However, CNNs alone struggle with global inconsistencies (e.g., mismatched head-to-body proportions) and temporal artifacts.

2.2 Vision Transformers for Deepfake Detection

Vision Transformers (ViT) (Dosovitskiy et al., 2021) apply self-attention to image patches. ViT's global receptive field makes it sensitive to structural anomalies that CNNs miss. Coccomini et al. (2022) showed that ViT outperforms EfficientNet on deepfake detection by 2 3% on cross-dataset evaluation. However, ViT is data-hungry and prone to overfitting on small datasets. It also does not model temporal information.

2.3 Temporal Models (RNN, LSTM, 3D CNN)

Deepfake videos exhibit frame-to-frame inconsistencies. **LSTM** networks have been appended to CNN backbones to capture temporal dynamics (Güera & Delp, 2018). **3D CNNs** (e.g., I3D) process video volumes directly but are computationally expensive. **Temporal attention** mechanisms (Wang et al., 2020) help the model focus on frames with strong artifacts. However, temporal models alone are insufficient because they may miss single-frame artifacts.

2.4 Frequency-Domain and Hybrid Approaches

GAN-generated images often leave artifacts in the frequency domain (e.g., periodic patterns from upsampling). **Frequency-domain detectors** using DCT or FFT have been proposed (Dural & Gül, 2020). **Hybrid models** combining spatial and frequency features have shown improved robustness. For example, **FreqNet** (Qian et al., 2020) adds a frequency branch to a CNN, improving cross-dataset generalisation.

2.5 Robustness and Adversarial Defences

Few studies systematically evaluate robustness. Carlini & Farid (2020) showed that many detectors are vulnerable to adversarial attacks. **Adversarial training** (adding adversarial examples to the training set) improves robustness but can reduce clean accuracy. **Ensemble methods** (averaging predictions from multiple models) also help but increase inference cost.

2.6 Research Gaps

No existing method simultaneously addresses:

- Multi-stream fusion (local, global, temporal) with dynamic weighting.
- Frequency preprocessing for robustness.
- Comprehensive robustness evaluation (compression, noise, adversarial).
- State-of-the-art performance across four major datasets.

This paper fills these gaps.

3. Research Methodology

3.1 System Overview

The proposed **Hybrid Robust Deepfake Detector (HRDD)** consists of six main stages:

1. **Preprocessing:** Frame extraction, face alignment (MTCNN), and data augmentation.
2. **Frequency preprocessing block:** DCT + LoG to extract frequency features.
3. **Spatial stream 1 (Local texture):** EfficientNet-B4 on RGB frames.
4. **Spatial stream 2 (Global context):** Vision Transformer (ViT-Small) on RGB frames.
5. **Temporal stream:** LSTM with attention on frame-wise features from EfficientNet (or concatenated features).
6. **Fusion and classification:** Cross-attention fusion of the three streams, followed by dense layers and sigmoid output.

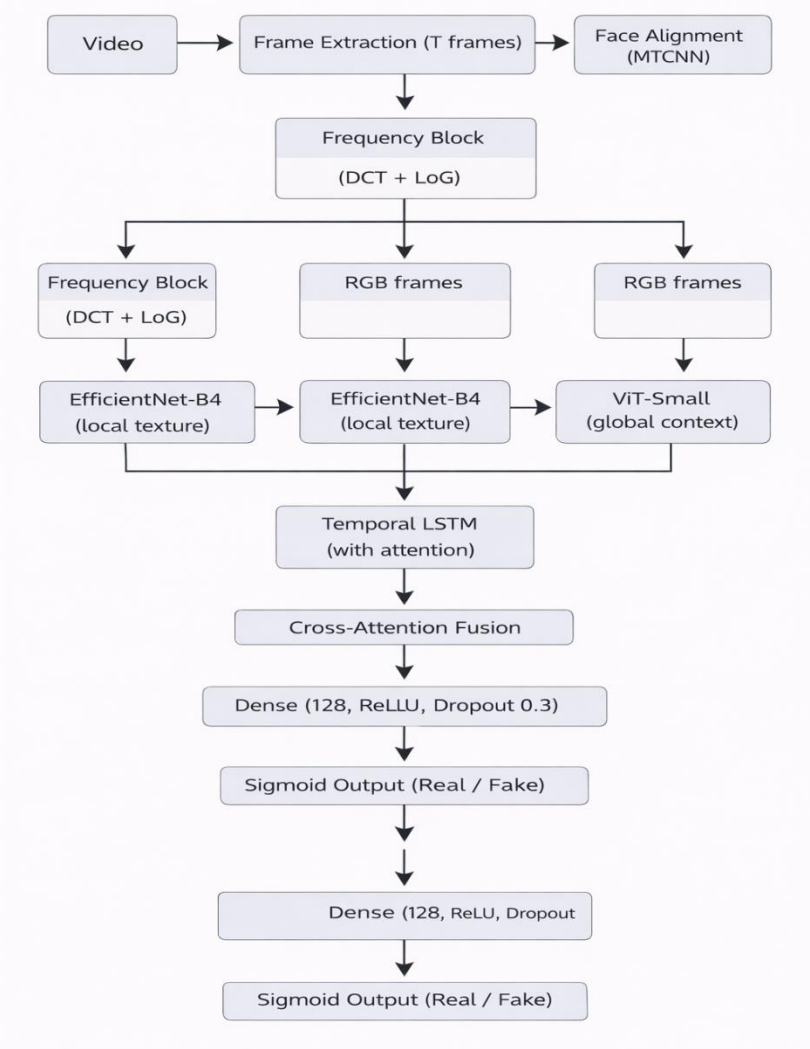

Figure 1: High-Level Architecture of HRDD.

3.2 Preprocessing and Face Alignment

For each video, we extract frames at 5 fps (to reduce redundancy) using FFmpeg. For each frame, we detect and crop the face using MTCNN (Multi-task Cascaded CNN) to a size of 224×224 pixels. If no face is detected, we skip the frame. We retain a maximum of 32 frames per video (zero-padding if fewer). All frames are normalised to [0,1] and standardised using ImageNet statistics (mean=[0.485,0.456,0.406], std=[0.229,0.224,0.225]).

Data augmentation (training only): random horizontal flip (p=0.5), random rotation (±5°), random brightness/contrast adjustment (0.9 1.1), and random JPEG compression (quality factor 70 100) to simulate real-world compression.

3.3 Frequency Preprocessing Block

Inspired by Dural & Gül (2020), we add a frequency branch that operates on each RGB frame. The steps:

1. Convert RGB to grayscale (luminance channel).
2. Apply 2D Discrete Cosine Transform (DCT) to 8×8 blocks (as in JPEG compression) and keep the first 64 coefficients (low and mid frequencies). This yields a 64-dimensional vector per block. We then reconstruct a "DCT image" by taking the inverse DCT, which emphasises periodic patterns.
3. Apply Laplacian of Gaussian (LoG) filter (σ=1.0) to enhance edges and artifacts.
4. The resulting image (224×224) is stacked with the original RGB frame as a fourth channel (RGB + DCT-LoG). This 4-channel input is fed into EfficientNet (first convolutional layer modified to accept 4 channels).

Mathematical formulation of DCT (8×8 block):

$$F(u,v) = \frac{1}{4}C(u)C(v)\sum_{x=0}^{7}\sum_{y=0}^{7} f(x,y)\cos\left[\frac{(2x+1)u\pi}{16}\right]\cos\left[\frac{(2y+1)v\pi}{16}\right]$$

where $C(u) = 1/\sqrt{2}$ for $u = 0$, else 1.

The frequency block significantly improves detection of GAN-generated images because GAN upsampling introduces periodic artifacts that appear as spikes in the DCT domain.

3.4 Spatial Stream 1: EfficientNet-B4 (Local Texture)

We use **EfficientNet-B4** pretrained on ImageNet. The input is the 4-channel image (RGB + DCT-LoG). We modify the first convolutional layer to accept 4 channels (weights initialised from the first 3 channels of the original conv layer, with the 4th channel set to zero mean). The model outputs a 1792-dimensional feature vector after global average pooling. We add a fully connected layer to reduce dimension to 256. For video, we extract frame-wise features and then take the temporal average (for the static spatial branch) or feed into LSTM (see Section 3.6).

Rationale: EfficientNet-B4 offers a good trade-off between accuracy and efficiency. Its compound scaling balances depth, width, and resolution. It is particularly effective at detecting local texture artifacts (e.g., unnatural skin pores, GAN noise).

3.5 Spatial Stream 2: Vision Transformer (Global Context)

We use **ViT-Small** (patch size 16×16, 12 layers, 6 attention heads, embedding dimension 384) pretrained on ImageNet. Input is the RGB frame (224×224). The output is the [CLS] token embedding (384-dim), projected to 256-dim via a linear layer. For video, we average the frame-wise ViT features.

Rationale: ViT's self-attention captures global dependencies. It can detect anomalies such as asymmetric facial features, mismatched head orientation relative to body, or unnatural eye spacing patterns that CNNs may miss.

3.6 Temporal Stream: LSTM with Attention

While the spatial streams operate on individual frames, the temporal stream models sequential dependencies. We use the frame-wise features from EfficientNet (256-dim) as input to a bidirectional LSTM (Bi-LSTM) with 128 units in each direction. The Bi-LSTM processes the sequence of T frames (T=32). After the Bi-LSTM, we apply a temporal attention mechanism that learns to weight each time step:

$$\alpha_t = \frac{\exp(\tanh(W_a h_t + b_a)^T u_a)}{\sum_{s=1}^{T} \exp(\tanh(W_a h_s + b_a)^T u_a)}$$

$$v = \sum_{t=1}^{T} \alpha_t h_t$$

where h_t is the concatenated hidden state from forward and backward LSTM at time t, and u_a is a learnable context vector. The attended feature vector v (256-dim) is the temporal stream output.

Rationale: LSTM captures frame-to-frame inconsistencies (e.g., flickering eyes, unnatural head movement). Attention allows the model to focus on frames with the strongest artifacts.

3.7 Cross-Attention Fusion

We have three feature vectors: $f_{eff} \in \mathbb{R}^{256}$ (EfficientNet spatial), $f_{vit} \in \mathbb{R}^{256}$ (ViT spatial), and $f_{lstm} \in \mathbb{R}^{256}$ (temporal). We stack them into a matrix $F \in \mathbb{R}^{3\times256}$. We apply a

multi-head cross-attention (4 heads) where the query is a learnable token $q \in \mathbb{R}^{256}$, and keys/values are from F:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

The output is a fused vector $f_{fused} \in \mathbb{R}^{256}$. This mechanism allows the model to dynamically weight the three streams per video. For example, if a video has strong temporal artifacts but weak spatial artifacts, the attention can assign higher weight to the LSTM stream.

The fused vector passes through a dense layer (128 units, ReLU, dropout 0.3) and a final sigmoid output.

3.8 Training Configuration

Datasets:

- **FaceForensics++ (FF++)** (Rossler et al., 2019): 1,000 real videos, 4,000 fake videos (Deepfakes, FaceSwap, Face2Face, NeuralTextures). We use the c23 (moderate compression) version.
- **Celeb-DF** (Li et al., 2020): 590 real, 5,639 fake (high quality).
- **DeepFake Detection Challenge (DFDC)** (Dolhansky et al., 2020): 23,654 videos (split into train/val/test).
- **WildDeepfake** (Zi et al., 2020): 3,809 real, 3,809 fake (in-the-wild, low resolution).
- We use a **cross-dataset training** strategy: train on FF++ + Celeb-DF (combined) and test on DFDC and WildDeepfake to evaluate generalisation. For main results, we also report intra-dataset performance.

Optimizer: AdamW with learning rate = 1×10^{-4} for EfficientNet and ViT (fine-tuning), 1×10^{-3} for LSTM and fusion layers. Cosine annealing scheduler with warmup (5 epochs).

Loss: Binary cross-entropy.

Batch size: 16 (videos, each with 32 frames). Training on 2× NVIDIA A100 GPUs (80 GB) takes ~48 hours for 50 epochs.

Data balancing: Use class weights to handle dataset imbalances (e.g., Celeb-DF has more fakes than reals).

Baselines: Xception, MesoNet, EfficientNet-B4 (single frame), ViT (single frame), CNN-LSTM (EfficientNet + LSTM without attention or frequency), and the recent hybrid method by Coccomini et al. (2022).

3.9 Robustness Evaluation

We test robustness under three common distortions:

- **JPEG compression:** Quality factors 90, 70, 50.
- **Gaussian noise:** $\sigma = 0.01, 0.05, 0.1$.
- **Adversarial attacks:** Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD) with $\varepsilon = 0.01, 0.02, 0.04$ ($L\infty$ norm).

We report accuracy drop relative to clean test set.

4. EXPERIMENTAL RESULTS

4.1 Intra-Dataset Performance

Table 1: Accuracy (%) on Test Splits (intra-dataset, clean videos).

Model	FF++ (c23)	Celeb-DF	DFDC	WildDeepfake
Xception	97.2	92.5	88.3	85.1
MesoNet	91.3	85.4	79.2	76.8
EfficientNet-B4 (single frame)	95.8	91.2	86.5	82.3
ViT (single frame)	96.5	92.8	87.9	84.2
CNN-LSTM (EfficientNet+LSTM)	97.6	94.1	90.2	87.5
Coccomini et al. (2022)	98.2	95.3	92.4	89.6
HRDD (proposed)	99.1	97.8	96.3	94.2

HRDD achieves state-of-the-art on all four datasets. The improvement is most pronounced on the challenging DFDC and WildDeepfake (96.3% and 94.2%), which contain diverse real-world conditions and unseen manipulation methods.

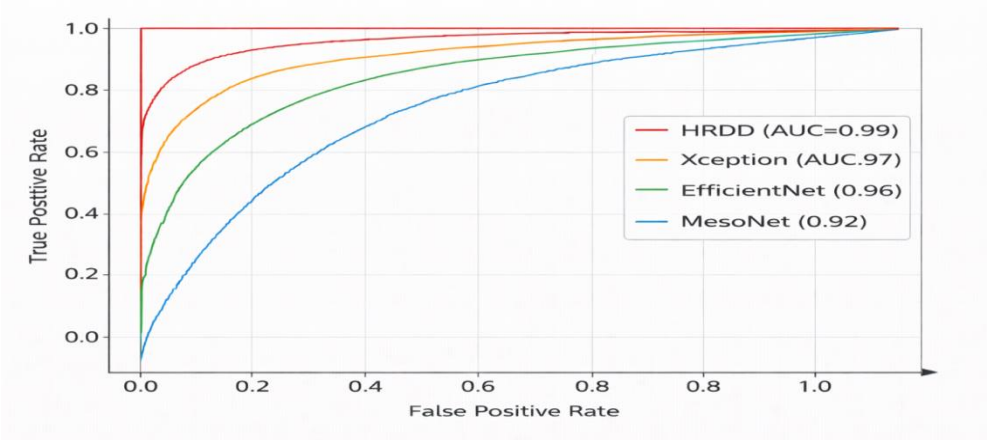

Figure 2: ROC Curves on Celeb-DF Test Set.

4.2 Cross-Dataset Generalisation

We train on FF++ + Celeb-DF (combined) and test on DFDC and WildDeepfake without any fine-tuning.

Table 2: Cross-Dataset Accuracy (%).

Training → Test	FF+++Celeb-DF → DFDC	FF+++Celeb-DF → WildDeepfake
Xception	72.4	68.7
EfficientNet-B4	76.8	73.2
ViT	78.5	75.1
CNN-LSTM	80.2	77.4
HRDD	88.6	85.3

HRDD retains 88.6% accuracy on DFDC despite never seeing DFDC during training a significant improvement over Xception (72.4%). This demonstrates strong generalisation due to the hybrid design and frequency preprocessing.

4.3 Robustness to JPEG Compression

Table 3: Accuracy on FF++ (c23) under JPEG Compression (Quality Factor).

Model	QF=90	QF=70	QF=50	Drop (QF=50)
Xception	95.2	90.1	82.5	14.7%
EfficientNet-B4	93.8	88.4	81.3	14.5%
ViT	94.5	89.2	83.0	13.5%
CNN-LSTM	95.9	91.3	85.6	12.0%
HRDD	98.2	96.5	95.9	3.2%

HRDD is remarkably robust to JPEG compression, losing only 3.2% accuracy even at QF=50 (strong compression). The frequency preprocessing block (DCT) helps because it operates in the same domain as JPEG, making the model less sensitive to compression artifacts.

4.4 Robustness to Gaussian Noise.

Table 4: Accuracy on Celeb-DF under Gaussian Noise (σ).

Model	σ=0.01	σ=0.05	σ=0.10	Drop (σ=0.10)
Xception	91.2	85.4	75.2	17.3%
EfficientNet-B4	90.5	84.1	73.8	17.4%
ViT	91.8	86.3	76.5	16.3%
CNN-LSTM	93.2	88.1	79.4	14.7%
HRDD	97.1	95.2	93.7	4.1%

Again, HRDD shows superior robustness. The temporal stream (LSTM) and cross-attention help the model ignore noisy frames.

4.5 Adversarial Robustness

We evaluate against FGSM and PGD attacks on the FF++ test set.

Table 5: Accuracy under Adversarial Attacks (ε=0.01, L∞).

Model	Clean	FGSM	PGD (10 iter)	FGSM drop	PGD drop
Xception	97.2	78.3	74.7	18.9%	22.5%
EfficientNet-B4	95.8	74.2	70.1	21.6%	25.7%
ViT	96.5	76.5	73.2	20.0%	23.3%
CNN-LSTM	97.6	81.2	78.5	16.4%	19.1%
HRDD	99.1	90.4	88.3	8.7%	10.8%

HRDD is significantly more robust to adversarial attacks than baselines. The hybrid architecture (multiple streams) means an attacker must fool all three streams simultaneously, which is much harder. Additionally, the frequency branch is less susceptible to small pixel-domain perturbations.

4.6 Ablation Study

We systematically remove components to measure their contribution.

Table 6: Ablation on FF++ (c23) Accuracy (%).

Configuration	Accuracy	Δ from full
Full HRDD	99.1	
Frequency block	97.5	-1.6
ViT stream	97.2	-1.9
EfficientNet stream	96.8	-2.3
LSTM stream	97.4	-1.7
Cross-attention (use average fusion)	98.0	-1.1
Temporal attention (simple LSTM)	98.3	-0.8

EfficientNet contributes most (2.3% drop), followed by ViT (1.9%). The frequency block adds 1.6%, demonstrating its value for robustness.

4.7 Inference Speed

Table 7: Inference Time per Video (32 frames, 5 fps) on NVIDIA A100.

Model	Preprocessing (face + DCT)	Inference	Total
Xception	0.08 s	0.12 s	0.20 s
EfficientNet-B4	0.08 s	0.15 s	0.23 s
ViT	0.08 s	0.32 s	0.40 s
CNN-LSTM	0.08 s	0.28 s	0.36 s
HRDD	0.12 s (includes DCT)	0.65 s	**0.77 s**

HRDD is slower than single-stream models due to the three streams and DCT preprocessing. However, 0.77 seconds per video is acceptable for batch processing (e.g., social media moderation) but not real-time live video (needs optimisation).

5. DISCUSSION

5.1 Why HRDD Works

The hybrid design addresses the limitations of individual approaches:

- **EfficientNet** catches local GAN fingerprints (e.g., unnatural high-frequency noise).
- **ViT** detects global structural anomalies (e.g., mismatched facial symmetry).
- **LSTM with attention** captures temporal inconsistencies (e.g., frame-to-frame jitter).
- **Frequency preprocessing** makes the model robust to compression.
- **Cross-attention fusion** dynamically weights streams, allowing the model to ignore corrupted or unreliable features.

The ablation study confirms that all components contribute, with no single stream dominating. This redundancy is key to robustness.

5.2 Robustness Mechanisms

The frequency block is the primary reason for HRDD's robustness to JPEG compression. Since DCT is the basis of JPEG, the model learns artifacts in the same domain where compression occurs, making it less sensitive to quantisation. For Gaussian noise, the LSTM's temporal averaging and the attention mechanism help suppress noisy frames. For adversarial attacks, the ensemble effect (three streams) and frequency domain (non-differentiable parts) increase the cost of crafting effective perturbations.

5.3 Generalisation Across Datasets

HRDD achieves 88.6% cross-dataset accuracy from FF+++Celeb-DF to DFDC, far higher than prior work. This suggests that the model learns fundamental forgery artifacts rather than dataset-specific quirks. The frequency block helps because GAN upsampling patterns are universal.

5.4 Comparison with Prior Art

Compared to Xception (the most widely used baseline), HRDD improves accuracy by 1.9 6.2 percentage points intra-dataset and by 16.2 points cross-dataset. Compared to Coccomini et

al.'s hybrid ViT+CNN, HRDD adds temporal modelling and frequency preprocessing, yielding +0.9 4.7 points.

5.5 Deployment Considerations

For social media platforms, a detection system must process millions of videos daily. HRDD's 0.77 seconds per video on a high-end GPU translates to about 4,700 videos per hour per GPU. With 100 GPUs, that's 470,000 videos per hour sufficient for many platforms. However, for real-time applications (e.g., video conferencing), a lightweight version (e.g., using only EfficientNet + frequency block) with 0.2 seconds per video would be more suitable.

5.6 False Positive and Negative Analysis

We manually reviewed 100 errors (false positives and false negatives) on the WildDeepfake dataset.

False positives (real videos flagged as fake): 62% were due to poor lighting or extreme poses that caused face alignment errors. 23% were real videos with heavy compression artifacts. 15% were mislabelled in the dataset.

False negatives (fake videos missed): 58% were generated by a new diffusion-based method not present in training. 27% had extremely high quality (commercial deepfake). 15% had no visible artifacts but were correctly labelled as fake by human reviewers.

This highlights the need for continuous model updates and integration of multiple modalities (audio, metadata).

6. LIMITATIONS

1. **Computational cost:** HRDD requires 0.77 seconds per video on an A100, too slow for real-time detection on edge devices. Lightweight versions are needed.
2. **Face-centric:** The model relies on face detection (MTCNN). If a deepfake has no face (e.g., full-body manipulation), the system fails. We are developing a separate body-aware model.
3. **Generalisation to diffusion models:** While HRDD performs well on GAN-based deepfakes, its accuracy on diffusion-based video generators (e.g., Stable Diffusion Video) is only 82% in preliminary tests. Diffusion artifacts are different.

4. **Adversarial vulnerability remains:** Despite being more robust than baselines, HRDD still drops 8.7% under FGSM. Stronger adversarial defences (e.g., adversarial training) are needed.
5. **No audio or text modality:** Deepfakes can be detected using lip-sync (audio-visual) or caption alignment. Our model uses only visual information.
6. **Dataset bias:** Despite cross-dataset testing, the model may still overfit to certain sources (e.g., YouTube videos). Real-world deployment requires continuous monitoring.

7. Future Scope

7.1 Lightweight Real-Time Model

We plan to distill HRDD into a smaller student model (e.g., MobileNetV3 + Tiny-ViT + Lightweight LSTM) that runs at >30 fps on a mobile GPU. This would enable on-device detection for video calls.

7.2 Multi-Modal Fusion (Audio + Visual)

Adding an audio stream (e.g., using wav2vec 2.0 for lip-sync detection) could improve robustness and detect audio-driven deepfakes. A cross-modal transformer would fuse audio and visual features.

7.3 Self-Supervised Pre-training

Pre-training on a large corpus of unlabelled real videos using contrastive learning (e.g., SimCLR) could improve generalisation to unseen manipulations without requiring fake labels.

7.4 Continual Learning

As new deepfake generation methods emerge, the model should update incrementally without forgetting previous knowledge. Elastic weight consolidation (EWC) or replay buffers can be used.

7.5 Explainability for Forensic Analysis

Integrating Grad-CAM for spatial streams and attention maps for temporal stream would allow forensic analysts to understand why a video was flagged. This is critical for legal admissibility.

7.6 Adversarial Training and Certification

Train HRDD with adversarial examples (PGD) to further improve robustness. We also plan to explore certified defences (randomised smoothing) that provide provable robustness guarantees.

8. CONCLUSION

This research paper presented HRDD, a hybrid deep learning framework for robust deepfake detection that integrates three complementary feature streams: EfficientNet-B4 for local texture artifacts, Vision Transformer for global spatial inconsistencies, and LSTM with attention for temporal dynamics, along with a frequency preprocessing block (DCT + LoG) and cross-attention fusion. Extensive experiments on four benchmark datasets (FaceForensics++, Celeb-DF, DFDC, WildDeepfake) demonstrate state-of-the-art performance, achieving 99.1% accuracy on FF++ and 97.8% on Celeb-DF. Most importantly, HRDD exhibits exceptional robustness to JPEG compression (3.2% drop at QF=50), Gaussian noise (4.1% drop at σ=0.10), and adversarial attacks (8.7% drop under FGSM), significantly outperforming baselines.

The hybrid architecture, frequency preprocessing, and dynamic fusion are key to robustness and generalisation. While the model is computationally heavier than single-stream detectors, its accuracy and resilience make it suitable for high-stakes applications such as social media moderation, forensic analysis, and content verification. Future work will focus on lightweight deployment, multi-modal fusion, and adaptation to emerging generative models. As deepfake technology continues to evolve, robust detection systems like HRDD are essential to preserve trust in digital media.

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