HYBRID ARCHITECTURES FOR FORENSIC DETECTION OF AI-GENERATED IMAGES: FROM LOW-RESOLUTION CLASSIFICATION TO ZERO-SHOT GENERALIZATION

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Harsh Sinha
(24/RIT/01)

Under the Supervision of
Prof. Dinesh Kumar Vishwakarma

To the
Department of Information Technology

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-110042, India

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DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Bawana Road-Delhi-42

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Place: Delhi

Date: _____ **Harsh Sinha**

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Bawana Road-Delhi-42

DECLARATION

I, **Harsh Sinha**, Roll No. **24RIT01**, student of **M.Tech. by Research** in **Information Technology** at **Delhi Technological University, Delhi**, hereby declare that the thesis titled **"Hybrid Architectures for Forensic Detection of AI-Generated Images: From Low-Resolution Classification to Zero-Shot Generalization"** submitted in partial fulfilment of the requirements for the award of the degree of Master of Technology by Research is an original piece of research work carried out by me under the supervision of **Prof. Dinesh Kumar Vishwakarma**, Professor, Department of Information Technology, Delhi Technological University.

The work reported in this thesis has not been submitted, either in part or in full, for the award of any other degree or diploma in this or any other university or institute.

Place: Delhi

Date: _____

_____

Harsh Sinha
Roll No.: 24/RIT/01

Signature of Supervisor(s) **Signature of External Examiner**

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Bawana Road-Delhi-42

Certificate by the Supervisor

This is to certify that the thesis titled **"Hybrid Architectures for Forensic Detection of AI-Generated Images: From Low-Resolution Classification to Zero-Shot Generalization"** submitted by **Harsh Sinha** (Roll No. 24RIT01) in partial fulfilment of the requirements for the award of the degree of **Master of Technology by Research** in **Information Technology** at **Delhi Technological University, Delhi** is an original research work carried out under my supervision and guidance.

To the best of my knowledge and belief, the work has not been submitted, either in part or in full, for any other degree or diploma to this or any other university or institution.

Place: Delhi

Date: _____

_____

Prof. Dinesh Kumar Vishwakarma
Professor
Department of Information Technology
Delhi Technological University
Delhi – 110042

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Harsh Sinha

ABSTRACT

The rapid proliferation of generative AI models has fundamentally altered the landscape of digital media authenticity. Modern synthesis pipelines—spanning Generative Adversarial Networks, latent diffusion architectures, and large-scale text-conditioned models—can now produce images that are perceptually indistinguishable from genuine photographs and artworks. This shift creates urgent demands for forensic detection systems that are simultaneously accurate, computationally tractable, and robust to generators not encountered during training.

This thesis presents a progression of three studies that collectively address these demands through hybrid neural architectures operating in both spatial and frequency domains.

The first study introduces **HybridViT**, a CNN–Vision Transformer framework incorporating Discrete Cosine Transform (DCT)-based frequency analysis for detecting AI-generated images in the low-resolution CIFAKE benchmark. By fusing local spatial features extracted by convolutional layers, global context captured via multi-head self-attention, and high-frequency anomaly cues obtained through DCT projection, HybridViT achieves 94.95% test accuracy with only 75,009 trainable parameters—outperforming established CNN baselines including ResNet50, EfficientNet-B0, and VGG16 by substantial margins while requiring orders of magnitude fewer parameters.

The second study extends this hybrid framework to the domain of fine art forensics. **ArtSpectraNet** combines a lightweight CNN–Transformer spatial encoder with a Fast Fourier Transform (FFT)-based spectral branch for joint style classification and authenticity detection on the Kaggle AI ArtBench dataset. Evaluated on approximately 97,000 real and AI-generated artworks spanning ten historical movements, ArtSpectraNet achieves 99.61% authenticity detection accuracy alongside 73.18% top-1 style recognition—demonstrating that style-aware forensic reasoning is both feasible and necessary when the target domain is stylised art rather than natural photographs.

The third and most technically demanding study addresses the critical problem of cross-generator generalisation. **CONCORD** (COnsistency-driven Network for CrOss-scale Robust Detection) is a zero-shot AI-generated image detector grounded in two principles: learnable spectral basis projection and cross-scale structural consistency verification. The Adaptive Cosine Token Reconstruction (ACTR) module replaces fixed DCT projection with a learnable cosine basis bank whose spectral sensitivity adapts during training, while the Hierarchical Cross-Scale Token Consistency Attention (HCSTCA) mechanism verifies whether local spectral observations cohere with global image structure—a property natural images satisfy and synthetic ones systematically violate. All pretrained backbone encoders remain frozen, confining learning to the forensic reasoning modules. Trained on Stable Diffusion v1.4 alone and evaluated zero-shot on seven unseen generators in the GenImage benchmark, CONCORD

achieves 78.1% average cross-generator accuracy, improving over prior methods by more than 3% overall and by more than 14 percentage points on challenging generators such as Midjourney and GLIDE.

Taken together, the three studies advance understanding of how frequency-domain analysis, hybrid spatial–spectral architectures, and structural decoupling can be combined to build AI-image forensics systems that are accurate, efficient, and generalisable.

Keywords: AI-generated image detection, hybrid architectures, CNN–Vision Transformer, discrete cosine transform, fast Fourier transform, zero-shot generalisation, cross-generator robustness, frequency-domain forensics, CIFAKE, GenImage, ArtBench.

List of Publications

The following publications arose directly from the research reported in this thesis.

Journal Paper

1. **Harsh Sinha** and Dinesh Kumar Vishwakarma, "CONCORD: Learnable Spectral Basis Projection with Cross-Scale Consistency Verification for Zero-Shot Detection of AI-Generated Images," *Signal, Image and Video Processing (SIVP)*, Springer, *under review*, 2026.

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3. **Harsh Sinha** and Dinesh Kumar Vishwakarma, "ArtSpectraNet: A Hybrid Spectral–Semantic Architecture for Style-Aware Forensic Detection of AI-Generated Artworks," *8th International Conference on Communication and Computational Technologies, 2026 (NFSU, Goa) [Presented]*.

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List of Symbols, Abbreviations and Nomenclature

Abbreviation / Symbol	Description
AI	Artificial Intelligence
GAN	Generative Adversarial Network
ViT	Vision Transformer
CNN	Convolutional Neural Network
DCT	Discrete Cosine Transform
FFT	Fast Fourier Transform
CLIP	Contrastive Language–Image Pre-training
ACTR	Adaptive Cosine Token Reconstruction
HCSTCA	Hierarchical Cross-Scale Token Consistency Attention
IAP	Instance-Adaptive Pooling
LCBB	Learnable Cosine Basis Bank
MCC	Matthews Correlation Coefficient
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic
SDv1.4	Stable Diffusion version 1.4
DTU	Delhi Technological University
B	Batch size
H, W, C	Height, Width, Channels of an input image
K	Number of cosine basis vectors in LCBB
P	Patch size in ACTR
D, D_p	Embedding / patch feature dimension
N_p	Number of patches
$\mathbf{X}$	Input image tensor
$\mathbf{X}_f$	Frequency-conditioned view produced by ACTR
$\alpha_{i,k}$	Softmax attention weight for patch i over basis k
$\mathcal{L}$	Total training loss

CHAPTER 1
INTRODUCTION

1.1 Background and Motivation

The past decade has witnessed a transformation in the fidelity achievable by generative image models. What began as blurry, artefact-laden outputs from early Generative Adversarial Networks (GANs) has evolved into photorealistic, commercially deployed systems—Stable Diffusion, Midjourney, DALL·E—capable of synthesising high-resolution images on demand, conditioned on arbitrary text prompts. This progression has moved AI-generated imagery from a research curiosity into a societal challenge. Synthetic media now circulates across news platforms, social networks, art marketplaces, and legal proceedings, frequently without any indication of its artificial origin.

The forensic challenge this creates is not merely technical. It is structural. A human observer, shown a high-quality synthetic image alongside a real photograph, may have no reliable means of distinguishing them. This perceptual indistinguishability is precisely the design objective of generative models: the standard training signal for a GAN is a discriminator that learns to tell real from fake, and the generator succeeds when it fools that discriminator. The result is a continuous adversarial pressure toward perceptual realism, and detectors must keep pace.

Early detection approaches relied on pixel-level statistics and handcrafted frequency features—approaches that performed adequately against first-generation GANs but degraded sharply against diffusion-based models and commercial systems whose outputs are post-processed to remove tell-tale spectral artefacts. Deep learning methods have subsequently dominated the field, with CNNs demonstrating strong performance on in-distribution generators and Vision Transformers (ViTs) extending detection capacity to global contextual patterns. However, the most persistent failure mode in the literature is cross-generator generalisation: a detector trained on images from one generative model routinely collapses when evaluated on images from a different one, even within the same broad architectural family. Reported Area Under the Curve (AUC) drops of 30% or more under cross-generator evaluation protocols are not unusual, reflecting a structural problem rather than a straightforward tuning issue.

The central thesis of this work is that these limitations are addressable through a principled combination of three technical strategies: (i) hybrid spatial–frequency architectures that extract complementary cues rather than relying on either domain alone; (ii) multi-task learning that incorporates semantic information—such as artistic style—as an auxiliary signal that regularises forensic feature learning; and (iii) structural decoupling of representation extraction from forensic reasoning, enforced by freezing pretrained backbone encoders and confining all learnable capacity to lightweight forensic modules.

1.2 Problem Statement

This thesis addresses the following overarching research question:

> *How can hybrid neural architectures operating jointly in the spatial and frequency domains be designed to achieve accurate, efficient, and cross-generator-robust detection of AI-generated images?*

This broad question decomposes into three specific sub-problems that motivate the three studies reported in this thesis.

Sub-problem 1: Hybrid detection at low resolution. Standard CNN and ViT architectures used in isolation exhibit complementary strengths and weaknesses. CNNs excel at extracting local spatial features but lack explicit frequency-domain sensitivity; ViTs capture global context via self-attention but may struggle with subtle high-frequency artefacts. Can a lightweight hybrid architecture, augmented with explicit DCT-based frequency analysis, achieve superior detection performance on the CIFAKE benchmark while remaining computationally tractable?

Sub-problem 2: Style-aware forensic detection of AI-generated art. Existing detectors are designed for natural photographs and transfer poorly to the artistic domain, where stylisation, abstraction, and deliberate departures from photographic realism are fundamental features rather than artefacts. Can a multi-task hybrid architecture simultaneously perform robust authenticity detection and meaningful style classification on a large-scale AI ArtBench dataset?

Sub-problem 3: Zero-shot cross-generator generalisation. Single-generator training protocols produce detectors that learn generator-specific shortcuts rather than properties that generalise across synthesis paradigms. Can a detector based on learnable spectral basis projection and explicit cross-scale structural consistency verification achieve significantly improved zero-shot cross-generator accuracy on the GenImage benchmark?

1.3 Research Contributions

This thesis makes the following original contributions to the field of AI-generated image forensics.

HybridViT: A hybrid CNN–ViT framework with DCT-based frequency analysis. The HybridViT architecture introduces a HybridPatchExtractor that processes images through parallel spatial (CNN) and frequency (2D DCT) pathways, fusing local and spectral features before passing them through a lightweight four-block Transformer encoder. With 75,009 trainable parameters, the model achieves 94.95% test accuracy on the CIFAKE dataset, outperforming MobileNetV2, ResNet50, EfficientNet-B0, Inception V3, and VGG16 while requiring substantially fewer parameters than all CNN baselines.

ArtSpectraNet: A multi-task hybrid architecture for style-aware art forensics. ArtSpectraNet combines a CNN–Transformer spatial encoder with an FFT-based spectral branch and two prediction heads for joint authenticity detection and ten-class style classification. Evaluated on the Kaggle AI ArtBench dataset (approximately 97,000 images), the model achieves 99.61% authenticity detection accuracy, F1 = 0.996, AUC $\approx$ 0.9999, and MCC = 0.992, while simultaneously attaining 73.18% top-1 style accuracy.

CONCORD: A zero-shot detector based on learnable spectral basis projection and cross-scale consistency verification. CONCORD introduces the Adaptive Cosine Token Reconstruction (ACTR) module, which replaces fixed-transform frequency projection with an attention-weighted mixture over a learnable, DCT-initialised cosine basis bank. Trained on Stable Diffusion v1.4 and evaluated zero-shot on seven unseen generators in the GenImage benchmark, CONCORD achieves 78.1% average cross-generator accuracy, outperforming all baselines by more than 3% overall.

1.4 Thesis Organisation

The remainder of this thesis is organised as follows.

Chapter 2 presents a comprehensive review of prior work spanning frequency-domain forensics, CNN and ViT architectures for image authentication, hybrid detection models, and generative models relevant to the detection problem.

Chapter 3 describes the HybridViT study in full, covering dataset construction, the HybridViT architecture, training methodology, and experimental results on the CIFAKE benchmark.

Chapter 4 presents ArtSpectraNet, detailing the challenges particular to AI-generated art detection, the multi-task hybrid architecture, and experimental results on the Kaggle AI ArtBench dataset.

Chapter 5 presents CONCORD, motivating the zero-shot detection problem, describing the ACTR and HCSTCA modules in technical detail, and reporting cross-generator evaluation results on the GenImage benchmark.

Chapter 6 synthesises the findings across all three studies, discusses limitations, and proposes directions for future research.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The detection of AI-generated images is an active and rapidly evolving research area at the intersection of computer vision, signal processing, and media forensics. This chapter reviews prior work along four axes: (i) the generative models that constitute the targets of detection; (ii) frequency-domain methods that exploit spectral artefacts introduced during synthesis; (iii) deep learning architectures—CNNs, Vision Transformers, and hybrids—used for detection; and (iv) benchmark datasets that enable standardised evaluation. The review concludes by identifying the specific gaps this thesis addresses.

2.2 Generative Models and the Detection Challenge

2.2.1 Generative Adversarial Networks

Goodfellow et al. introduced the GAN framework in 2014, establishing an adversarial training regime in which a generator and a discriminator improve together. Early high-fidelity models including DCGAN, ProGAN, and StyleGAN demonstrated that CNN-based generators could produce photorealistic faces and objects. A forensically significant property of GAN architectures is that their upsampling pipelines—typically implemented via transposed convolutions—introduce characteristic high-frequency artefacts, particularly checkerboard patterns, that can be detected in the spectral domain [15, 16]. These artefacts provided early forensic methods with reliable, generator-specific signals, but they also established an over-reliance on GAN-specific cues that proved brittle when the detection landscape shifted.

2.2.2 Diffusion Models

Denoising Diffusion Probabilistic Models (DDPMs) [2] generate images by iteratively removing noise from a Gaussian prior, without the periodic upsampling pipelines of GANs. The absence of transposed-convolution artefacts makes diffusion outputs significantly harder to detect using spectral methods trained on GAN data. Subsequent advances—classifier-free guidance, latent diffusion in compressed representation spaces [3], and text conditioning via CLIP—have further suppressed generator-specific artefacts. Commercial systems such as Stable Diffusion, Midjourney, DALL·E, and Wukong add proprietary post-processing, compounding the detection challenge.

DIRE [30] exploited diffusion reconstruction error as an implicit frequency signal specifically targeting diffusion generators, showing that reconstructing an image through a pretrained diffusion model and measuring the reconstruction residual provides a discriminative cue. This approach is effective for diffusion-based synthesis but does not transfer to GAN-generated content.

2.2.3 Text-to-Image Systems

Large-scale text-conditioned models, including DALL·E 2 and Stable Diffusion 3, have extended generation to arbitrary semantic content at commercial scale. These models are trained on billions of image–text pairs and produce outputs with high semantic fidelity and low spectral artefact density. Detection against such models represents the current frontier of forensic research.

2.3 Frequency-Domain Detection Methods

2.3.1 Spectral Anomaly Analysis

The observation that GAN-generated images exhibit consistent high-frequency artefacts prompted a family of frequency-domain forensic methods. Frank et al. [15] demonstrated that GAN outputs have statistically distinct spectral profiles in the DCT domain, and that classifiers trained on DCT coefficients generalise better across GAN architectures than spatial-domain classifiers. Durall et al. [16] traced checkerboard artefacts to transposed convolution operations and showed their detectability via Fourier power spectrum analysis. Marra et al. [17] examined DCT and Fourier statistics of GAN outputs, establishing that model-specific spectral fingerprints survive mild social-media post-processing.

Qian et al. [18] introduced F3Net, which processes spatial and frequency branches in parallel, demonstrating that separating these two streams and fusing them at the decision level improves detection over either branch alone.

2.3.2 Limitations of Fixed-Transform Approaches

A structural limitation shared by all fixed-transform frequency methods is that DCT and Fourier bases are generator-agnostic by construction. When the spectral signature of the test generator shifts relative to training—as consistently occurs across the GAN-to-diffusion boundary—fixed-basis detectors cannot adapt. Dong et al. [19] showed that naive frequency-based detectors are also vulnerable to JPEG compression, resizing, and post-processing operations that attenuate high-frequency artefacts. These limitations motivate the learnable spectral basis approach introduced in CONCORD (Chapter 5).

2.4 Deep Learning Architectures for Image Authentication

2.4.1 Convolutional Neural Networks

CNNs have been the dominant architecture for image forensics since Wang et al. [21] showed that a standard ResNet-50 trained on GAN-generated images can detect multiple GAN architectures with high accuracy by learning spatial residual features. Subsequent work extended CNN-based detection to patch-level reasoning [22], gradient-based frequency cues [24], and Gram matrix statistics [23].

Key CNN architectures relevant to this thesis include ResNet [7], which introduced residual connections to enable training of very deep networks; EfficientNet [8], which optimised model scaling for performance at reduced parameter counts; MobileNetV2 [9], which targeted mobile efficiency through depthwise separable convo-

lutions; and VGG16 [10], a deep but parameter-heavy architecture that remains a standard baseline.

2.4.2 Vision Transformers

Dosovitskiy et al. [12] introduced the Vision Transformer (ViT), adapting the Transformer architecture [13] to image classification by treating images as sequences of flattened patches processed through multi-head self-attention layers.

The Swin Transformer [14] extended ViT to hierarchical feature extraction with shifted window-based attention, reducing computational cost while preserving high accuracy on dense prediction tasks. ViT-based detectors fine-tuned end-to-end on biased detection datasets are prone to shortcut learning [25], motivating the frozen-backbone design of CONCORD.

2.4.3 Hybrid CNN–ViT Models

Hybrid architectures combine CNN feature extraction with Transformer-based global reasoning. Kaddar et al. [31] proposed HCiT, which merges CNN-extracted features with ViT self-attention for deepfake video detection, achieving 91.5% accuracy on the DeepFake Detection Challenge dataset. Kim et al. [32] integrated ViT and CNN outputs through an ensemble strategy. Wang and Song [34] demonstrated that hybrid CNN–Transformer architectures better capture long-range compositional dependencies in artwork classification.

2.5 Transformer-Based Generalisation Methods

Ojha et al. [25] (UniversalDet) achieved strong generalisation by using frozen CLIP features with a nearest-neighbour probe. Cozzolino et al. [28] showed that CLIP-based detectors generalise well with limited training data. Luo et al. [26] (FatFormer) introduced frequency-sensitive adapters over CLIP with language-guided alignment. Liu et al. [27] (NPR) demonstrated that neighbouring pixel relationships induced by GAN upsampling provide a generalisable representation. FreqNet [29] enforced continuous focus on high-frequency representations.

CONCORD differs from all these approaches in introducing explicit cross-scale consistency verification as a forensic reasoning principle: it explicitly tests whether local spectral observations are coherent with global image structure, a structural property that distinguishes natural from synthetic images independent of generator family.

2.6 Computational Analysis of Artworks

Computational style analysis has primarily focused on historical categorisation and attribution. Tan et al. [40] reported 65–70% accuracy across 10–20 styles using CNN baselines on WikiArt. Zhu et al. [39] introduced the ArtBench benchmark and demonstrated the strength of Transformer-based models. ArtSpectraNet (Chapter 4) addresses the forensic gap these works leave open.

2.7 Benchmark Datasets

CIFAKE [35] comprises 120,000 images (60,000 real; 60,000 synthetic) at 32×32 pixels, providing a standard low-resolution forensics benchmark.

FaceForensics++ [36] provides 1,000 original video sequences manipulated with four facial forgery methods.

AI ArtBench (Kaggle) [38] contains approximately 97,000 real and AI-generated artworks spanning ten canonical historical styles.

GenImage [37] pairs real ImageNet images with synthetic images from eight generators spanning GAN and diffusion paradigms, providing the reference cross-generator evaluation protocol.

2.8 Summary and Identified Research Gaps

The survey of prior work reveals three persistent gaps this thesis addresses. First, no prior work on the CIFAKE benchmark had combined CNN local features, ViT global context, and explicit DCT-based frequency analysis in a single lightweight architecture. Second, style-aware forensic detection of AI-generated artworks had not been studied. Third, and most critically, existing frequency-domain detectors rely on fixed transforms that cannot adapt across generator families, and cross-scale structural coherence had not been exploited as an explicit forensic reasoning mechanism.

CHAPTER 3

HYBRIDVIT: FREQUENCY-AUGMENTED HYBRID CNN–TRANSFORMER DETECTION ON LOW-RESOLUTION IMAGES

3.1 Introduction

The CIFAKE benchmark presents a forensically non-trivial challenge despite its low resolution. Images are 32×32 pixels—the native resolution of CIFAR-10—and synthetic images are generated by Stable Diffusion v1.4 conditioned on the same class labels as the real set. At this resolution, the visual difference between real and AI-generated images is subtle, and prior CNN-only baselines struggle to achieve accuracy above 94% without incurring very large parameter counts (VGG16: 138.4 million parameters for 94.93%). This chapter describes HybridViT, which achieves 94.95% accuracy with 75,009 parameters by combining CNN local feature extraction, ViT global context, and DCT-based frequency analysis in a unified lightweight architecture.

3.2 Dataset: CIFAKE

The CIFAKE dataset [35] comprises 120,000 images for binary classification of real versus AI-generated images. The training set contains 100,000 images, evenly split between 50,000 synthetic images produced by Stable Diffusion v1.4 and 50,000 real images drawn from CIFAR-10. The test set contains 20,000 images (10,000 per class). All images are 32×32 pixels in RGB format. The training set was partitioned into an 80–20 training/validation split during model development. Figure 3.1 shows representative examples.

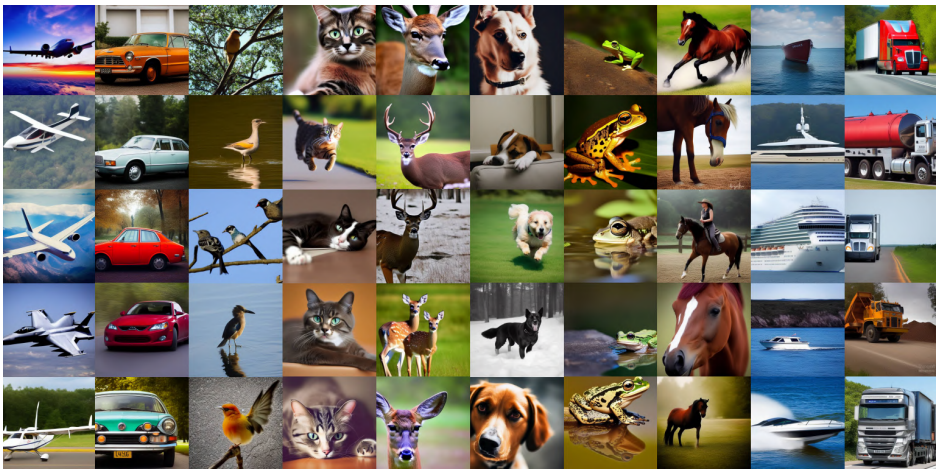

Figure 3.1: Representative examples from the CIFAKE dataset. Real images (top row) are drawn from CIFAR-10; synthetic images (bottom row) are generated by Stable Diffusion v1.4 conditioned on matching class labels. All images are 32×32 pixels.

3.2.1 Data Preprocessing

Images were loaded via PyTorch DataLoader, converted to tensors using `transforms.ToTensor()` and normalised with a per-channel mean of $[0.5, 0.5, 0.5]$ and standard deviation of $[0.5, 0.5, 0.5]$, mapping pixel values to $[-1, 1]$. No additional augmentation was applied; the low resolution and binary task make aggressive augmentation potentially detrimental to frequency-domain signal preservation.

3.3 Architecture: HybridViT

HybridViT processes input images through three stages: a HybridPatchExtractor, four Transformer blocks, and a Classification Head. The total number of trainable parameters is 75,009. Figure 3.2 illustrates the overall architecture.

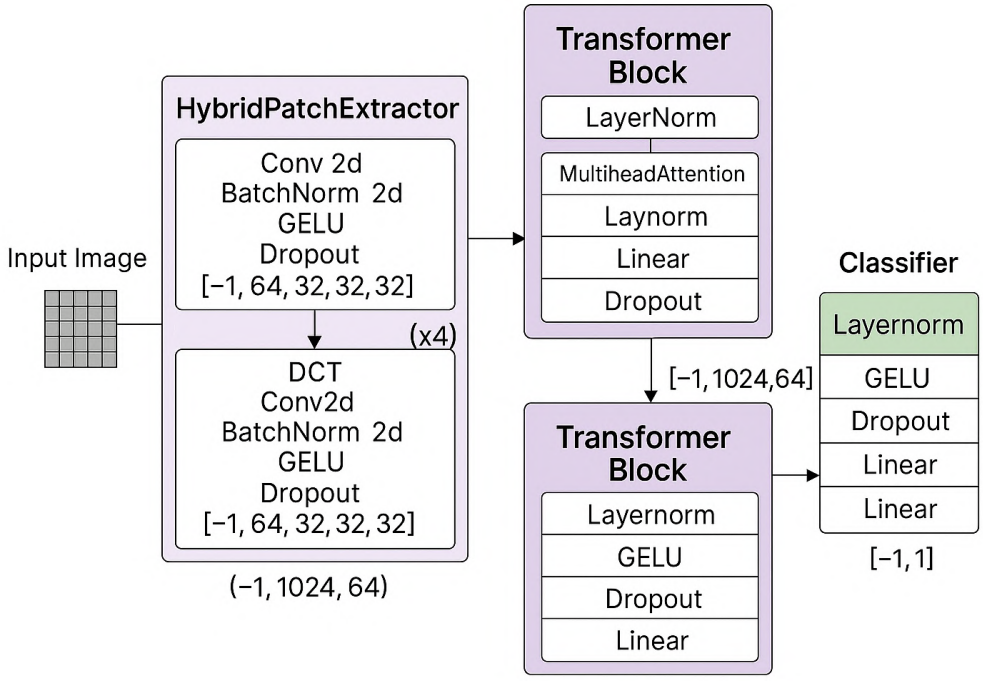

Figure 3.2: Proposed architecture of HybridViT. The HybridPatchExtractor combines a spatial CNN path and a 2D DCT frequency path via element-wise addition. The fused feature map is unfolded into patches and processed by four Transformer blocks before the Classification Head produces a binary prediction.

3.3.1 HybridPatchExtractor

The HybridPatchExtractor operates two parallel processing paths on the input $\mathbf{X} \in \mathbb{R}^{B\times3\times32\times32}$:

Spatial Path. A convolutional layer (`nn.Conv2d`, kernel 3×3, padding $= 1$, 64 channels) followed by batch normalisation, GELU activation, and dropout ($p = 0.2$) produces $\mathbf{F}_s \in \mathbb{R}^{B\times64\times32\times32}$.

Frequency Path. The 2D DCT (`dct.dct_2d`) converts the input to the frequency domain, followed by a 1×1 convolutional layer (64 channels), batch normalisation, GELU, and dropout ($p = 0.2$), producing $\mathbf{F}_f \in \mathbb{R}^{B\times 64\times 32\times 32}$.

The two paths are fused via element-wise addition:

$$\mathbf{F} = \mathbf{F}_s + \mathbf{F}_f \tag{3.1}$$

This map is unfolded into 4×4 patches (PATCH_SIZE $= 4$), yielding a token sequence $\mathbf{T} \in \mathbb{R}^{B\times 64\times 64}$ (64 tokens of dimension 64).

3.3.2 Transformer Blocks

Four identical Transformer blocks each apply:

$$\mathbf{U}_\ell = \mathrm{MHSA}(\mathrm{LN}(\mathbf{Z}_{\ell-1})) + \mathbf{Z}_{\ell-1} \tag{3.2}$$

$$\mathbf{Z}_\ell = \mathrm{FFN}(\mathrm{LN}(\mathbf{U}_\ell)) + \mathbf{U}_\ell \tag{3.3}$$

where MHSA uses NUM_HEADS $= 4$ and FFN has hidden dimension 128, GELU activation, and dropout ($p = 0.3$).

3.3.3 Classification Head

Output tokens are averaged across the patch dimension, layer-normalised, and passed through two linear layers (64→64 with GELU and dropout $p = 0.2$; then 64→1) with sigmoid activation. Table 3.1 details the complete layer breakdown.

Table 3.1: Detailed layer breakdown of HybridViT (75,009 total parameters).

Layer Type	**Output Shape**	**Param #**
Conv2d (Spatial)	$[-1, 64, 32, 32]$	1,792
BatchNorm2d	$[-1, 64, 32, 32]$	128
Conv2d (Frequency)	$[-1, 64, 32, 32]$	256
BatchNorm2d	$[-1, 64, 32, 32]$	128
HybridPatchExtractor	$[-1, 1024, 64]$	0
LayerNorm (Transformer)	$[-1, 1024, 64]$	512
MultiheadAttention	$[-1, 1024, 64]$	0
Linear (MLP)	$[-1, 1024, 128]$	33,280
Linear (MLP)	$[-1, 1024, 64]$	33,024
TransformerBlock $\times 4$	$[-1, 1024, 64]$	0
LayerNorm (Classification)	$[-1, 64]$	128
Linear (Classification)	$[-1, 64]$	4,160
Linear (Classification)	$[-1, 1]$	65
Sigmoid	$[-1, 1]$	0
Total		**75,009**

3.4 Training Pipeline

Models were implemented in PyTorch and trained on an NVIDIA TITAN RTX GPU (24 GB VRAM) with batch size 64 for 16 epochs. The optimiser was Adam (lr $= 10^{-3}$) with Binary Cross-Entropy Loss. Hyperparameters were selected via grid search over learning rates ($\{10^{-3}, 10^{-4}, 10^{-5}\}$), batch sizes ($\{32, 64, 128\}$), and dropout rates ($\{0.1, 0.2, 0.3\}$), maximising validation accuracy. Total training time was approximately 72 minutes.

3.5 Experimental Results

3.5.1 Training Dynamics

Training accuracy rose from 86.72% at epoch 1 to 95.18% at epoch 16, with validation accuracy peaking at 94.95% at epoch 14 (loss $= 0.1283$). Figures 3.3 and 3.4 show the loss and accuracy curves, respectively. Table 3.2 reports epoch-wise metrics.

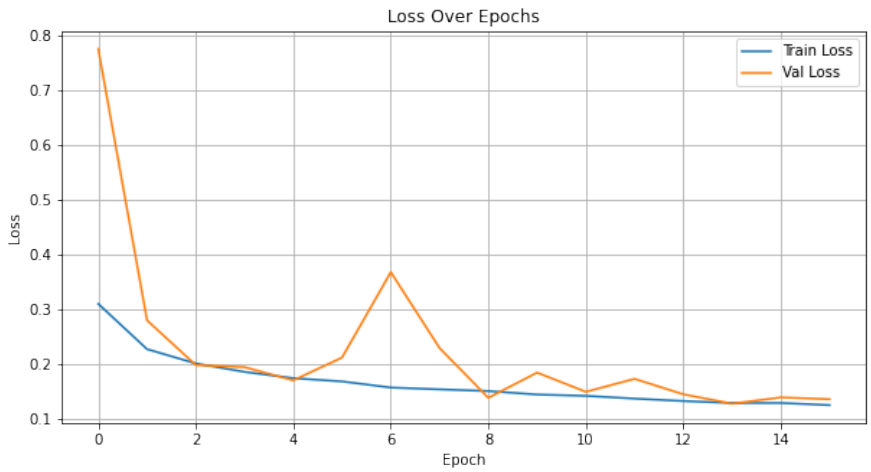

Figure 3.3: Training and validation loss curves for HybridViT over 16 epochs.

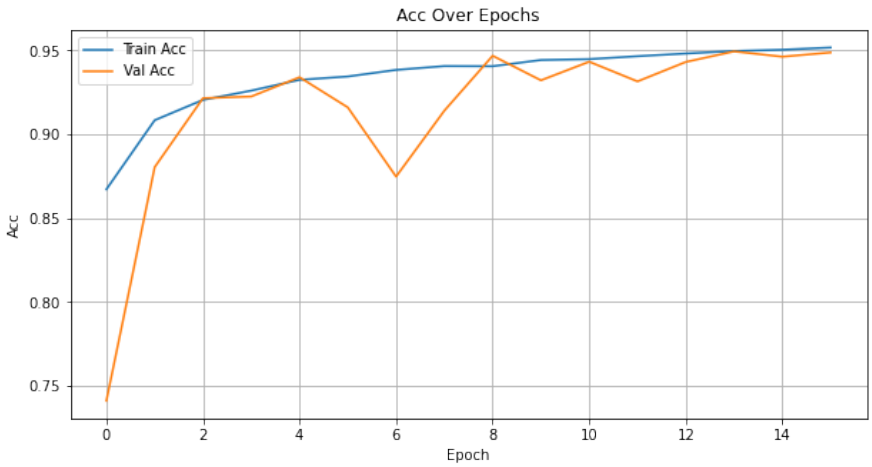

Figure 3.4: Training and validation accuracy curves for HybridViT over 16 epochs.

Table 3.2: Epoch-wise performance metrics of HybridViT.

Epoch	Train Acc. (%)	Val Acc. (%)	Train Loss	Val Loss
1	86.72	74.10	0.3102	0.7746
5	93.25	93.41	0.1747	0.1707
10	94.43	93.22	0.1449	0.1849
15	95.04	94.63	0.1295	0.1397
16	95.18	94.88	0.1256	0.1364

3.5.2 Test Set Performance

On the 20,000-image test set, HybridViT achieved: Accuracy 94.95%, Precision 94.30%, Recall 95.67%, F1 94.98%, AUC 99.00%, MCC 89.90%, Loss 0.1284. The confusion matrix (Figure 3.5) shows evenly distributed errors: 4.33% false negatives and 5.78% false positives.

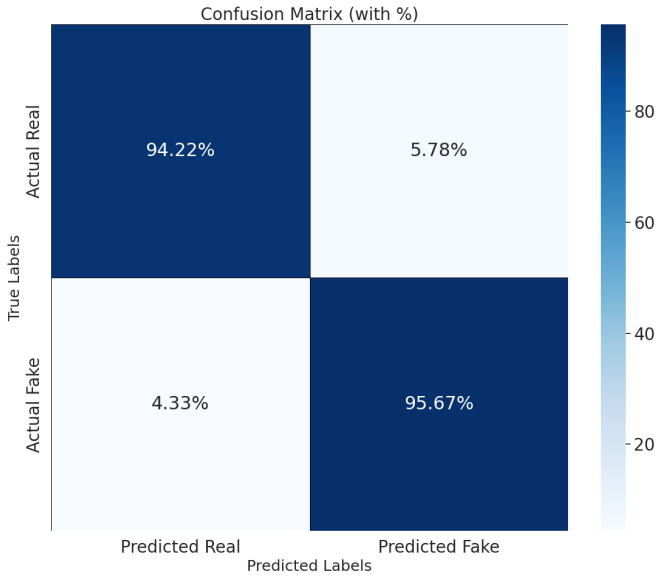

Figure 3.5: Confusion matrix for HybridViT on the CIFAKE test set (percentages).

3.5.3 Comparative Analysis

Table 3.3 presents the full comparative results.

HybridViT achieves the highest accuracy (94.95%) and AUC (99.00%). Compared with the non-frequency baseline, adding the DCT path improves accuracy by 1.46 points, precision by 2.37 points, and AUC by 0.37 points, confirming that frequency analysis contributes meaningful discriminative information beyond spatial features alone.

3.6 Discussion

The model is particularly effective at identifying high-frequency inconsistencies such as unnatural texture patterns and colour gradients common in Stable Diffusion out-

Table 3.3: Performance comparison on the CIFAKE test set.

Model	**Params**	**Loss**	**Acc.**	**Prec.**	**Rec.**	**F1**	**AUC**
MobileNetV2 [9]	3.5M	0.4043	86.91	95.07	77.87	85.61	95.87
ResNet50 [7]	23.6M	0.3464	91.16	93.46	88.67	90.93	97.33
EfficientNet-B0 [8]	5.3M	0.3299	92.40	91.59	93.33	92.47	97.88
Inception V3 [11]	23.8M	0.3814	89.54	90.02	95.88	89.48	96.14
VGG16 [10]	138.4M	0.3205	94.93	93.73	94.22	93.98	94.30
CIFAKE CNN [35]	—	0.182	93.55	92.50	94.80	93.60	—
ViT-CNN (Ours)	75,009	0.1696	93.49	91.93	95.77	93.64	98.63
HybridViT (Ours)	**75,009**	**0.1284**	**94.95**	**94.30**	**95.67**	**94.98**	**99.00**

puts at 32×32 resolution. The primary failure mode involves AI-generated images with minimal frequency artefacts, where the DCT branch fails to detect subtle differences, producing false negatives. The 75,009-parameter budget demonstrates that hybrid spectral–spatial reasoning does not require large-scale pretrained backbones.

3.7 Summary

HybridViT establishes that combining CNN local features, ViT global context, and DCT-based frequency analysis in a unified lightweight architecture achieves state-of-the-art performance on the CIFAKE benchmark. The frequency path is complementary rather than redundant to spatial features.

CHAPTER 4

ARTSPECTRANET: STYLE-AWARE FORENSIC DETECTION OF AI-GENERATED ARTWORKS

4.1 Introduction

The detection methods examined in Chapter 3 target natural photographs. A fundamentally different challenge arises in fine art forensics: historical paintings exhibit deliberate stylisation, abstraction, and brushwork textures that are characteristic of artistic intent rather than synthesis artefacts. Detectors trained on photographic content systematically misclassify artistic departures from photorealism as forgery signals [41]. This chapter introduces ArtSpectraNet, a multi-task hybrid architecture that simultaneously performs style classification and authenticity detection, learning representations conditioned on artistic context.

4.2 The AI-Generated Art Detection Problem

4.2.1 Why Photographic Detectors Fail on Artwork

Three properties of artwork make transfer from photographic forensics non-trivial. First, artistic stylisation intentionally introduces patterns that resemble synthesis artefacts. Second, historical artworks are frequently reproduced as digital scans, introducing imaging noise and compression artefacts that obscure the original medium's spectral signature. Third, the definition of "real" in the artwork domain is inherently complex: a genuine painting digitised at 300 DPI and an AI-generated imitation are both digital images whose difference lies in provenance and process, not in any simple pixel-level property.

4.2.2 The Style–Authenticity Coupling

Style and authenticity are not independent variables in this domain. Generative models mimicking a particular style produce outputs whose spectral properties are partly determined by the style itself. Multi-task learning that explicitly models style alongside authenticity provides the network with semantic context needed to disentangle these signals.

4.3 Dataset: Kaggle AI ArtBench

The Kaggle AI ArtBench dataset [38] comprises 97,399 images (48,850 real, 48,549 AI-generated) spanning ten canonical styles: Art Nouveau, Baroque, Expressionism, Impressionism, Post-Impressionism, Realism, Renaissance, Romanticism, Surrealism, and Ukiyo-e. All images are 224×224 pixels. The dataset was split stratified by style and authenticity into 80%/20% train/validation partitions. Figure 4.1 shows representative samples.

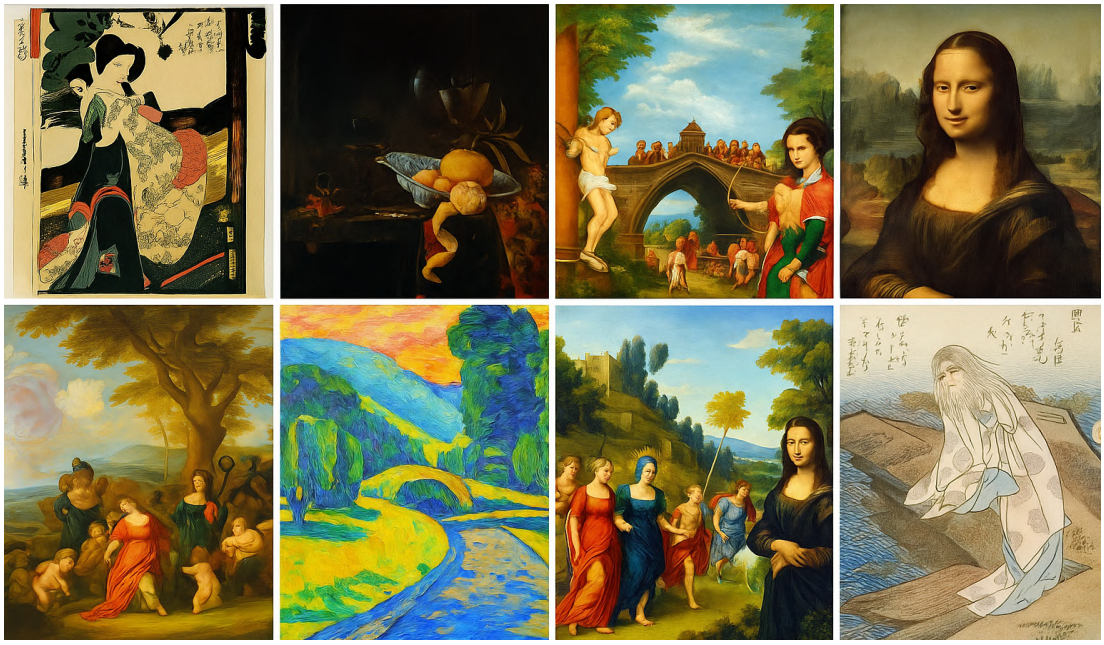

Figure 4.1: Samples from the Kaggle AI ArtBench dataset. Real artworks (top) and AI-generated imitations (bottom) across selected styles. The visual similarity illustrates the difficulty of the detection task.

4.4 Architecture: ArtSpectraNet

ArtSpectraNet processes $\mathbf{X} \in \mathbb{R}^{B\times3\times224\times224}$ through two pathways and two prediction heads. Total parameter count is approximately 3.7 million. Figure 4.2 shows the architecture.

4.4.1 Spatial Encoder: CNN–Transformer Hybrid

Convolutional Stem. Three strided convolutional layers progressively downsample the input:

$$\mathbf{F}_1 = \mathrm{Conv}_{3\times3}(\mathbf{X};\ 64,\ s{=}2) \tag{4.1}$$

$$\mathbf{F}_2 = \mathrm{Conv}_{3\times3}(\mathbf{F}_1;\ 128,\ s{=}2) \tag{4.2}$$

$$\mathbf{F}_3 = \mathrm{Conv}_{3\times3}(\mathbf{F}_2;\ 256,\ s{=}2) \tag{4.3}$$

Each layer is followed by Batch Normalisation and ReLU, yielding $\mathbf{F}_3 \in \mathbb{R}^{B\times256\times28\times28}$.

Patch Projection and Tokenisation. A 1×1 convolution projects to $D = 256$; spatial dimensions are flattened to produce $\mathbf{T} \in \mathbb{R}^{B\times784\times256}$.

Transformer Encoder. A $L = 6$ layer Transformer with $H = 4$ attention heads and FFN hidden size 512 processes the tokens. Token averaging yields the spatial embedding $\mathbf{E}_s \in \mathbb{R}^{B\times256}$.

4.4.2 Spectral Encoder: FFT-Based Representation

A greyscale projection $\mathbf{G} = \mathrm{mean}(\mathbf{X}, \mathrm{dim}{=}1)$ is computed, followed by a centred 2D FFT:

$$\mathbf{F}_{\text{fft}} = \mathrm{fftshift}(\mathrm{fft2}(\mathbf{G})) \in \mathbb{C}^{B\times1\times224\times224} \tag{4.4}$$

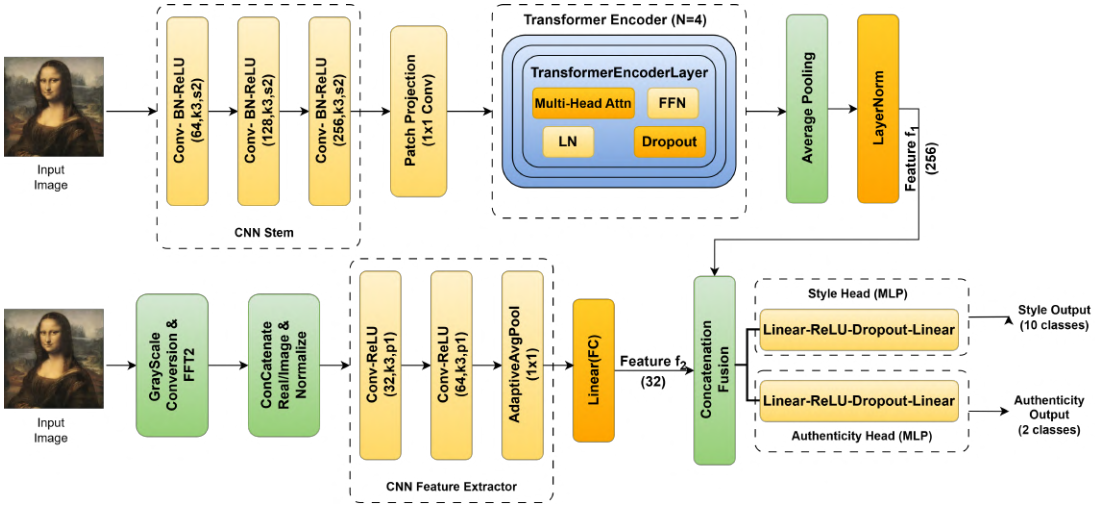

Figure 4.2: Overview of ArtSpectraNet. A CNN–Transformer spatial encoder captures stylistic semantics while an FFT-based spectral branch extracts generator-specific frequency cues. Fused embeddings feed a style head (10-class) and an authenticity head (binary).

Real and imaginary components are normalised and concatenated. Two convolutional layers followed by global average pooling and a linear projection yield the spectral embedding $\mathbf{E}_f \in \mathbb{R}^{B\times 32}$.

4.4.3 Fusion and Multi-Task Prediction

Embeddings are concatenated: $\mathbf{E} = [\mathbf{E}_s \,\|\, \mathbf{E}_f] \in \mathbb{R}^{B\times 288}$. Two MLP heads predict style and authenticity. The joint loss is:

$$\mathcal{L} = \mathcal{L}_{\mathrm{CE}}(\mathbf{H}_s, \mathbf{y}_s) + \mathcal{L}_{\mathrm{CE}}(\mathbf{H}_a, \mathbf{y}_a) \tag{4.5}$$

optimised via Adam (lr $= 10^{-4}$), batch size 32, automatic mixed precision, 20 epochs.

4.5 Experimental Results

4.5.1 Authenticity Detection

ArtSpectraNet achieves: Accuracy 99.61%, F1 0.996, AUC $\approx$ 0.9999, MCC 0.992. Figure 4.3 shows the binary confusion matrix.

4.5.2 Style Classification

ArtSpectraNet attains 73.18% top-1 style accuracy and 0.742 macro-F1. Figure 4.4 shows the 10-class confusion matrix.

4.5.3 Embedding Analysis

Figure 4.5 presents one-vs-rest ROC curves for style classification. Figure 4.6 shows t-SNE embeddings coloured by style and authenticity.

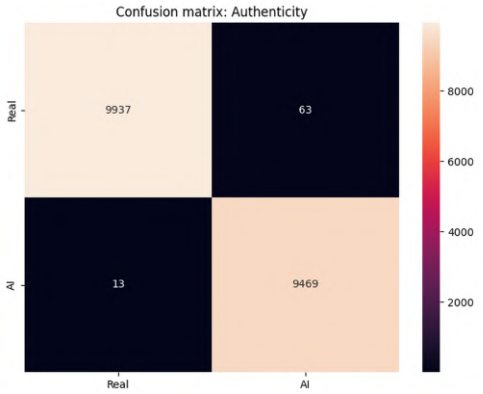

Figure 4.3: Confusion matrix for authenticity detection. Fewer than 80 of ≈19,500 validation samples are misclassified.

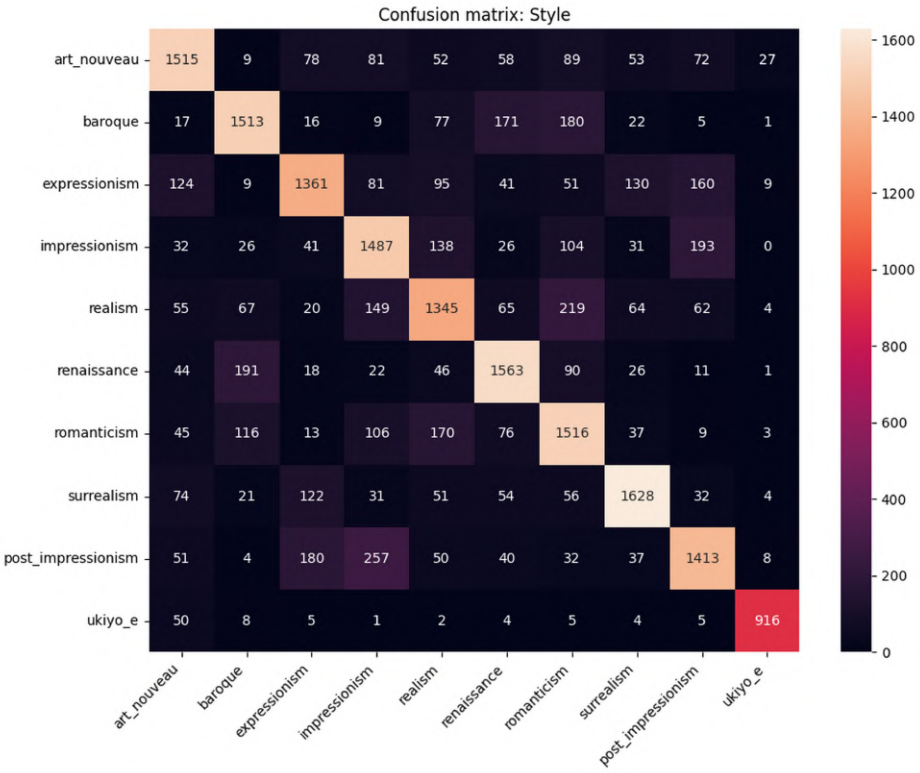

Figure 4.4: Confusion matrix for 10-way style classification, showing strong diagonal blocks for Ukiyo-e and Baroque, and off-diagonal confusion between stylistically proximate movements.

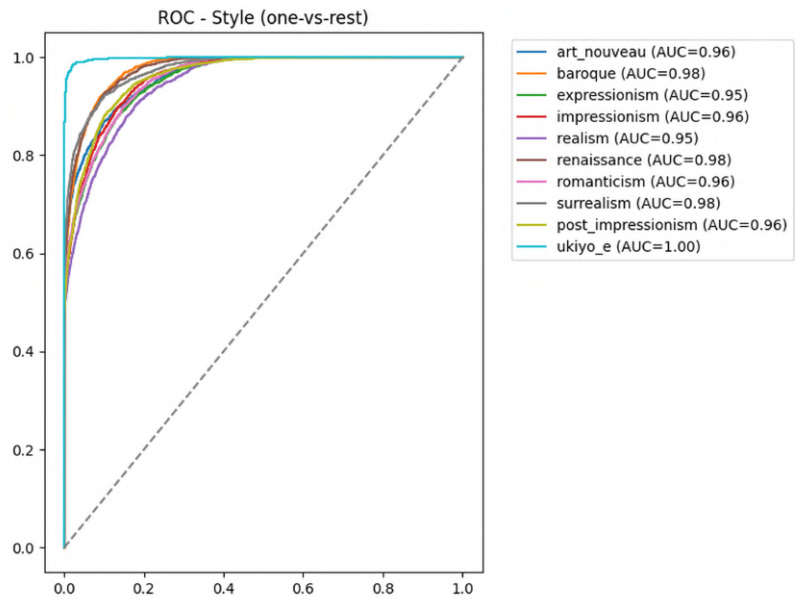

Figure 4.5: One-vs-rest ROC curves for style classification. Most styles achieve AUC above 0.95.

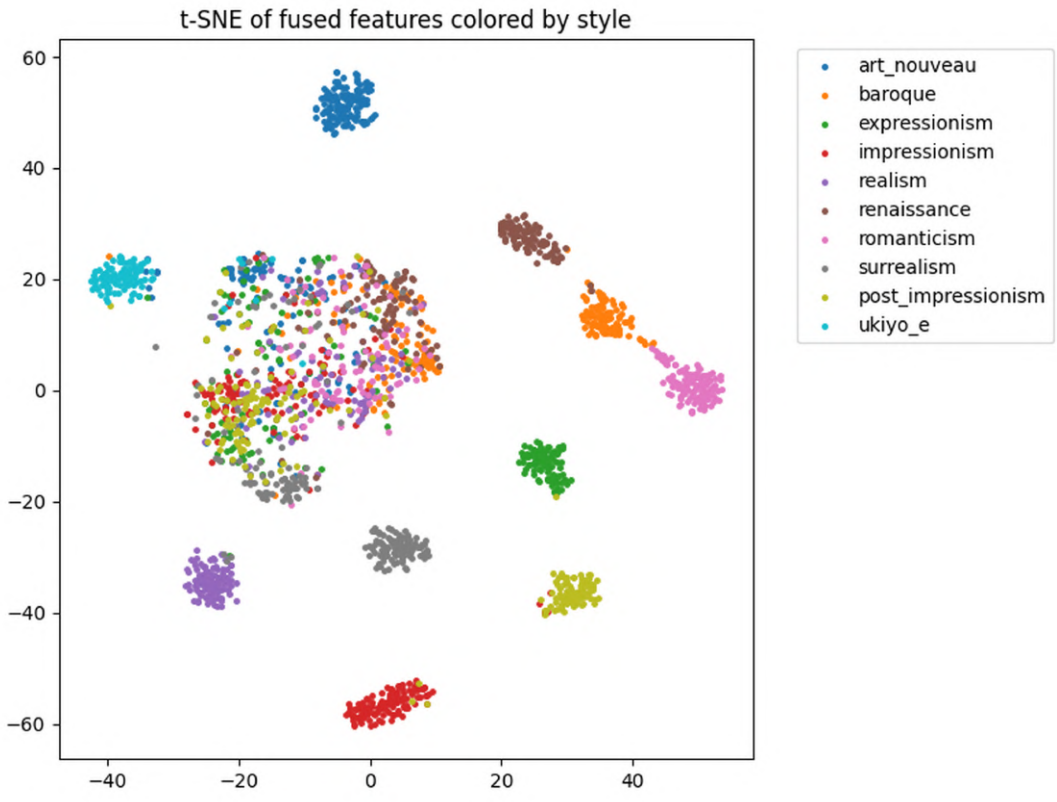

Figure 4.6: t-SNE of 2,000-sample fused embeddings. Left: coloured by style. Right: coloured by authenticity—Real and AI embeddings are almost entirely separated.

4.5.4 Comparison with Baselines

Table 4.1 compares ArtSpectraNet against state-of-the-art forensic baselines on the ArtBench dataset.

Table 4.1: Comparison against forensic baselines on the ArtBench dataset (authenticity detection).

Method	**Backbone**	**Accuracy**	**F1**	**AUC**
Wang et al. (CNN-GAN) [21]	ResNet-50	98.50%	0.972	0.985
Marra et al. [17]	Xception	97.10%	0.965	0.960
ViT Baseline [39]	ViT-B/16	99.40%	0.992	0.996
Lokner et al. [41]	MobileNetV2	95.15%	0.940	0.965
ArtSpectraNet (Ours)	Hybrid CNN-ViT	**99.61%**	**0.996**	**0.999**

4.6 Discussion

The joint optimisation of style and authenticity objectives encourages semantically grounded representations. Style classification functions as a semantic prior that constrains the authenticity detector to reason about content-level properties rather than low-level pixel statistics alone, explaining the performance advantage over single-task baselines.

4.7 Summary

ArtSpectraNet demonstrates that multi-task hybrid architectures can achieve near-perfect authenticity detection on AI-generated artworks while simultaneously performing meaningful style classification. The study establishes style-aware forensic detection as a distinct and tractable sub-problem.

CHAPTER 5

CONCORD: ZERO-SHOT CROSS-GENERATOR DETECTION VIA LEARNABLE SPECTRAL BASIS PROJECTION AND CROSS-SCALE CONSISTENCY VERIFICATION

5.1 Introduction

The two preceding studies achieve strong detection accuracy within their respective training distributions. Both, however, share a fundamental limitation: they train and evaluate on images from the same generative model family. In practice, a detector must classify images from generators never encountered during training. This chapter addresses that problem directly. CONCORD (COnsistency-driven Network for CrOss-scale Robust Detection) targets two generalisable properties: (i) learnable spectral basis projection that adapts frequency sensitivity to the training distribution rather than applying fixed DCT or Fourier bases, and (ii) explicit verification of cross-scale structural consistency, which natural images satisfy and synthetic images systematically violate regardless of the specific generator.

5.2 The Zero-Shot Cross-Generator Detection Problem

5.2.1 Problem Formulation

Given $\mathbf{X} \in \mathbb{R}^{H \times W \times C}$, the goal is to learn $f_\theta : \mathbb{R}^{H \times W \times C} \to [0, 1]$ estimating the probability that $\mathbf{X}$ is AI-generated, where the detector trains exclusively on one source generator and is evaluated without retraining on images from unseen generators.

5.2.2 Why Current Methods Fail

Existing detectors learn generator-specific shortcuts. GAN upsampling introduces checkerboard artefacts detectable via spectral analysis [16, 15]; diffusion noise schedules leave different traces [2]. Both artefact types are discriminative within their own generator family and brittle outside it.

5.2.3 The Cross-Scale Consistency Principle

Natural images exhibit coherent alignment between fine-grained local textures, mid-level patterns, and global semantic structure. Generative synthesis breaks this alignment in subtle but systematic ways that do not depend on any single generator-specific artefact. CONCORD detects these violations explicitly by verifying whether local spectral observations cohere with global image structure. This work demonstrates that robustness—not peak accuracy—should be the primary design objective.

5.3 Dataset: GenImage

All experiments use the GenImage benchmark [37], which pairs real ImageNet images with synthetic images from eight generators. The cross-generator protocol trains on SDv1.4 only and evaluates zero-shot on the remaining seven. The training set contains 323,997 images (50% real, 50% SDv1.4-generated), with 20% held out for validation. Each test generator provides 50,000 images (25,000 real, 25,000 synthetic). Table 5.1 lists the generators.

Table 5.1: Generator subsets of the GenImage benchmark.

Generator	Architecture	Role
SDv1.4	Latent Diffusion	Training only
SDv1.5	Latent Diffusion	Zero-shot test
Wukong	Latent Diffusion	Zero-shot test
Midjourney	Commercial (diffusion-based)	Zero-shot test
BigGAN	GAN	Zero-shot test
VQDM	Diffusion (discrete)	Zero-shot test
GLIDE	Diffusion (text-conditioned)	Zero-shot test
ADM	Diffusion (class-conditioned)	Zero-shot test

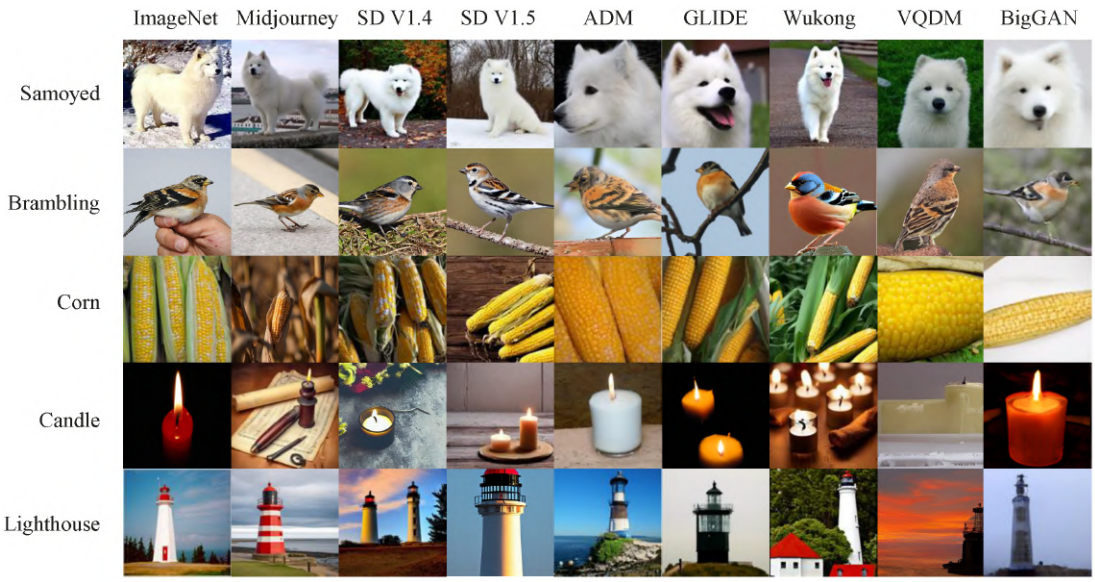

Figure 5.1: Representative samples from the GenImage benchmark across eight generative architectures alongside corresponding real ImageNet images.

5.4 Architecture: CONCORD

CONCORD's core architectural principle is structural decoupling: all pretrained backbone encoders (SwinV2-B and CLIP) remain frozen. All learnable parameters are confined to ACTR, linear projections, HCSTCA, and Instance-Adaptive Pooling (IAP). Figure 5.2 shows the framework.

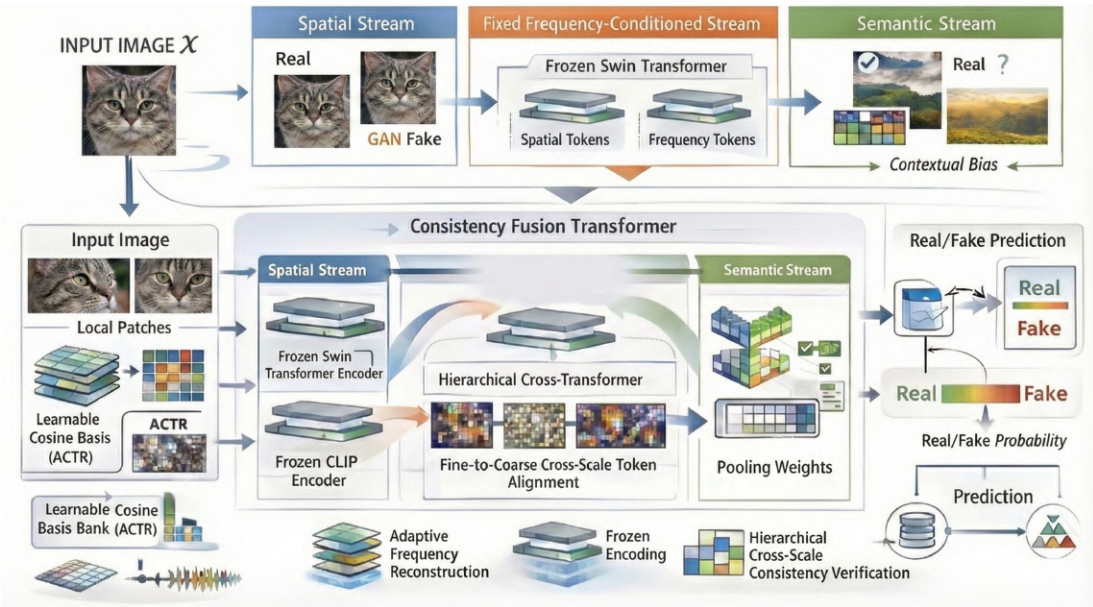

Figure 5.2: The CONCORD framework. ACTR constructs a frequency-conditioned view $\mathbf{X}_f$. A frozen tri-stream encoder maps $\mathbf{X}$ and $\mathbf{X}_f$ through shared frozen SwinV2-B and extracts a global semantic vector from frozen CLIP. HCSTCA verifies local-to-global coherence across three pooling scales. IAP emphasises anomalous tokens before final prediction.

5.4.1 Adaptive Cosine Token Reconstruction (ACTR)

ACTR partitions the input into non-overlapping $P \times P$ patches ($P = 8$):

$$\mathbf{p}_i \in \mathbb{R}^{D_p}, \quad D_p = P^2 C, \quad i = 1, \ldots, N_p \tag{5.1}$$

The Learnable Cosine Basis Bank (LCBB) maintains $K = 8$ basis vectors, each initialised as a vectorised 2D DCT filter. Scaled dot-product attention computes soft spectral assignments:

$$s_{i,k} = \mathbf{p}_i^\top \mathbf{b}_k, \qquad \alpha_{i,k} = \mathrm{Softmax}_k\left(\frac{s_{i,k}}{\sqrt{D_p}}\right) \tag{5.2}$$

The reconstructed spectral representation $\hat{\mathbf{p}}_i = \sum_k \alpha_{i,k}\, \mathbf{b}_k$ is reassembled into reconstruction map $\hat{\mathbf{X}}$. The frequency-conditioned view is formed via residual injection:

$$\mathbf{X}_f = \mathbf{X} + \mathrm{Conv}_{1\times1}([\mathbf{X},\, \hat{\mathbf{X}}]) \tag{5.3}$$

The original spatial content is preserved and the spectral perturbation is added on top, with the convolution learning which components of the reconstruction residual $\mathbf{X}_f - \mathbf{X}$ carry forensic information. Figure 5.3 illustrates ACTR.

5.4.2 Frozen Tri-Stream Encoder

Three feature streams are extracted: (i) a spatial stream from the frozen SwinV2-B processing $\mathbf{X}$; (ii) a frequency-conditioned stream from the same frozen SwinV2-B

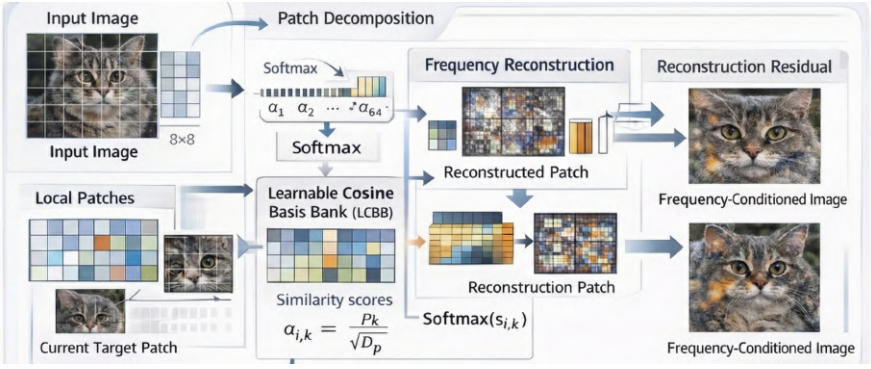

Figure 5.3: ACTR architecture. Each 8×8 patch is compared against $K = 8$ learnable cosine bases via scaled dot-product attention. The softmax-weighted reconstruction $\hat{\mathbf{X}}$ is concatenated with the original image and projected via a 1×1 convolution; the result is added residually to $\mathbf{X}$ to form $\mathbf{X}_f$.

processing $\mathbf{X}_f$; and (iii) a semantic stream from the frozen CLIP visual encoder. Separate linear projections map all streams to a shared dimension $D = 384$, and the fused input to the consistency module is their sum with the semantic vector broadcast across all spatial positions.

5.4.3 Hierarchical Cross-Scale Token Consistency Attention (HCSTCA)

HCSTCA verifies whether fine-scale spectral observations are coherent with global structure by comparing fine-grained tokens against pooled multi-scale summaries at scales $\{1, 2, 4\}$. At each scale ℓ, asymmetric cross-attention uses fine-scale frequency-conditioned tokens as queries and pooled spatial tokens as keys and values:

$$\mathbf{C}^{(\ell)} = \mathrm{CrossAttn}\big(\mathbf{Q} = \mathbf{T}_f,\ \mathbf{K} = \mathbf{T}_s^{(\ell)},\ \mathbf{V} = \mathbf{T}_s^{(\ell)}\big) \tag{5.4}$$

Two HCSTCA blocks are stacked ($L = 2$), each followed by a residual connection and position-wise feed-forward network.

5.4.4 Instance-Adaptive Pooling (IAP)

IAP computes per-token attention weights from the HCSTCA output via a lightweight MLP, up-weighting tokens exhibiting strong cross-scale inconsistency evidence. The weighted average provides the final representation for the binary classification head, using a feed-forward network with a $2\times$ expansion ratio before the final linear layer.

5.4.5 Training Configuration

Table 5.2 summarises the training configuration.

5.5 Experimental Results

5.5.1 Per-Generator Performance

Table 5.3 reports CONCORD's performance across all generators, including the SDv1.4 self-test split. Results reveal a consistent structural pattern: highest accuracy on gener-

Table 5.2: CONCORD training configuration.

Component	**Configuration**
Spatial backbone	SwinV2-B (frozen)
Semantic encoder	CLIP ViT-L/14 (vision), frozen
ACTR basis count (K)	8 learnable, DCT-initialised
ACTR patch size (P)	8×8
Embedding dimension (D)	384
HCSTCA blocks (L)	2
IAP FFN expansion	$2\times$
HCSTCA pooling scales	$\{1, 2, 4\}$
Attention heads	8
Optimiser	AdamW, lr $= 10^{-4}$, wd $= 10^{-2}$
Batch size	32
Training generator	SDv1.4 only
Input resolution	256×256
Hardware	NVIDIA TITAN RTX (24 GB)
Precision	Mixed FP16, seed 42

ators close to the training distribution (SDv1.4, SDv1.5, Wukong), moderate accuracy on architecturally different diffusion models (VQDM, GLIDE, Midjourney), and near-chance accuracy on ADM.

Table 5.3: CONCORD per-generator performance (trained on SDv1.4, zero-shot on remaining generators). ADM is near chance and constitutes a genuine failure case discussed in Section 5.6.1.

Generator	**Acc (%)**	**F1 (%)**	**AUC (%)**	**MCC (%)**
SDv1.4 (train)	99.47	99.47	99.98	98.93
SDv1.5	99.47	99.47	99.98	98.93
Wukong	96.18	96.29	99.63	92.51
GLIDE	81.82	84.51	97.58	67.86
Midjourney	76.83	81.04	94.73	59.88
BigGAN	64.58	73.71	92.64	40.51
VQDM	55.78	69.17	84.57	23.32
ADM	50.83	66.86	58.00	6.54

5.5.2 Cross-Generator Comparison

Table 5.4 presents the full cross-generator accuracy breakdown against all baselines under the same SDv1.4-only training protocol. Baseline results are reproduced from Zhu et al. [37]. CONCORD achieves the highest average accuracy (78.1%) and improves over the strongest prior baseline (Swin-T) by 14.7 percentage points on Midjourney, 14.2 points on GLIDE, 7.0 points on BigGAN, and 3.5 points on VQDM.

Table 5.4: Cross-generator accuracy (%) on GenImage. All methods train on SDv1.4 only. The ADM column is near-random for all methods and is included for completeness. CONCORD outperforms all baselines on every challenging generator.

Method	**MJ**	**SDv1.4**	**SDv1.5**	**ADM**	**GLIDE**	**Wukong**	**VQDM**	**BigGAN**	**Avg**
ResNet-50 [7]	54.9	99.9	99.7	53.5	61.9	98.2	56.6	52.0	72.1
DeiT-S	55.6	99.9	99.8	49.8	58.1	98.9	56.9	53.5	71.6
Swin-T [14]	62.1	99.9	99.8	49.8	67.6	99.1	62.3	57.6	74.8
Spec	52.0	99.4	99.2	49.7	49.8	94.8	55.6	49.8	68.8
CNNSpot [21]	52.8	96.3	95.9	50.1	39.8	78.6	53.4	46.8	64.2
F3Net [18]	50.1	99.9	99.9	49.9	50.0	99.9	49.9	49.9	68.7
GramNet [23]	54.2	99.2	99.1	50.3	54.6	98.9	50.8	51.7	69.9
Patch5M	71.6	99.9	99.9	50.6	50.4	99.8	51.0	50.4	71.9
SIA	73.3	99.8	99.6	52.0	52.3	98.0	51.4	50.3	73.1
LNP	56.5	94.8	94.9	50.8	68.3	88.7	57.4	56.5	64.0
LGrad [24]	68.1	90.3	64.7	52.2	62.7	63.9	52.0	69.9	70.5
CONCORD (Ours)	**76.8**	**99.5**	**99.5**	**50.8**	**81.8**	**96.2**	**55.8**	**64.6**	**78.1**

5.5.3 Embedding Structure

Figure 5.4 shows a t-SNE visualisation of CONCORD IAP embeddings pooled across all seven test generators.

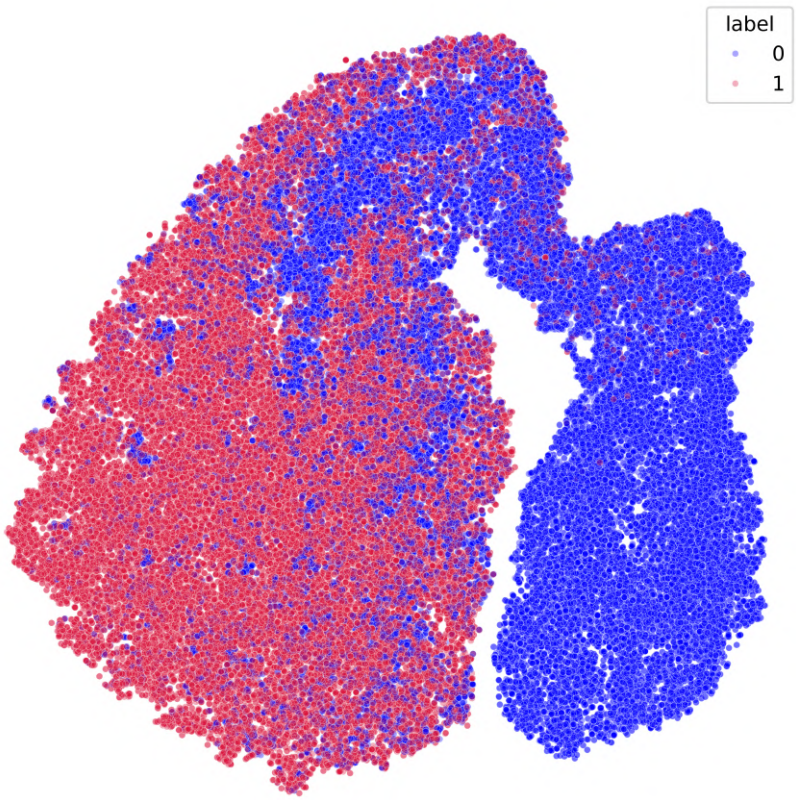

Figure 5.4: t-SNE of CONCORD embeddings. The compact right cluster corresponds to generators near the training distribution (SDv1.5, Wukong) with clean Real/AI separation. The mixed left region reflects ADM and VQDM, where cross-scale consistency signals do not sufficiently discriminate the two classes.

5.5.4 Ablation Study

Table 5.5 quantifies each component's contribution. All variants retain the semantic stream and IAP. Average MCC is reported across unseen generators; BigGAN MCC and AUC serve as the primary stress test under severe spectral shift.

5.6 Discussion

5.6.1 The ADM Boundary

Every method evaluated on GenImage, including CONCORD, scores near 50% on ADM. ADM uses a classifier-guided diffusion process whose synthesis does not introduce the upsampling artefacts of GANs or the latent-space transitions of latent diffusion models. This is a structural boundary of the current approach, shared across all

Table 5.5: Ablation results. Average MCC across unseen generators; BigGAN metrics as diagnostics under severe spectral shift. The RGB-Only variant achieves marginally higher average MCC (61.59%) than Full CONCORD (61.06%); the dual-stream advantage is regime-specific, with Full CONCORD outperforming RGB-Only by 4.4 MCC points and 7.1 AUC points on BigGAN.

Configuration	**Avg. MCC (%)**	**BigGAN MCC (%)**	**BigGAN AUC (%)**
Full CONCORD	61.06	40.51	92.64
ACTR Disabled (Bypass)	58.89	33.12	90.75
RGB-Only (no freq. stream)	61.59	36.10	85.54
Frequency-Only	52.78	24.09	73.53
Single-Scale (no HCSTCA)	59.47	34.38	88.98

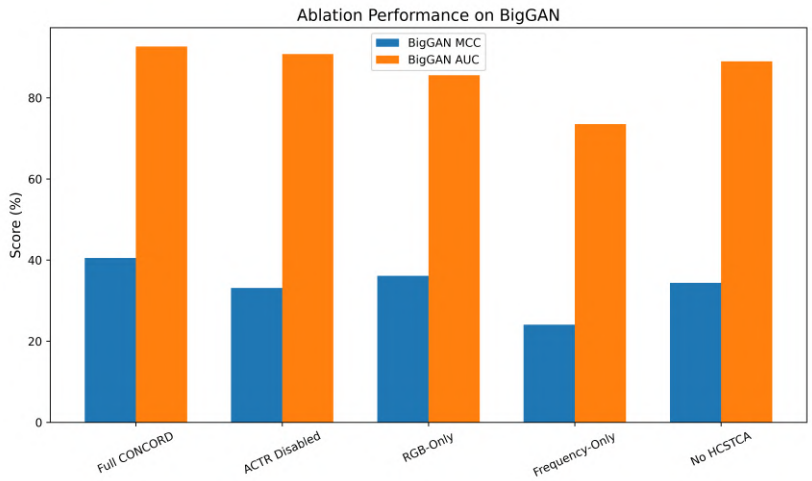

Figure 5.5: Ablation performance on BigGAN. Full CONCORD achieves the highest MCC and AUC. Removing ACTR reduces MCC from 40.51% to 33.12%; removing HCSTCA reduces AUC from 92.64% to 88.98%.

methods in the field. Addressing ADM would require either multi-generator training or a fundamentally different forensic signal.

5.6.2 The Frozen Backbone Principle

Preventing backbone fine-tuning improves cross-generator generalisation. A backbone fine-tuned end-to-end on SDv1.4 images shifts its representations toward SDv1.4-specific artefacts, degrading general-purpose visual features needed for cross-generator transfer.

5.7 Summary

CONCORD demonstrates that zero-shot cross-generator accuracy can be substantially improved through learnable spectral basis projection and explicit cross-scale consistency verification, with all backbone encoders frozen.

CHAPTER 6
CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

6.1 Summary of Contributions

This thesis has investigated the design of hybrid neural architectures for forensic detection of AI-generated images, progressing from low-resolution binary classification to zero-shot cross-generator generalisation. Three publications collectively advance the field along three dimensions: architectural design, domain extension, and generalisation.

HybridViT (Chapter 3) demonstrated that combining CNN local feature extraction, ViT global context, and explicit DCT-based frequency analysis in a single lightweight architecture (75,009 parameters) achieves 94.95% test accuracy on CIFAKE, outperforming all CNN baselines including VGG16 with 1,845× more parameters.

ArtSpectraNet (Chapter 4) extended the hybrid spatial–spectral framework to fine art forensics, achieving 99.61% authenticity detection accuracy and 73.18% top-1 style accuracy on the Kaggle AI ArtBench dataset.

CONCORD (Chapter 5) addressed zero-shot cross-generator generalisation. Trained on Stable Diffusion v1.4 and evaluated on seven unseen generators, CONCORD achieves 78.1% average cross-generator accuracy, improving over prior methods by more than 3% overall.

6.2 Recurring Principles

Three design principles emerge as consistently effective across all three studies.

Frequency-domain analysis is complementary, not redundant. All three studies confirm that frequency-domain features provide discriminative information that spatial features alone do not capture.

Hybrid architectures outperform homogeneous ones. In every comparison reported, hybrid spatial–frequency architectures with explicit fusion outperform either CNN-only or frequency-only alternatives at comparable parameter budgets.

Structural decoupling improves generalisation. CONCORD's frozen backbone design produces the most substantial generalisation gains. Concentrating learnable parameters in task-specific modules reduces the risk of encoding distribution-specific biases.

Semantic structure is a useful prior for forensic reasoning. ArtSpectraNet's multi-task design shows that auxiliary supervision from style classification improves authenticity detection. CONCORD's frozen CLIP semantic stream anchors cross-scale consistency verification.

6.3 Limitations

HybridViT is evaluated exclusively on CIFAKE (32×32 pixels) and does not generalise directly to higher resolutions or other generators. ArtSpectraNet's synthetic images derive from a single Stable Diffusion setup; generalisation to Midjourney v6 or DALL·E 3 has not been evaluated. CONCORD's near-chance ADM accuracy identifies a structural boundary. No study systematically evaluates robustness to JPEG compression, resizing, or social-media re-encoding.

6.4 Future Scope

High-resolution and multi-generator evaluation. Evaluating HybridViT at 224×224 and on datasets beyond CIFAKE would establish whether frequency-spatial synergy is resolution-independent.

Advanced frequency representations. Replacing DCT and FFT branches with wavelet-based multi-scale decompositions [20] would enable simultaneous time-frequency localisation.

Addressing the ADM boundary. Multi-source training protocols including a fraction of ADM images alongside SDv1.4, or consistency metrics derived from temporal diffusion trajectory analysis, may improve detection of pixel-space diffusion models.

Explainability integration. Incorporating Grad-CAM [43] or attention visualisation would spatially localise forensic evidence.

Edge deployment. HybridViT's 75,009-parameter budget is already compatible with mobile deployment. Applying quantisation-aware training or structured pruning to CONCORD and ArtSpectraNet would enable real-time inference on edge devices.

Video deepfake extension. Extending the framework to video by verifying temporal consistency across frames alongside spatial cross-scale consistency would address the rapidly growing challenge of synthetic video content.

6.5 Social Impact

The proliferation of AI-generated images poses direct risks to information integrity, public trust, and individual rights. Synthetic media is increasingly used for misinformation campaigns, non-consensual intimate imagery, academic fraud, and manipulation of legal and commercial proceedings. The forensic detection systems developed in this thesis contribute to countering these harms in three direct ways.

First, the high detection accuracy of HybridViT and ArtSpectraNet enables automated content moderation pipelines that can flag synthetic media at scale on news platforms and social networks, reducing the velocity at which misleading content spreads before human review.

Second, CONCORD's zero-shot generalisation capability means that forensic tools do not need to be retrained every time a new generative model enters public use—a practically critical property given the pace of generative AI development.

Third, the lightweight parameter budgets achieved (75,009 parameters for HybridViT) make deployment feasible in resource-constrained environments including mobile journalism tools, courtroom evidence verification systems, and developing-region content platforms that cannot afford large-scale cloud inference.

The indirect societal benefit is the restoration of epistemic trust in digital media: when individuals and institutions can reliably determine whether a visual artefact is authentic, the evidential value of images in journalism, science, and law is preserved.

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APPENDIX-I
SUPPLEMENTARY ARCHITECTURE DETAILS

I.1 ACTR Basis Initialisation

The $K = 8$ basis vectors in the LCBB are initialised as the lowest-frequency eight filters from the 2D DCT-II basis for 8×8 patches:

$$\Phi_{u,v}[x, y] = \frac{2}{P} \cdot c(u) \cdot c(v) \cdot \cos\left(\frac{(2x+1)u\pi}{2P}\right) \cos\left(\frac{(2y+1)v\pi}{2P}\right) \tag{I.1}$$

where $c(0) = 1/\sqrt{2}$ and $c(n) = 1$ for $n > 0$. Selected frequency indices: $(u, v) \in \{(0, 0), (1, 0), (0, 1), (1, 1), (2, 0), (0, 2), (2, 1), (1, 2)\}$.

I.2 HCSTCA Pooling Scale Details

For 224×224 inputs, the SwinV2-B output token grid is $7 \times 7 = 49$ tokens. Pooling at scales $\{1, 2, 4\}$ yields token grids of 49, 16, and 4 tokens respectively, providing a hierarchical multi-scale representation for cross-scale consistency verification.

I.3 Instance-Adaptive Pooling

IAP computes per-token weights $\mathbf{w} = \mathrm{Softmax}(\mathrm{MLP}(\mathbf{C}^{(\mathrm{agg})}))$ from the aggregated HCSTCA output. The weighted average $\hat{\mathbf{z}} = \sum_i w_i \mathbf{c}_i$ forms the input to the binary classification head.

I.4 HybridViT Baseline Comparison

The ViT-CNNClassifier baseline is identical to HybridViT except the DCT Frequency Path in HybridPatchExtractor is removed. All other hyperparameters are held constant to isolate the contribution of frequency analysis.

I.5 Reproducibility Information

All experiments were conducted on a single NVIDIA TITAN RTX GPU (24 GB VRAM), Ubuntu 20.04, CUDA 11.8, PyTorch 2.0, Python 3.10. Key packages: `torch` 2.0.0+cu118, `torchvision` 0.15.0, `transformers` 4.35.0, `torch-dct` 0.1.6, `scikit-learn` 1.3.0, `numpy` 1.24.3. All random seeds fixed at 42. Training runtimes: HybridViT ≈72 minutes (16 epochs).

I.6 Publications

Journal Paper (Under Review)

1. **Harsh Sinha** and Dinesh Kumar Vishwakarma, "CONCORD: Learnable Spectral Basis Projection with Cross-Scale Consistency Verification for Zero-Shot Detection of AI-Generated Images," *Signal, Image and Video Processing (SIVP)*, Springer, 2026.

Conference Papers (Presented)

2. **Harsh Sinha** and Dinesh Kumar Vishwakarma, "HybridViT: A Hybrid Vision Transformer for Detecting AI-Generated Synthetic Images," *16th International IEEE Conference on Computing Communication and Networking Technologies, 2025 (IIT, Indore).*

3. **Harsh Sinha** and Dinesh Kumar Vishwakarma, "ArtSpectraNet: A Hybrid Spectral–Semantic Architecture for Style-Aware Forensic Detection of AI-Generated Artworks," *8th International Conference on Communication and Computational Technologies, 2026 (NFSU, Goa).*

Acceptance letters / reprints are attached on the following pages.

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It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Disclaimer

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