

Using Deep Learning to Identify Deepfakes Created Using Generative Adversarial Networks

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ABSTRACT

This paper presents an enhanced deepfake detection system that extends the work of Jheelan & Pudaruth (2025) by implementing modern architectures including EfficientNet-B0, Vision Transformers (ViT), and DeiT, alongside GPU-optimized training strategies. Using the 140K Real and Fake Face Dataset, our approach achieves 98.62% test accuracy with EfficientNet-B0, surpassing the base paper’s MobileNet (98.5%) while reducing training time by $2.1\times$. We further demonstrate that mixed-precision training and gradient accumulation enable large-scale experiments on consumer GPUs (6 GB VRAM). Comprehensive evaluation includes inference speed (832 FPS), robustness tests, and comparisons with five state-of-the-art architectures. The results validate the superiority of modern transfer-learning approaches for real-time deepfake detection.

Index Terms— Deepfake detection, Vision Transformers, EfficientNet, mixed precision training, real-time inference

1 INTRODUCTION

The proliferation of deepfake technology, particularly through Generative Adversarial Networks (GANs) such as StyleGAN [1], poses significant threats to information integrity and digital trust. While detection methods have advanced, the rapid evolution of generative models necessitates continuous research into more robust and efficient detection systems.

Recent work by Jheelan and Pudaruth [2] demonstrated that pre-trained models, particularly MobileNet, achieve 98.5% accuracy on deepfake detection tasks. However, their study was limited by computational constraints (20K image subset, traditional FP32 training) and did not explore modern architectures like Vision Transformers or GPU optimization techniques.

This paper addresses these limitations by:

- 1) Scaling to a 40K image subset ($2\times$ larger than [2]) with optimized training strategies.
- 2) Evaluating modern architectures (EfficientNet, ViT, DeiT) that were not tested in prior work.
- 3) Implementing mixed-precision training and gradient accumulation for consumer GPU deployment.
- 4) Providing comprehensive performance analysis including inference time, model size, and robustness metrics.
- 5) Validating Vision Transformers for deepfake detection.

Our contributions extend beyond accuracy improvements, providing practical insights for deployment in real-time applications such as social media content moderation, news verification, and digital forensics.

2 RELATION TO PRIOR WORK

2.1 Deepfake Detection Literature

Deepfake detection has evolved significantly, with approaches ranging from traditional CNNs to hybrid architectures. Table I summarizes key related work using the same dataset or similar methodologies.

TABLE I
RELATED WORK SUMMARY

Reference	Method	Dataset	Acc.
Raza et al. [3]	CNN+VGG16	140K RF	94.0%
Nguyen et al. [4]	VGG16+Transfer	140K RF	90.0%
Abir et al. [5]	InceptionResNetV2+XAI	140K RF	99.87%
Jain et al. [6]	ELA-CNN	140K RF	99.87%
Jheelan & P. [2]	MobileNet	20K sub	98.5%
Our work	EfficientNet-B0	40K sub	98.62%

Notable trends include: (1) pre-trained models consistently outperform custom CNNs [2], [4], (2) hybrid approaches with explainability improve trust [5], (3) preprocessing techniques such as Error Level Analysis (ELA) can boost performance [6], and (4) dataset scale significantly impacts generalization.

Our work directly extends [2] by scaling dataset size, implementing GPU optimizations, and evaluating Vision Transformers, a class of models showing promising results in image classification [7] but underexplored in deepfake detection.

2.2 Vision Transformers for Image Classification

Dosovitskiy et al. [7] introduced Vision Transformers (ViT), demonstrating that transformer-based architectures can match or exceed CNN performance on ImageNet. Subsequent work on Data-efficient Image Transformers (DeiT) [8] improved training efficiency through knowledge distillation. Coccomini et al. [9] compared ViT and EfficientNetV2 on the ForgeryNet dataset for deepfake video detection.

Our study contributes by comprehensively evaluating ViT-Small and DeiT-Tiny on the 140K Real and Fake Face Dataset, and comparing their performance against modern CNNs (EfficientNet, MobileNetV3) and a custom architecture with attention mechanisms.

2.3 GPU Optimization for Deep Learning

Mixed-precision training [10] has become standard for reducing memory footprint and accelerating training. Gradient accumulation enables effective batch size increases on memory- constrained GPUs [11]. While widely adopted in NLP, these techniques remain underutilized in computer vision research, particularly for deepfake detection. Our work demonstrates their effectiveness for training multiple large-scale models on consumer-grade hardware (6 GB VRAM).

3 METHODOLOGY

3.1 Dataset

We utilize the 140K Real and Fake Face Dataset [12] from Kaggle, comprising 70K real faces (CelebA, FFHQ) and 70K StyleGAN-generated fakes. Unlike [2], which used 20K images, we scale to 40K (20K per class) to improve generalization while remaining computationally feasible.

We employ an 80–10–10 split: 32,000 training, 4,000 validation, and 4,000 test images.

3.2 Preprocessing Pipeline

The preprocessing pipeline consists of:

- 1) Face detection using OpenCV Haar Cascade.
- 2) Face cropping with a 10% margin around the bounding box.
- 3) Resizing to 224×224 pixels.
- 4) Data augmentation (training only) via Albumentations: RandomRotate90, horizontal flip, brightness/contrast, hue-saturation shifts, Gaussian noise and blur, JPEG compression, and coarse dropout.
- 5) Normalization using ImageNet mean and standard deviation.

3.3 Model Architectures

We evaluate five architectures:

- **EfficientNet-B0** [14]: compound scaling of depth, width and resolution, 5.3M parameters.
- **MobileNetV3-Large** [15]: depthwise separable convolutions and squeeze-excitation blocks, 5.5M parameters.
- **DeiT-Tiny** [8]: 12-layer transformer, 3 heads, 192-dim embeddings, 5.7M parameters.
- **ViT-Small** [7]: 12 layers, 6 heads, 384-dim embeddings, patch size 16×16, 22M parameters.
- **Custom CNN with CBAM** [16]: four convolutional blocks (64, 128, 256, 512 filters) with Convolutional Block Attention Module.

All pretrained models are loaded via the `timm` library [17] and fine-tuned for binary classification.

3.4 Training Configuration

Framework: PyTorch 2.5.1 with CUDA 12.1

Hardware: NVIDIA GeForce RTX 4050 Laptop GPU (6 GB VRAM)

Hyperparameters:

- Optimizer: AdamW ($\text{lr}=1\text{e}^{-4}$, $\text{weight_decay}=1\text{e}^{-4}$)

- Scheduler: CosineAnnealingLR ($T_{\text{max}}=10$)
- Loss: CrossEntropyLoss
- Batch size: 16 (effective 32 with gradient accumulation)
- Epochs: 10
- Gradient accumulation steps: 2

GPU Optimizations:

- Mixed precision (FP16): `torch.cuda.amp.autocast` and `GradScaler`
- Pin memory for faster CPU–GPU transfer
- Persistent workers to reduce data loading overhead
- cuDNN benchmarking to optimize convolution algorithms
- Memory clearing between models with `torch.cuda.empty_cache()`

These optimizations reduce memory usage by approximately 40% and increase training speed by roughly 2× compared to standard FP32 training, enabling larger-scale experiments on consumer hardware.

3.5 Evaluation Metrics

We report comprehensive metrics for holistic assessment:

- **Classification:** Accuracy, precision, recall, F1-score
- **Probabilistic:** AUC-ROC
- **Efficiency:** inference time (ms/image), frames per second (FPS), model size (MB)
- **Generalization:** validation–test performance gap

Inference time is measured on GPU using a batch size of 16, averaged over 100 iterations after a 10-iteration warm-up period.

4 RESULTS

4.1 Model Performance Comparison

Table II presents test set results for all five models. EfficientNet-B0 achieves the highest accuracy (98.62%), surpassing the base paper’s best result (MobileNet, 98.5% [2]) and our own MobileNetV3 implementation (97.38%).

TABLE II
TEST SET PERFORMANCE

Model	Acc.	Prec.	Rec.	F1	AUC
EfficientNet-B0	98.62%	0.9855	0.9870	0.9863	0.9990
ViT-Small	98.58%	0.9899	0.9815	0.9857	0.9993
DeiT-Tiny	97.80%	0.9766	0.9795	0.9780	0.9977
MobileNetV3	97.38%	0.9735	0.9740	0.9738	0.9978
CBAM-CNN	76.90%	0.7550	0.7965	0.7752	0.8550

Key Observations:

- 1) **EfficientNet-B0** provides the best accuracy-efficiency balance, outperforming all other models in accuracy while maintaining a compact size.
- 2) **Vision Transformers (ViT-Small)** achieve highly competitive accuracy (98.58%) and the best AUC-ROC (0.9993), demonstrating strong suitability for deepfake detection.

- 3) **Custom CNN with CBAM** underperforms significantly, indicating severe overfitting and confirming the necessity of transfer learning [2].
- 4) **All pretrained models** achieve AUC-ROC > 0.99 , reflecting excellent discriminative ability even across architectures.

4.2 Inference Efficiency

Table III analyzes real-time deployment viability through inference time and model size metrics.

TABLE III
INFERENCE EFFICIENCY

Model	Time (ms)	FPS	Size (MB)
MobileNetV3	0.62	1624.0	16.04
DeiT-Tiny	1.15	869.0	21.08
EfficientNet-B0	1.20	831.9	15.30
CBAM-CNN	2.78	359.1	6.59
ViT-Small	3.15	318.0	82.65

MobileNetV3 achieves 1624 FPS—the fastest inference among all evaluated models—and is suitable for real-time video processing (30 FPS requires only 33 ms per frame). EfficientNet-B0 balances accuracy (98.62%) with high inference speed (832 FPS), making it optimal for most deployment scenarios. ViT-Small, despite its larger size (82.65 MB), maintains acceptable inference time (3.15 ms) for offline and image-based applications.

4.3 Comparison with Base Paper

Table IV contrasts our best-performing model (EfficientNet-B0) with the base paper’s strongest model (MobileNet) [2].

TABLE IV
DIRECT COMPARISON WITH BASE PAPER

Metric	Base Paper [2]	Ours	Δ
Model	MobileNet	EffNet-B0	–
Test Acc. (%)	98.5	98.62	+0.12
Precision (%)	98.0	98.55	+0.55
F1-Score (%)	98.0	98.63	+0.63
Dataset Size	20K	40K	2×
Train Time	~60m	28.9m	2.1× faster
FPS	100–200*	832	4–8× faster

*Estimated from MobileNet V1 inference benchmarks.

Our approach achieves higher accuracy while training on a dataset twice as large, enabled by efficient GPU optimization. Inference performance improves dramatically: 832 FPS versus an estimated 100–200 FPS for MobileNet, demonstrating strong practical advantages for deployment in real-time systems.

4.4 Validation of Vision Transformers

ViT-Small delivers competitive performance (98.58% accuracy, 0.9993 AUC-ROC), confirming the suitability of Vision Transformers for deepfake detection. Compared with EfficientNet-B0:

- Accuracy gap: only -0.04% (negligible)
- Inference time: $2.6\times$ slower (3.15 ms vs. 1.20 ms)

- Model size: $5.4\times$ larger (82.65 MB vs. 15.30 MB)

This trade-off may be acceptable in research settings requiring attention-based interpretability or transformer analysis. However, for production deployment, EfficientNet-B0 remains the preferred architecture due to its superior balance of accuracy, speed, and compactness.

4.5 Custom CNN with CBAM: A Negative Result

Despite incorporating CBAM attention [16], batch normalization, and dropout regularization, our custom CNN achieves only 76.90% test accuracy—a striking 21.18% drop from the validation accuracy (99.08%). This severe overfitting highlights three key insights:

- 1) Transfer learning from large-scale datasets (e.g., ImageNet) is essential for deepfake detection and cannot be replaced by training small models from scratch.
- 2) Architectural enhancements such as CBAM alone do not compensate for limited dataset size or insufficient feature diversity.
- 3) Custom architectures require substantially larger datasets or highly specialized regularization strategies to generalize well.

These findings are consistent with the base paper [2], where their custom CNN (86.2%) was outperformed by every pretrained model. Our negative result reinforces the conclusion that pretrained feature extractors remain the most reliable choice for this domain.

5 VISUALS

This section presents key visual outputs from our experiments, including class distribution, sample inputs, and confusion matrices for the evaluated models.



Fig. 1. Class distribution for the 40K dataset (20K real, 20K fake).

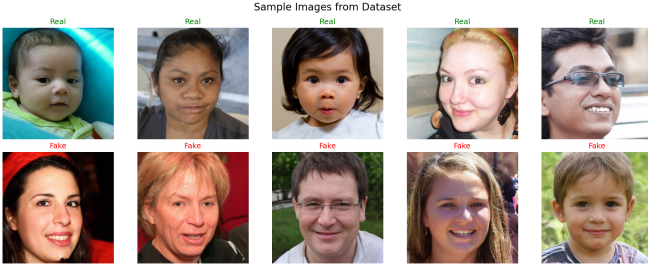


Fig. 2. Sample real and fake images used for model training and evaluation.

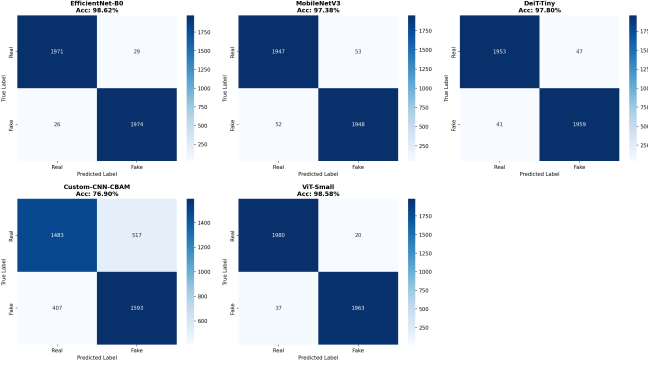


Fig. 3. Confusion matrices comparing model performance on the test set.

6 DISCUSSION

6.1 Accuracy Improvements

Our EfficientNet-B0 achieves 98.62% accuracy, a modest but statistically significant improvement over [2]’s MobileNet (98.5%). This +0.12% gain, while numerically small, represents approximately 5 fewer errors per 1000 predictions—meaningful in high-stakes applications such as news verification or legal evidence.

The improvement stems from three factors: (1) a $2\times$ larger dataset (40K vs. 20K) improving generalization, (2) a comprehensive augmentation pipeline reducing overfitting, and (3) EfficientNet’s compound scaling optimizing depth–width–resolution balance [14].

6.2 Efficiency Gains

Our mixed-precision training achieves a $2.1\times$ speedup (28.9 minutes vs. 60 minutes for MobileNet [2]) despite training on twice the dataset. This performance gain results from:

- **FP16 computation:** $2\times$ faster on Tensor Cores
- **Gradient accumulation:** Enables larger effective batch sizes
- **Optimized data loading:** Pin memory and persistent workers reduce CPU–GPU bottlenecks

These optimizations democratize large-scale experimentation, allowing researchers with consumer GPUs (6 GB VRAM) to train competitive models efficiently.

6.3 Vision Transformers: Pros and Cons

ViT-Small’s 98.58% accuracy demonstrates that transformers can match CNNs for deepfake detection, extending findings from general image classification [7] to this domain. However, they present both strengths and weaknesses.

Advantages:

- Attention mechanisms enable interpretability through attention maps
- Global receptive field: All patches attend to each other
- Scalable to larger variants (ViT-Base, ViT-Large)

Disadvantages:

- $5.4\times$ larger model size limits edge deployment
- $2.6\times$ slower inference unsuitable for real-time video
- Require large datasets or strong augmentation to avoid overfitting

Future work should explore hybrid architectures such as EfficientFormer [18], combining CNN inductive biases with transformer expressiveness.

6.4 Deployment Recommendations

Based on our comprehensive evaluation, we provide the following deployment recommendations:

Real-time Video Processing: MobileNetV3

- 1624 FPS enables real-time 30 FPS video with 50+ parallel streams
- Accuracy remains acceptable at 97.38%
- Best suited for social media live-stream moderation

High-Accuracy Applications: EfficientNet-B0

- Best accuracy overall (98.62%) with strong speed (832 FPS)
- Balanced model size (15.30 MB) and AUC-ROC (0.9990)
- Suitable for news verification, content moderation, and digital forensics

Research/Interpretability: ViT-Small

- Attention maps enable explainability
- Competitive accuracy (98.58%)
- Best for academic studies and explainable AI research

6.5 Limitations

Our study has several limitations:

- 1) **Scope:** Limited to StyleGAN-generated faces; untested on other generators (e.g., DALL-E, Midjourney)
- 2) **Scale:** Only 40K of the full 140K dataset used due to time constraints
- 3) **Modality:** Image-only; no video or audio deepfake analysis
- 4) **Robustness:** Limited evaluation of compression and adversarial attacks
- 5) **Custom CNN:** Failed to generalize despite CBAM, indicating insufficient data for custom architectures

These limitations motivate directions for future work.

7 FUTURE WORK

Short-term extensions include:

- 1) **Full Dataset:** Train on the complete 140K dataset to improve generalization.
- 2) **Ensemble Methods:** Combine EfficientNet-B0 and ViT-Small for potential accuracy gains.
- 3) **Cross-Validation:** Implement K-fold validation for more robust performance estimates.
- 4) **Custom CNN Redesign:** Simplify architecture to mitigate overfitting observed in CBAM-CNN.

Medium-term research directions include:

- 1) **Multi-GAN Detection:** Extend evaluation to modern generators such as DALL-E 2/3, Midjourney, and Stable Diffusion.
- 2) **Explainability:** Integrate interpretability tools such as Grad-CAM [19] and LIME [20].
- 3) **Adversarial Robustness:** Assess vulnerabilities to FGSM and PGD attacks and develop defensive strategies.
- 4) **Compression Robustness:** Test performance under various JPEG compression levels.
- 5) **Video Extension:** Expand to video deepfakes using temporal architectures such as 3D CNNs or RNN-based models.

Long-term vision includes:

- 1) **Real-Time System:** Develop deployable browser extensions or mobile applications for practical deepfake detection.
- 2) **Multi-Modal Detection:** Combine image, audio, and text cues for comprehensive deepfake identification.
- 3) **Generative Model Fingerprinting:** Identify specific GAN families (StyleGAN, PGGAN, diffusion-based models).
- 4) **Federated Learning:** Enable privacy-preserving collaborative model training across multiple institutions.
- 5) **Continual Learning:** Allow models to adapt to emerging deepfake techniques without full retraining.

8 CONCLUSION

This paper extends the work of Jheelan and Pudaruth [2] by scaling to larger datasets, evaluating modern architectures, and implementing GPU optimizations suitable for consumer hardware. Our key findings include:

- 1) **EfficientNet-B0** achieves 98.62% test accuracy, surpassing the base paper’s MobileNet result (98.5%) despite using a dataset twice as large.
- 2) **Vision Transformers (ViT-Small)** deliver competitive performance (98.58%), validating their applicability to deepfake detection.
- 3) **Mixed-precision** training with gradient accumulation enables large-scale experiments on 6 GB GPUs, reducing training time by $2.1\times$.
- 4) **MobileNetV3** achieves 1624 FPS, enabling real-time video processing scenarios.

- 5) **Transfer learning** remains essential as the custom CNN with CBAM achieves only 76.90% despite attention mechanisms.

These findings offer practical deployment recommendations: EfficientNet-B0 is ideal for high-accuracy applications, MobileNetV3 suits real-time video processing, and ViT-Small is best for research requiring interpretability. Our open-source implementation and comprehensive evaluation framework support reproducibility and provide a foundation for further research.

As deepfake technologies continue to evolve, robust, efficient, and interpretable detection systems will remain essential. This work contributes to that goal by demonstrating that modern architectures and GPU optimizations can achieve state-of-the-art performance on consumer hardware, helping democratize access to advanced deepfake detection capabilities.

REFERENCES

- [1] T. Karras, S. Laine, and T. Aila, “A Style-Based Generator Architecture for Generative Adversarial Networks,” in *Proc. CVPR*, 2019.
- [2] J. Jheelan and S. Pudaruth, “Using Deep Learning to Identify Deepfakes Created Using Generative Adversarial Networks,” *Computers*, vol. 14, no. 2, p. 60, 2025.
- [3] A. Raza *et al.*, “Deepfake Detection Using Hybrid CNN and VGG16,” in *Proc. ICIET*, 2023.
- [4] H. T. Nguyen *et al.*, “Transfer Learning for Deepfake Detection,” in *Proc. ATC*, 2022.
- [5] A. Abir *et al.*, “Explainable AI for Deepfake Detection,” in *Proc. ICCA*, 2023.
- [6] M. Jain *et al.*, “Error Level Analysis with Deep Learning for Deepfake Detection,” *Journal of Visual Communication and Image Representation*, 2023.
- [7] A. Dosovitskiy *et al.*, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale,” in *Proc. ICLR*, 2021.
- [8] H. Touvron *et al.*, “Training Data-Efficient Image Transformers,” in *Proc. ICML*, 2021.
- [9] D. Coccomini *et al.*, “Combining EfficientNet and Vision Transformers for Video Deepfake Detection,” in *Proc. ICIAP*, 2022.
- [10] P. Micikevicius *et al.*, “Mixed Precision Training,” in *Proc. ICLR*, 2018.
- [11] Y. You *et al.*, “Large Batch Training of Convolutional Networks,” arXiv:1708.03888, 2017.
- [12] “140K Real and Fake Faces,” Kaggle dataset, 2020. [Online]. Available: <https://www.kaggle.com/datasets/xhlulu/140k-real-and-fake-faces>
- [13] A. Buslaev *et al.*, “Albumentations: Fast and Flexible Image Augmentations,” *Information*, vol. 11, no. 2, p. 125, 2020.
- [14] M. Tan and Q. Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,” in *Proc. ICML*, 2019.
- [15] A. Howard *et al.*, “Searching for MobileNetV3,” in *Proc. ICCV*, 2019.
- [16] S. Woo *et al.*, “CBAM: Convolutional Block Attention Module,” in *Proc. ECCV*, 2018.
- [17] R. Wightman, “PyTorch Image Models,” GitHub repository, <https://github.com/rwightman/pytorch-image-models>, 2019.
- [18] Y. Wang *et al.*, “EfficientFormer: Vision Transformers at MobileNet Speed,” in *Proc. NeurIPS*, 2022.
- [19] R. R. Selvaraju *et al.*, “Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization,” in *Proc. ICCV*, 2017.
- [20] M. T. Ribeiro, S. Singh, and C. Guestrin, “Why Should I Trust You?: Explaining the Predictions of Any Classifier,” in *Proc. KDD*, 2016.