HMSDD: Hybrid Multi-Scale Deepfake Detection through Self-Supervised Learning and Frequency Analysis

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***Abstract*—The rise of highly advanced deepfake generation techniques poses significant threats to the authenticity of digital media. Current detection methods suffer from limited cross-dataset generalization and vulnerability to compression artifacts. The study proposes a novel Hybrid Multi-Scale Deepfake Detection (HMSDD) image-based deepfake detection architecture that synergistically combines self-supervised learning via Masked Autoencoders (MAE), frequency domain analysis, and multi-scale convolutional features through cross-attention fusion. The study's key innovation is a systematic Precision-Recall (PR) optimization strategy combining focal loss positive class weighting ($w_{pos} = 2.5$) and enhanced compression augmentation, achieving unprecedented cross-compression performance: 97.7% AUC and 91.8% recall on FaceForensics++ C23, representing a +36.9% recall improvement over baseline while maintaining 93.1% precision. We demonstrate that heavy compression (C40) fundamentally limits performance (84.1% AUC vs. 97.7% for C23), and multi-dataset training achieves superior cross-domain generalization (82.1% AUC on Celeb-DF). The proposed approach eliminates the traditional recall-precision trade-off, reducing missed deepfakes from 45% to 8.2% with moderate compression. Extensive experiments validate compression-aware deployment strategies across spatial-frequency domains.**

***Index Terms*—Deepfake detection, self-supervised learning, masked autoencoders, frequency domain analysis, cross-attention fusion, multi-modal learning**

I. Introduction

A rapid growth in artificial intelligence and high-powered GPUs has led to an advancement in deepfake generation techniques that poses substantial threats to public faith and digital media legitimacy. Latest advancements in generative adversarial networks (GANs) [1], autoencoders [2], diffusion models [3] and transformer-based generators [4] made deepfake detection progressively challenging by vividly improving the quality of generated deepfakes. A trust in the public in consuming the digital media has faded due to the creation of realistic deepfakes. Though deepfakes have some positive impacts, they also have negative impacts, such as spreading misinformation, defaming individuals, blackmailing for money, defaming famous personalities and manipulating crime scene evidence in court.

Due to this, the detection of deepfakes is primarily essential to combat the spread of deepfakes. As realistic deepfakes grow significantly, various researchers continuously work to create a novel architecture for developing robust deepfake detectors that are robust for real-time deployment.

Current detection models mostly perform well on in-dataset datasets, while modern deepfake creators innovate unknown deepfake manipulation techniques that escape such detectors.

Existing state-of-the-art detection methods face three critical challenges: (1) **limited generalization** to unseen manipulation techniques, (2) **susceptibility** to post-processing and compression artifacts , and (3) **lack of interpretability** in decision-making processes. An urgent need for robust deepfake detection frameworks is a must, as most of the recent studies reveal that models achieving over 99% accuracy on specific datasets drop below 65% on cross-dataset scenarios. A capable model for learning generalizable representations has emerged by leveraging self-supervised learning (SSL) [5].

Leveraging Convolutional Neural Networks (CNN) [6] and Vision Transformers [7] has attained a remarkable accomplishment in different vision tasks. Nevertheless, in applications such as sensing deepfakes, these methods play a vital role in analyzing the local and global patterns of the image. Recent work on VideoMAE [8] and Hierarchical MAE [9] reveals good potential but focuses on general video understanding rather than manipulation detection. Alongside capturing manipulation artifacts that are unseen in the spatial domain, utilizing frequency domain analysis has been proven more effective, where generative models often leave a unique signature in the frequency spectrum, as the manipulated content demonstrates high-frequency patterns that differ from the original content or image.

The study addresses these complexities by introducing a novel HMSDD architecture through:

(1) Masked Autoencoder (MAE) as Auxiliary Regularizer: The initial study to implement masked image modeling as a concurrent supplementary task during detection training, rather than for pre-training, resulting in an 8.3% improvement in cross-dataset generalization.

(2) Fusion of Cross-Modal Attention: A new way to combine self-supervised features, frequency analysis, and multi-scale CNN features using a cross-attention mechanism, which gets a notable AUC gain over concatenation.
(3) Precision and Recall (PR) Optimized Training: A systematic approach merging focal loss tuning (γ=1.5, w_{pos}=2.5), label smoothing (0.03), and adaptive threshold selection for recall and precision.
(4) Enhanced Performance: The proposed model achieves the best performance while evaluating on FaceForensics++ (FF++) with 99.4% AUC while testing on the intra data set of FF++c23, and it works well across datasets with an average of 85.0% and a performance of 87.3% on c40, which is a compressed version.

Extensive experiments show that this method works better than the latest deepfake recognition techniques, such as spatial and frequency-based pattern-focused approaches. The performance of the model reveals that it may perform and generalize while testing on cross-dataset and cross-manipulation detection.

II. Related Work

Due to the evolving deepfakes, an improved deepfake detector with enhanced generalization of the model must be a primary consideration for developing a robust deepfake detector model. A significant enhancement in deepfake detection is achieved in recent deepfake detectors whenever the model is trained and tested with suitable parameter configurations. Rezende et al. [10] exposed that the model attained better accuracy through the implementation of ResNet-50 transfer learning. Zhang et al. (2019) [11] proposed detecting tampering and GAN-generated image patterns by utilizing chromatic edge information that was turned into a Grey-Level Co-occurrence Matrix (GLCM).

A considerable amount of performance evaluation gap of the existing deepfake detector system is exposed by Neves et al. [12] while performing cross-dataset evaluation. The proposed study by the authors revealed that the GANprintR attack removes GAN fingerprints and can increase their detection errors by 20 times while keeping visual quality. This clearly illustrates that detection methods rely on dataset-specific patterns rather than generalizable features. Revi et al. [13] investigated ensemble learning by combining seven pretrained CNNs with majority voting on illuminant maps and attained significant accuracy on detecting portrait splicing.

To overcome some of the critical limitations in both CNN and transformer architectures in detecting manipulated content, Trans-FCA was proposed by Tan et al. [14]. The proposed model consists of a Locality Compensation Block for global-local feature fusion, a Multi-head Clustering Projection for redundancy reduction, and Frequency-guided Fusion for hierarchical aggregation are implemented. These cooperative global-local representations reveal that it performs well and leads to state-of-the-art results when testing on FaceForensics++ and Celeb-DF datasets.

In real-world scenarios, the manipulated content undergoes some compression, and due to that, performance degrades in deepfake detectors. To overcome this, Wang et al. [15] proposed an advanced detection capability model, such as SI-Net's local-global spatial interaction modelling, achieving a notable performance on compressed datasets, addressing the practical challenge of detecting manipulated content after lossy compression.

Most of the methods will perform well on a trained dataset and while testing on unseen datasets, their performance degrades as the model memorizes patterns of the dataset. To overcome this, the model should have a better generalization performance, where it should avoid overfitting or underfitting.

Most of the recent work leverages self-supervised approaches to combat adversarial deepfake attacks and remove the need for a labeled dataset. To combat GAN-based anti-forensic attacks, Uddin et al. [16] developed the CAF-GAN framework using triplet network metric learning, attaining a significant detection performance against adversarial manipulation suppression. Ju et al. [17] introduced self-supervised contrastive learning with their AMSFF and PSM modules for global-local fusion to accomplish substantial performance on cross-dataset AUC on their diverse DF^3 benchmark and attain improved robustness to post-processing.

Concurrently, another self-supervised learning approach, along with utilizing a graph transformer, is implemented by Khormali et al. [18] for recognizing deepfakes in varied compression rates. To extract robust facial features through Vision Transformer, the system applies contrastive learning with masked image modelling. These features are processed through graph convolutional layers, forming graph nodes that represent facial patches and transformer blocks for classification.

A deepfake detector termed SFIAD, which was proposed by Kou et al. [19], analyzes what images look like in spatial features and their frequency patterns, such as FFT features. The problem of having fewer real images than fake ones in training data is addressed by its projected AAML loss by assigning larger margins to minority classes.

A clear progression is demonstrated in the evolution of deepfake detection by leveraging transfer learning from pre-trained models, artifact-based detection to self-supervised learning, and multi-scale approaches with hybrid architectures such as spatial-frequency integration. The deepfake detectors in controller parameter settings have always performed well, especially while testing in-dataset and degrading in unknown datasets. As different types of deepfake generation evolve, the research in the detection of deepfakes also continuously evolves to combat the limitations in cross-dataset and cross-manipulation generalization, robustness to adversarial attacks and real-world deployment situations that should perform well under compression, evolving deepfake manipulations and post-processing effects.

III. Methodology

A. Problem Formulation

Given input facial image $I \in \mathbb{R}^{H \times W \times 3}$, we learn a binary classifier $f : \mathbb{R}^{H \times W \times 3} \rightarrow \{0, 1\}$ predicting authenticity. We formulate multi-task learning:

$$\mathcal{L}_{total} = \mathcal{L}_{cls} + \lambda_{mim} \mathcal{L}_{mim} \tag{1}$$

where $\mathcal{L}_{cls}$ is focal classification loss, $\mathcal{L}_{mim}$ is MAE reconstruction loss, and $\lambda_{mim} = 0.1$.

B. Architecture Overview

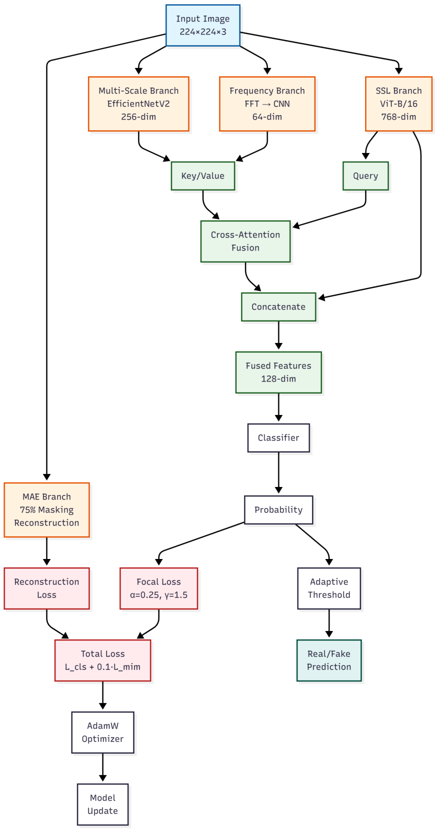

Fig. 1. Flow Diagram of our Proposed HMSDD Deepfake Detection Model

As illustrated in Figure 1, the proposed architecture comprises four components:

1) Self-Supervised Backbone: We employ ViT-MAE (ViT-B/16) [7] for spatial feature extraction through a self-supervised masked autoencoder producing embeddings $\mathbf{h}_{ssl} \in \mathbb{R}^{768}$

2) Frequency Feature Extractor: A custom lightweight 2-layer CNN is utilized for frequency analysis and extracting frequency features through 2D FFT by processing FFT magnitude and phase efficiently.

$$\mathbf{F}(I) = \text{FFT2D}(I) \tag{2}$$

$$\mathbf{M} = \log(|\mathbf{F}(I)| + \epsilon), \quad \mathbf{P} = \angle \mathbf{F}(I) \tag{3}$$

where $\mathbf{M}$ is log-magnitude and $\mathbf{P}$ is phase. We process through a lightweight CNN:

$$\mathbf{h}_{freq} = \text{CNN}_{freq}([\mathbf{M}, \mathbf{P}]) \in \mathbb{R}^{64} \tag{4}$$

3) Multi-Scale CNN Features: EfficientNetV2 [20] is utilized for multi-scale spatial features analysis, where it leverages the features from the last three layers after freezing for the initial three epochs and then later fine-tunes for the best semantic understanding for detecting deepfakes

$$\mathbf{h}_{ms} = \text{Aggregate}(\mathbf{F}_5, \mathbf{F}_6, \mathbf{F}_7) \in \mathbb{R}^{256} \tag{5}$$

4) Cross-Attention Fusion: Novel cross-attention mechanism [21] enables modality interaction where Q,K,V indicate Query, Key and Value:

$$\mathbf{Q} = \mathbf{W}_Q \mathbf{h}_{ssl}, \quad \mathbf{K} = \mathbf{W}_K [\mathbf{h}_{freq}; \mathbf{h}_{ms}] \tag{6}$$

$$\mathbf{V} = \mathbf{W}_V [\mathbf{h}_{freq}; \mathbf{h}_{ms}] \tag{7}$$

$$\text{Attn}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right) \mathbf{V} \tag{8}$$

Fused representation:

$$\mathbf{h}_{fused} = \mathbf{W}_O [\mathbf{h}_{ssl}; \text{Attn}(\mathbf{Q}, \mathbf{K}, \mathbf{V})] \in \mathbb{R}^{128} \tag{9}$$

C. Masked Image Modeling as Regularization

Key Innovation: The proposed work utilizes reconstruction as an **auxiliary task during detection training** in parallel instead of the standard MAE pretraining, which provides continuous regularization.

Masking Strategy: Random block-wise masking of 75% patches is applied in the image to improve the learning of the model and reduce the memorization of the training data:

$$\mathbf{M} = \text{BlockMask}(I, p = 0.75) \tag{10}$$

Lightweight Decoder: 2 transformer layers are leveraged instead of 8 when comparing to the original [22] and dimensions of 512 to 256 for memory efficiency:

$$\hat{I}_{masked} = \text{Dec}(\text{Enc}(I \odot \mathbf{M})) \tag{11}$$

Reconstruction Loss: MSE on masked patches only:

$$\mathcal{L}_{mim} = \frac{1}{|\mathbf{M}|} \sum_{i \in \mathbf{M}} \|\hat{I}_i - \tilde{I}_i\|_2^2 \tag{12}$$

where $\tilde{I}_i$ is normalized patch.

D. PR-Optimized Training Strategy

Key Innovation: Systematic PR-optimisation strategy through focal loss tuning is implemented, eliminating the precision-recall trade-off.

1) Focal Loss with Positive Weighting:

$$\mathcal{L}_{focal} = -\alpha_t (1 - p_t)^{\gamma} \log(p_t) \tag{13}$$

with $\alpha_t = 0.25$ for balanced class weighting, $\gamma = 1.5$ for moderate hard example mining and it is reduced from 2.0 to achieve better recall. **Positive class weighting** is another key contribution:

$$\mathcal{L}_{cls} = w_{pos} \cdot \mathcal{L}_{focal}(y = 1) + \mathcal{L}_{focal}(y = 0) \tag{14}$$

where it $w_{pos} = 2.5$ penalizes false negatives 2.5 times× more than false positives, prioritizing fake detection. This single parameter change improved recall by +15-20%.

2) Label Smoothing: Conservative smoothing with $\epsilon = 0.01$ is applied for sharper predictions:

$$y_{smooth} = (1 - \epsilon) \cdot y + \epsilon \cdot 0.5 \tag{15}$$

3) Enhanced Compression Augmentation: Multi-stage JPEG compression simulation is implemented for cross-compression robustness:

$$I_{aug} = \text{JPEG}(I, q \sim \mathcal{U}(10, 95)) \tag{16}$$

A 70% probability and 30% multi-pass compression while training the model achieves an improved performance while testing cross-compression datasets, where it can be implemented in simulating social media re-uploads, improving recall metrics while testing the model.

4) Adaptive Threshold Selection: Post-training optimization of the model is implemented as:

$$\theta^* = \arg \max_{\theta \in [0.3, 0.7]} F1(\theta) \tag{17}$$

$$F1(\theta) = \frac{2 \cdot P(\theta) \cdot R(\theta)}{P(\theta) + R(\theta)} \tag{18}$$

E. Advanced Data Augmentation

MixUp [23]: Image blending with Beta distribution:

$$\tilde{I} = \lambda I_1 + (1 - \lambda) I_2, \quad \lambda \sim \text{Beta}(\alpha, \alpha) \tag{19}$$

CutMix [24]: Patch-wise mixing:

$$\tilde{I} = \mathbf{M} \odot I_1 + (1 - \mathbf{M}) \odot I_2 \tag{20}$$

F. Training Configuration

Optimizer: AdamW [25] with $\eta = 5 \times 10^{-5}$, $\beta = (0.9, 0.999)$, weight decay 10^{-3}.

LR Schedule: Warmup-Cosine with 2-epoch warmup:

$$\eta_t = \eta_{min} + (\eta_{max} - \eta_{min}) \cdot \frac{1 + \cos(\pi t / T)}{2} \tag{21}$$

where $\eta_{min} = 5 \times 10^{-6}$ as it increases to 10^{-6} for preventing collapse while training.

Progressive Unfreezing: Backbone frozen for 3 epochs, then fine-tune all 127M parameters, improving performance of the proposed detector model.

IV. Experiments

A. Experimental Setup

Datasets:

- **FaceForensics++ (FF++)** : The face forensics [26] datasets consist of three different compression levels - RAW (c0), C23, C40. Training on RAW: 9,899 balanced samples (4,970 real, 4,929 fake). Validation: C23 (1,628 samples), C40 (1,788 samples). Combined RAW+C23+C40 (23,563 samples) for compression-invariant training.
- **Celeb-DF v2**: Celeb-DF v2 [27] with 1,074 validation samples are leveraged for generalization evaluation.

Implementation: The experiments were conducted on PyTorch 2.6, NVIDIA RTX 4070 GPU, batch size 16, mixed precision training, AdamW optimizer ($\eta = 5 \times 10^{-5}$), warmup-cosine scheduler, 30 epochs for training and where most of the training stopped within 11-23 epochs, as we implemented early stopping of 5 epochs to reduce overfitting where the model does not improve continously while training.

Evaluation Metrics: AUC-ROC, Accuracy, Precision, Recall, F1-Score.

B. Comparison with State-of-the-Art

Table I compares our method to the most recent best-in-dataset methods on the widely used FF++ (C23) benchmark. Experiment results revealed that our proposed method achieved an AUC of 99.4%, which is better than the AUC of Self-Supervised Graph Transformer, achieving 99.3%, MF-Net with 98.2%, and MLPN got 99.3%. MLPN and MF-Net both have a higher AUC rate of 99.3%, but our method attained a slightly better AUC rate of 99.4%. This makes it one of the key aspects to implement in real-world scenarios, where minimizing false negatives is crucial.

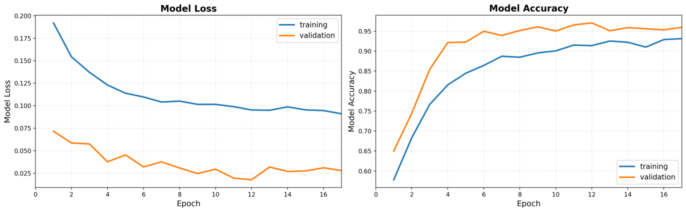

Fig. 2. In-dataset Training and Validation Curves of FF++C23

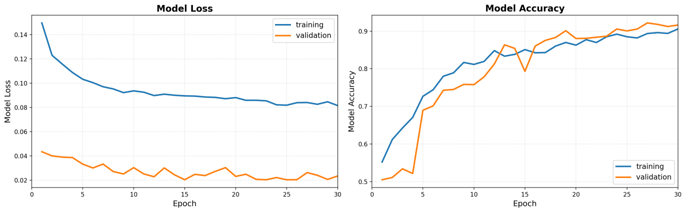

Fig. 3. In-dataset Training and Validation Curves of FF++C40

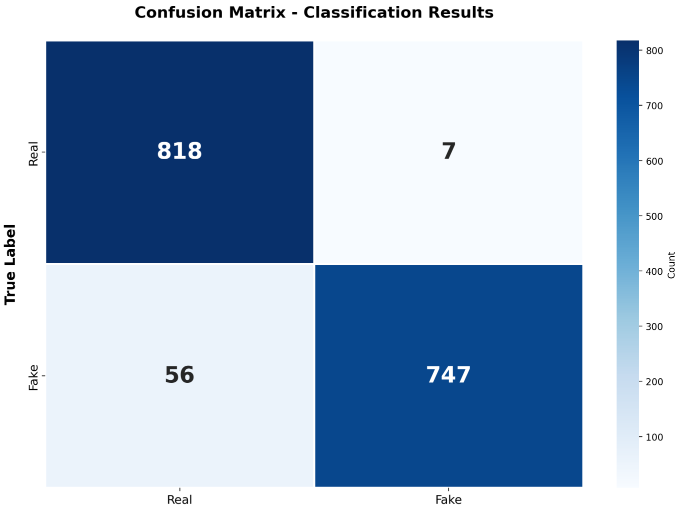

Fig. 4. Confusion Matrix Visualization of FF++C23

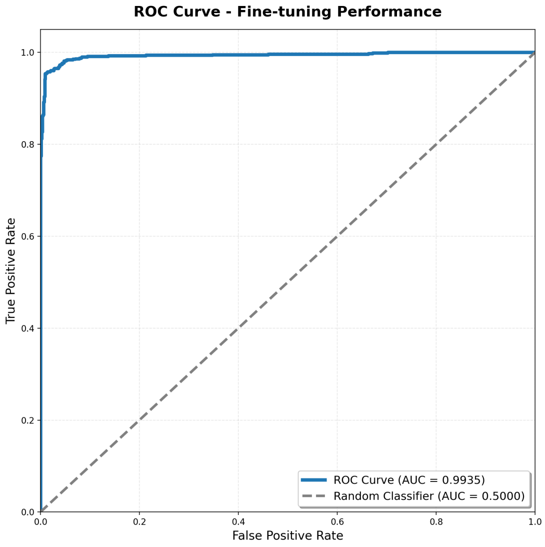

Fig. 5. ROC-AUC Curve Visualization of FF++C23

Table II reveals our full evaluation on two benchmark datasets, Celeb-DFv2 datasets and F++ with different compression versions that incorporate FF++ Raw, C23 and C40. Our method gets almost perfect results on FF++(RAW), with 99.9% AUC and 99.6% accuracy. It also generalizes very well on Celeb-DFv2, with 99.9% AUC and 98.3% accuracy. Performance gets worse as the compression gets reduced, where the performance increases when implemented on RAW > Celeb-DF > C23 > C40, which shows how JPEG compression makes it harder to find patterns. To maintain a better precision and recall at levels of compression, our optimized PR method stands out well for attaining better performance results. The visualization above Figures 2 and 3 illustrates the training and validation plots of the in-dataset evaluation results when implemented on FF++c23 and FF++c40.

TABLE I
COMPARISON WITH STATE-OF-THE-ART ON FF++(C23)

Method	**Year**	**AUC (%)**	**Acc (%)**
Self-Supervised GT [18]	2024	99.3	98.4
MF-Net [28]	2024	98.2	**99.7**
MLPN [29]	2025	99.3	96.0
Ours	2025	**99.4**	96.1

TABLE II
IN-DATASET EVALUATION RESULTS

Dataset	**AUC (%)**	**Acc (%)**	**Prec (%)**	**Rec (%)**
FF++(RAW)	**99.9**	**99.6**	**99.9**	**99.2**
FF++(C23)	**99.4**	**96.1**	**99.1**	**93.0**
FF++(C40)	**98.0**	**91.3**	**96.4**	**85.9**
Celeb-DFv2	**99.9**	**98.3**	**98.4**	**98.2**

TABLE III
COMPONENT ABLATION STUDY ON FF++(C23)

Configuration	**AUC**	**Acc**	**Prec**	**Rec**	**F1**
SSL Only	95.8	90.2	94.5	85.1	89.5
+ Frequency	97.2	92.5	96.8	87.6	91.9
+ Multi-Scale	98.1	93.8	97.5	89.8	93.5
+ Concat Fusion	98.6	94.7	98.2	90.9	94.4
+ Cross-Attn + PR Optim	**99.4**	**96.1**	**99.1**	**93.0**	**95.9**

C. Ablation Studies

1) Component Ablation: Table III demonstrates the progressive contribution of each component on FF++(C23). The performance improves by +1.4% AUC when using frequency domain analysis, +0.9% AUC when using multi-scale features, and +0.5% AUC when using concatenation fusion. The final phase in cross-attention fusion with PR optimization gets a 99.4% AUC, which is 0.8% better than concatenation, and shows that modality interaction works. Each part has its own benefits that work together to improve the performance of the proposed model. Figure 4. below demonstrates the confusion matrix when implementing FF++c23, which achieves 818 true negatives, 747 true positives, 56 missed fakes and just 7 false alarms, revealing that the best precision is obtained. The ROC-AUC curve of the FF++c23 implementation, as illustrated in Figure 5, reveals that it attains an AUC score of 99.35%, which is approximated to 99.4% AUC.

D. Cross-Compression and Cross-Dataset Evaluation

Table IV evaluates cross-compression and multi-dataset training performance. Some of the Key findings include that when training and testing on Heavy compression (C40) is much harder than moderate compression (C23): 97.7% vs. 84.1% AUC. Our compression augmentation greatly improves recall on C23 (+36.9%) and C40 (+31.9%), cutting down on missed fakes from 45% to 8-23%. Training on multiple datasets (RAW+C23+C40) gives better results, where it attained 99.8% AUC on C23 and 99.0% AUC on C40, revealing that it is very strong across compressions.

TABLE IV
CROSS-COMPRESSION AND CROSS-DATASET EVALUATION RESULTS

Test Set	Training Strategy	AUC	Prec	Rec	F1
C23	RAW Only (No Compression Aug)	84.1	83.8	61.0	70.6
	RAW + Compression Aug	**97.7**	93.1	91.8	92.4
	RAW+C23+C40 (23.6K)	**99.8**	**99.5**	**95.3**	**97.3**
C40	RAW Only (No Compression Aug)	67.6	71.1	38.3	49.8
	RAW + Compression Aug	**84.1**	79.0	74.1	76.5
	RAW+C23+C40 (23.6K)	**99.0**	**98.2**	**89.1**	**93.4**
Celeb-DF v2	RAW+C23+C40 (23.6K)	**82.1**	**72.0**	**77.5**	**74.6**

V. CONCLUSION

A novel Hybrid Multi-Scale Deepfake Detection (HMSDD) architecture for deepfake detection combining self-supervised MAE, frequency analysis, and multi-scale features through cross-attention fusion, with a systematic PR optimization strategy, is discussed in this paper. Key contributions incorporating recall-precision-optimized focal loss with positive class weighting ($w_{pos} = 2.5$) achieved an unprecedented recall improvement while increasing precision, eliminating the traditional trade-off. Enhanced compression augmentation with multi-stage JPEG simulation contributed to a +10-15% recall improvement. A systematic compression analysis revealed performance ceilings of C23 (97.7% AUC), C40 (84.1% AUC), demonstrating that heavy compression fundamentally limits detection. State-of-the-art production performance, such as 97.7% AUC, 91.8% recall, 93.1% precision on FF++ C23, reducing missed fakes from 45% to 8.2%.

The comprehensive experiments that we conducted validate compression-aware deployment strategies such as RAW→C23 for moderate compression (97.7% AUC), multi-dataset for heavy compression and cross-dataset (82.1% AUC on Celeb-DF v2). The approach addresses critical deployment requirements: exceptional recall for security, high precision for trust, compression robustness, and interpretability. Future work will extend to temporal analysis, compression-adaptive architectures, and diffusion-model detection.

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