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Cross-Manipulation Deepfake Detection: A Domain-Agnostic Deep Learning Framework for Unseen Forgery Types

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ABSTRACT

Deepfakes, which are synthetic films or photos that replace, edit, or generate a person's face with Artificial Intelligence, have become one of the gravest dangers to digital trust in recent years. Most of the available deepfake detection technologies are trained on certain manipulation techniques and perform poorly when they face a forgery type that they have never seen before. In this paper, we introduce Cross-ManipNet, a domain-agnostic deep learning framework to accurately detect deepfakes even if the forging method used to make them is completely unknown to the model during training. Our approach consists of a Frequency-Aware Convolutional Neural Network (FA-CNN) with a Transformer-based Temporal Consistency Analyser (TTCA) and a Domain Adversarial Training (DAT) module that encourages the model to learn manipulation-agnostic features. Cross-ManipNet is evaluated on six major deepfake datasets, including FaceForensics++ (FF++), Celeb-DF v2, DFDC, WildDeepfake, FaceShifter and DeeperForensics-1.0, achieving a cross-dataset AUC of 94.7% and a cross-manipulation generalisation accuracy of 91.2%, outperforming all current state-of-the-art baselines. The framework operates at video, frame and patch levels and does not need to be retrained when presented with new counterfeit domains, making it appropriate for real-world deployment in social media moderation, legal evidence verification and news authenticity systems.

Keywords: ***Deepfake Detection, Cross-Manipulation Generalisation, Domain-Agnostic Learning, Frequency Analysis, Vision Transformers, Adversarial Training***

1. INTRODUCTION

Deepfake is a portmanteau of 'deep learning' and 'fake' and refers to synthetic media, most often videos, in which a person's face, voice or body motions have been intentionally made or replaced using strong neural network algorithms. This technology, once restricted to research labs, is now widely available through free software tools and smartphone apps, enabling anyone to create a convincing fake video of a politician, celebrity, or private individual saying or doing something they never said or did. The repercussions are substantial and well documented. Deepfakes have been used to disseminate political lies, produce non-consensual pornography, impersonate companies for fraud, and erode trust in video evidence in court processes.

A 2023 analysis by Dutch cybersecurity startup Sensity AI estimates the quantity of deepfake videos online doubles about every 6 months, detecting over 500,000 synthetic video and speech recordings in 2023 alone [1]. In this regard, the creation of effective and strong deepfake detection technology has become one of the most urgent problems in computer science and digital security. The main problem with current deepfake detection methods is their lack of generalisability. Most of the state-of-the-art detectors are trained on specialized datasets that contain certain forgery types such as FaceSwap, DeepFaceLab, or Face2Face, and achieve great accuracy on those forgery kinds. But their accuracy declines sharply when tested on novel forging techniques that they have not encountered during training (referred to as cross-manipulation or unseen forgery testing). This is because these models learn to detect the unique artifacts and signs left by the particular GAN (Generative Adversarial Network) or diffusion model that was used to construct the training fakes, rather than learning fundamental, manipulation-agnostic signals of face forgery.

In this paper, we tackle this generalisation gap directly by introducing Cross-ManipNet, a novel deep learning framework based on three complementary principles: (1) frequency-domain analysis for detecting invisible artefacts left in high-frequency image components by all generative methods, (2) temporal inconsistency detection using a Vision Transformer to

identify unnatural patterns across video frames, and (3) domain adversarial training that explicitly trains the model to be blind to the specific forgery domain and sensitive only to general manipulation signals.

The main contributions of this paper are as follows:

Cross-ManipNet Architecture: A revolutionary three-module deepfake detection system with great generalisation capability to undetected forging schemes without retraining. **Frequency-Aware CNN (FA-CNN):** A new convolutional backbone that analyzes spatial (pixel-level) and frequency-domain (DCT and FFT spectrum) data in parallel in an explicit manner, capturing aberrations invisible to traditional RGB-trained networks. **Transformer Temporal Consistency Analyser (TTCA):** A Vision Transformer module for analysing sequences of video frames to find unnatural blinking, facial movement inconsistencies and temporal colour shifts between synthetic and genuine faces across time. **Domain adversarial training:** As a training process gradient reversal layers are used to make the feature extractor learn manipulation agnostic representations, thus increasing the generalisation capacity to unseen types of forgery at test time. **Comprehensive evaluation:** We conduct extensive tests on six public benchmarks to show state-of-the-art cross-dataset and cross-manipulation performance. We also perform detailed ablation investigations to verify the contribution of each component.

2. RELATED WORK

Methods of Detection: Initial deepfake detectors relied on hand-crafted features, such as physiological signals (eye blink rate) [2], head posture inconsistencies, or colour histogram difference between face and background to tell real and fake films apart [2]. These approaches were interpretable and computationally inexpensive, but they relied on particular visual artifacts that newer generative models rapidly learned to eradicate. By 2019 they had mainly become useless against high quality deepfakes.

Deep Learning Classifiers: Modern most used method considers deepfake detection as a binary classification problem. A CNN (often based on Xception [3], EfficientNet [4] or ResNet [5]) is trained on a labelled dataset of genuine and fake pictures or video frames, and learns to categorize fresh inputs. Rossler et al. [6] proposed the FaceForensics++ (FF++) benchmark dataset with strong baseline classifiers which became the standard assessment technique for the area. These models obtain >99% accuracy on in-distribution test sets, but fall below 60-70% accuracy when tested on unseen forgery methods -- barely beyond random guessing.

Methods in the Frequency Domain: It has been found that the images created by GANs exhibit some characteristic traces in the frequency domain, especially in high frequency components, recorded using Discrete Cosine Transform (DCT) or Fast Fourier Transform (FFT). In [7] Frank et al. showed that a simple classifier trained on FFT spectra of images can detect GAN-generated content with excellent accuracy. Liu et al. [8] proposed a Spatial-Phase Shallow Learning framework (SPSL) that leverages phase spectrum features for detection. These approaches give better generalization than the pure spatial methods but still have problems with the most advanced generation methods.

Transformer and Attention Based Approaches: Recently, Vision Transformer (ViT) [9] and its derivatives have been adopted for deepfake identification. Zhao et al. [10] introduced a Multi-Attentional Deepfake Detection network that utilizes several attention heads to focus on distinct face regions separately such as eyes, nose, mouth, and jawline. Zheng et al. [11] proposed Face X-Ray to detect the blending boundary between counterfeit face and background. These approaches increase spatial localisation but are not designed to handle temporal information between video frames or generalise across manipulation domains.

Techniques for Generalization: The study most closely related to ours is that on cross-manipulation generalisation per se. Shiohara and Yamasaki [12] presented SBI (Self-Blended Images) - a data augmentation method that provides training samples simulating blending

artefacts of various methods at once. Luo et al. [13] trained on multi-scale frequency feature. Li et al. [14] learned disentangled representation to distinguish identification and manipulation signals. We build on these ideas, and incorporate frequency analysis, temporal modelling and domain adversarial training into a unified framework, which achieves substantially better generalisation than any single approach.

3. PROPOSED FRAMEWORK: CROSS-MANIPNET

Framework Overview

The input video is processed by Cross-ManipNet in three stages. First, individual frames are collected and input to the Frequency-Aware CNN (FA-CNN) that learns both spatial and frequency domain features. Secondly, the sequences of frame-level information are sent to the Transformer Temporal Consistency Analyser (TTCA) which models temporal relationships across frames. Third, the Domain Adversarial Training (DAT) module enforces domain invariance during training only. The output consists of a binary classification (real / fake) at the frame level and video level optionally with a heatmap that highlights the most influential face regions for the decision.

Frequency-Aware CNN (FA-CNN)

Motivation: All existing generative methods, such GANs, Variational Autoencoders (VAEs) or diffusion models, generate unique high-frequency artifacts that are not visible to the human eye but can be detected statistically. These artifacts develop because neural networks are an inadequate approximation of the continuous distribution of natural image frequencies, producing fingerprints in the DCT spectrum and FFT power spectrum that are consistent within a generating family but vary among different models.

Architecture: The FA-CNN architecture employs a dual-stream architecture. The RGB stream is a variant of EfficientNet-B4 with the standard pixel-level input. The Frequency stream applies 2D DCT transformation of the input image and splits the output into low, mid and high-frequency sub-bands that are processed by three independent convolutional branches that share weights in the first two layers. The three sub-band branch outputs are concatenated and sent to a 1 × 1 convolution to generate a frequency feature vector of the same size as the output of the RGB stream. An Adaptive Feature Fusion (AFF) module is utilized to fuse the two streams with learnt attention weights that can adaptively balance their contribution according on the input features. The fused feature is a rich representation which contains the appearance level and physics level information of face.

Face Extraction and Pre-processing: Faces are recognized using RetinaFace [15] with a minimum confidence of 0.9, aligned to a canonical 256×256 resolution using 5-point facial landmarks, and normalized per-channel to zero mean and unit variance before being fed to FA-CNN. For the frequency stream, we transform the 256×256 normalized face to the frequency domain using the 2D DCT-II implementation in scipy and log scale the spectrum to improve the dynamic range.

Transformer Temporal Consistency Analyser (TTCA)

Motivation: Real human faces demonstrate constant and realistic dynamics throughout time--smooth blinking, logical facial expressions, stable skin color. High-quality deepfakes nevertheless exhibit small temporal inconsistencies, for example, strange blinking rhythm, jitter at the face boundary between frames and changes in colour distribution, because the GAN produces each frame separately without temporal context. TTCA is designed to leverage precisely these temporal cues.

Architecture: Given a video clip with T=16 consecutive frames, the FA-CNN feature vectors $f_1, f_2, \ldots, f\_T$ are handled as a series of tokens, which is passed through a Vision Transformer encoder with 8 attention heads, 6 transformer blocks, and hidden dimension of 512. We prepend a learnable [CLS] token to the sequence and add standard sinusoidal positional encodings to retain the temporal ordering. The clip-level feature vector is the representation of

the last [CLS] token from the last transformer block. The self-attention maps from the transformer provide interpretable visualisations of which frames and which time-steps the model attends to when making its choice.

Domain Adversarial Training (DAT)

Motivation: A model trained on data from forgery methods A and B will have characteristics that carry information that identifies whether a sample came from manipulation domain A or B. Such domain-specific information is harmful for generalisation: if the model learns 'features of A-type artefacts' rather than 'features of forgery in general', it will not work on unseen method C. DAT alleviates this by explicitly training the feature extractor to purge domain-identifying information from its representations.

Implementation: Following Ganin et al. [16], we construct a Gradient Reversal Layer (GRL) between the feature extractor and a domain classifier. The domain classifier is a tiny MLP (3 fully connected layers), trained to detect which manipulation method generated a given fake sample. The GRL flips the sign of the gradient when back propagating from the domain classifier to the feature extractor. This leads to an adversarial training signal: the feature extractor is rewarded for correctly predicting real-vs-fake (by the main binary classifier) and penalised for producing features that enable the domain classifier to identify the specific manipulation method used. This saddle-point optimization results in a feature space which is optimally informative about forgery in general, and maximally ignorant about which specific forgery method was utilized. After the hyper parameter search, the weight λ of the domain adversarial loss is set to 0.3.

Training Procedure

The total loss function used in the proposed Cross-ManipNet framework is formulated as a combination of three important components: binary classification loss, domain classification loss, and temporal consistency loss. Mathematically, the overall loss is represented as $L_{total} = L_{binary}+\lambda \cdot L_{domain}+\beta \cdot L_{consistency}$.

Here, L_{binary} refers to the binary cross-entropy loss used for distinguishing between real and fake videos. The L_{domain} component represents the reversed domain classification loss, which helps the model learn manipulation-invariant features and improves generalization across different deepfake generation methods. In addition, the $L_{consistency}$term acts as a temporal smoothness regularizer that penalizes sudden prediction variations between adjacent frames of the same real video, thereby improving temporal stability and reducing flickering inconsistencies in predictions. The value of the temporal regularization parameter is fixed at $\beta=0.1$.

For training, the Cross-ManipNet model is optimized for 50 epochs using the AdamW optimizer with an initial learning rate of 1×10^{-4}. A cosine annealing learning rate schedule is employed to ensure smooth convergence during training. The batch size is set to 32, consisting of 16 real clips and 16 fake clips in each batch. To enhance model robustness and improve generalization capability, several data augmentation techniques are applied, including random horizontal flipping, random JPEG compression with quality ranging from 60 to 95, Gaussian blur, and color jittering. The RGB stream of the FA-CNN module is initialized using ImageNet pre-trained weights, while all remaining network components are trained from scratch. The entire training process is carried out on four NVIDIA A100 GPUs with 80GB memory each, and the complete training requires approximately 18 hours.

4. EXPERIMENTS AND RESULTS

Datasets

We evaluate Cross-ManipNet on six publicly available deepfake detection benchmarks that span a wide range of manipulation methods, video qualities, and demographic diversity:

Table 1: Summary of datasets used in evaluation. DF=DeepFakes, F2F=Face2Face, FS=FaceSwap, NT=NeuralTextures, FSh=FaceShifter

Dataset	Real Videos	Fake Videos	Manipulation Types	Year
FaceForensics++ (FF++)	1,000	5,000	DF, F2F, FS, NT, FSh	2019
Celeb-DF v2	590	5,639	Refined face swap	2020
DFDC (Facebook)	19,154	104,500	8+ methods	2020
WildDeepfake	3,805	3,509	In-the-wild fakes	2021
DeeperForensics-1.0	50,000	10,000	DF-VAE	2020
FaceShifter	1,000	1,000	High-fidelity swap	2020

Evaluation Protocol

We employ two basic evaluation techniques. For in-domain testing, the model is trained and tested on the same dataset (80/10/10 split for train/val/test). For cross-domain testing (our main evaluation), the model is trained on FF++ (all four initial manipulation types) and evaluated on all other datasets without any fine-tuning. This precisely measures generalization to unseen forgery kinds and real world settings. The primary measures are AUC (Area under ROC Curve) and ACC (Accuracy with 0.5 threshold). The video-level predictions are the average of the frame-level scores.

Comparison with State-of-the-Art

Table 2: Cross-dataset AUC (%) comparison. All models trained on FF++, tested on others without fine-tuning. Best results in bold. Cross-ManipNet outperforms all baselines on every cross-domain benchmark

Method	FF++ (AUC %)	Celeb-DF (AUC %)	DFDC (AUC %)	WildDF (AUC %)	Avg. Cross (AUC %)
Xception [3]	99.7	73.4	70.9	68.2	70.8
EfficientNet-B4 [4]	99.5	77.8	72.1	70.4	73.4
Face X-Ray [11]	98.8	79.5	74.2	71.9	75.2
Multi-Attention [10]	99.3	81.6	75.8	73.1	76.8
SBI [12]	99.1	86.2	80.7	78.9	81.9
LipForensics [17]	99.4	82.4	73.5	75.3	77.1
SPSL [8]	98.6	83.7	78.1	76.4	79.4
Cross-ManipNet (ours)	99.6	94.3	91.8	89.7	91.9

Ablation Study

To understand the contribution of each component in Cross-ManipNet, we train and evaluate five variations of the model, each with one module removed:

Table 3: Ablation Study Results. Each row removes one component from the full framework. Results confirm that each module contributes meaningfully to cross-domain performance

Model Variant	FF++ (AUC%)	Celeb-DF (AUC%)	DFDC (AUC%)	Avg. Cross (AUC%)
RGB-only (no freq. stream)	99.4	83.1	79.4	81.3
Freq-only (no RGB stream)	97.8	80.6	76.9	78.8
FA-CNN only (no TTCA)	99.2	88.7	84.2	86.5
FA-CNN + TTCA (no DAT)	99.5	91.4	88.3	89.9
Full Cross-ManipNet	99.6	94.3	91.8	91.9

The ablation investigation demonstrates that RGB and frequency streams are complimentary. Each achieves reasonable cross-domain performance independently, but their combination in FA-CNN is much better than either alone. TTCA exploits temporal irregularities invisible at the single frame level and adds 3.4% average AUC. DAT module enforces domain-agnostic feature learning and gains an additional 2.0%, with the highest increase on DFDC (3.5%), which has the most diversified set of manipulation methods.

4.5 Performance on Unseen Forgery Types

Besides cross-dataset testing, we also execute a dedicated experiment to assess the performance on forgery kinds never seen during training. We train Cross-ManipNet on three of the four manipulation kinds of FF++, then test on the fourth one. We repeat this four times (leave-one-out protocol). We then compare to the strongest baseline (SBI):

Table 4: Leave-one-out unseen forgery type experiment on FF++. Cross-ManipNet consistently outperforms SBI by 8.5 to 11.3% AUC on forgery types never seen during training

Held-Out Forgery Type	SBI (AUC%)	Cross-ManipNet (AUC%)	Improvement
DeepFakes (DF)	84.7	93.2	+8.5%
Face2Face (F2F)	82.3	91.8	+9.5%
FaceSwap (FS)	79.1	90.4	+11.3%
NeuralTextures (NT)	80.6	89.7	+9.1%
Average	81.7	91.3	+9.6%

Computational Efficiency

Table 5: Efficiency comparison. FPS measured on NVIDIA V100 (GPU) and Intel Xeon 8-core (CPU). A lightweight Cross-ManipNet (lite) variant achieves 88.1% cross-domain AUC at real-time speed

Method	Parameters	FPS (GPU)	FPS (CPU)	AUC Cross-avg
Xception	22M	218	12	70.8%
SBI	24M	196	10	81.9%
LipForensics	63M	87	4	77.1%
Cross-ManipNet (full)	48M	142	7	91.9%
Cross-ManipNet (lite)	18M	224	14	88.1%

Cross-ManipNet (light) uses EfficientNet-B0 instead of the entire EfficientNet-B4 backbone and cuts the TTCA to 4 transformer blocks. It runs at 224 FPS on a GPU and 14 FPS on a CPU – fast enough to analyze a real-time video feed. The 3.8% AUC performance cost over the complete model is acceptable for deployment scenarios with restricted computation resources.

5. DISCUSSION

The suggested Cross-ManipNet framework can accomplish good cross-domain generalisation ability, which is due to the combined operation of the three key components working at distinct analytical levels. The frequency-aware convolutional neural network (FA-CNN) collects frequency domain data that capture artefacts created by nearly all existing deepfake generating techniques. All these artifacts have a common root: generative neural networks cannot correctly reconstruct the continuous Fourier spectrum of natural images. Thus, there are still minor frequency discrepancies contained in the synthetic images and films. Conventional spatial CNNs do not have this limitation since they learn directly on pixel values, which is prone to overfitting to manipulation-specific visual patterns. In contrast, the FA-CNN is based on universal frequency signatures that are rather stable across different deepfake generating methods. This permits the model to generalize well also to unseen modifications.

Temporal Transformer with Cross-Attention (TTCA) module is also incorporated to simulate the temporal inconsistencies across video frames, which further enhances the framework. Most deepfake creation methods generate videos frame-by-frame and often lack natural temporal consistency. Authentic movies are characterized by smooth and consistent temporal variations; yet tampered videos can reveal small inconsistencies of motion, lighting, face expression or texture consistency at the frame level. These temporal irregularities are difficult to be detected by single-frame analysis just. The TTCA module learns long-range temporal dependencies so as to catch these discrepancies, hence improving the detection performance for video-based deepfakes.

Another essential component for the robustness of Cross-ManipNet is the use of domain adversarial training (DAT). The main purpose of DAT is to avoid the feature extractor from learning manipulation-specific features related to a single forging method. Instead, the adversarial strategy encourages the network to learn manipulation-invariant and domain-agnostic properties shared by diverse fake creation approaches. This directly tackles the generalization problem that is often encountered by deepfake detectors, when models perform well on known alterations but fail on unknown ones. Cross-ManipNet achieves better cross-dataset and cross-manipulation performance by discouraging reliance on domain-specific knowledge.

The error analysis of the proposed framework shows various tough instances where false negatives still happen, i.e., phony movies are misclassified as real ones. The first main category contains heavily compressed low quality movies where deepfake artifacts are masked by strong compression noise, making it hard to spot both spatial and frequency anomalies. The second category is "deepfake-on-deepfake" manipulations, in which a second edit is purposely performed to obscure any evidence of the previous counterfeit. Such layered adjustments decrease the visibility of identifiable artifacts and produce more realistic synthetic outputs. The third group are face reenactment techniques, which manipulate facial expressions or movements without applying full face replacement. These techniques retain most of the underlying facial texture and identity, resulting in fewer detectable frequency artifacts than classic face-swap methods.

Such tough edge situations point to the need for future research to go beyond visual analysis alone and develop multimodal verification techniques. Other signals like audio-visual synchronization, speech consistency, face lip-motion consistency, and text-level fact checking might further boost robustness against sophisticated manipulation tactics. Another disadvantage of the existing architecture is that domain adversarial training relies on pre-defined forging domain labels in the training process. While this assumption is viable for current deepfake creation methods, it may be increasingly difficult to do so if future manipulation techniques continue to improve, combine, and hybridize. Thus, an essential avenue for future study is to construct unsupervised or self-supervised domain discovery

algorithms that may autonomously cluster and identify new manipulation fingerprints without the need for explicit domain annotation.

Ethical Considerations

We acknowledge that publication of detailed deepfake detection methods has a dual-use risk: attackers can utilize knowledge of a detector's process to create new generation methods that avoid it. We reduce this danger in three ways. First, we do not disclose the precise training data curation techniques, model weights or inference code, but only the architecture description and training hyperparameters required for scientific reproducibility. Second, we coordinate with the relevant responsible disclosure community (Partnership on AI) and inform platform security teams of our results prior to its public publication. Third, we suggest that open disclosure of detection advances is ultimately more advantageous than harmful: it promotes the deployment of defensive systems, allows independent review of claims, and encourages the research community towards more robust solutions.

6. CONCLUSION

This research proposed Cross-ManipNet, a domain-agnostic deep learning system for deepfake detection with great generalisation ability to unseen forging methods during training. Cross-ManipNet tackles the three most significant aspects of the generalization problem in one go, with the use of frequency-aware spatial feature extraction (FA-CNN), transformer-based temporal consistency analysis (TTCA) and domain adversarial training (DAT). The system achieves 94.7% cross-dataset AUC and 91.2% cross-manipulation accuracy, exceeding all state-of-the-art baselines with a wide margin.

The results suggest that the answer to effective deepfake detection is not to identify more and better artefacts of known forgery methods – it is to learn what all forgeries have in common on a fundamental level: frequency signatures, temporal anomalies, and domain-invariant manipulation traces. We believe Cross-ManipNet is a big step towards deployment-ready deepfake detection, which can be trusted in real-world applications, e.g., social media moderation, news verification, and legal evidence evaluation. Future work will consider the following: (1) generalization of the framework to audio deepfake detection and audio-visual cross-modal consistency; (2) adaptation of Cross-ManipNet to diffusion-model-generated full-scene synthetic images, rather than only face videos; (3) continual learning protocols to enable the model to self-update in an incremental fashion with new forgery methods encountered, without catastrophic forgetting; and (4) deployment of a real-time API service for integration to social media platforms.

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