Efficient Deepfake Detection Using GPU-Accelerated Feature Extraction and Temporal Attention Modeling

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Abstract—The rapid progress in generative adversarial net- works has led to the rise of highly realistic deepfake videos, rais- ing significant social and ethical challenges. This paper introduces a high-performance deepfake detection system that integrates GPU-accelerated facial feature extraction with an improved convolutional neural network (CNN) classifier. Evaluated on the Celeb-DF v2 dataset, our approach achieves a test accuracy of 97.33% and an AUC of 99.40%. Major contributions include a GPU-optimized pipeline for efficient facial feature extraction and a temporal attention mechanism that accurately identifies subtle artifacts in synthetic faces across video frames.

Index Terms—Deepfake Detection, Facial Feature Extraction, GPU Acceleration, Convolutional Neural Networks, Temporal Modeling

I. INTRODUCTION

Deepfake technology, which employs Generative Adversarial Networks (GANs) to generate synthetic media, poses substantial threats to the authenticity of digital content. As the quality of deepfakes continues to improve rapidly, distinguishing them from genuine media has become increasingly challenging. This escalation has profound consequences for the spread of misinformation, as well as for issues related to privacy and security.

In this paper, we propose a robust deepfake detection framework that utilizes GPU-accelerated facial feature extraction in conjunction with deep learning methodologies. Our system aims to detect subtle artifacts and inconsistencies that arise during the deepfake generation process—features that are often imperceptible to the human eye.

II.M ETHODOLOGY

A. Dataset

We used the Celeb-DF v2 dataset, a high-quality benchmark for deepfake detection research. It consists of 5,639 fake videos and 590 real videos. We split the dataset into training (70%), validation (15%), and test (15%) sets using stratified sampling to preserve class distribution across splits.

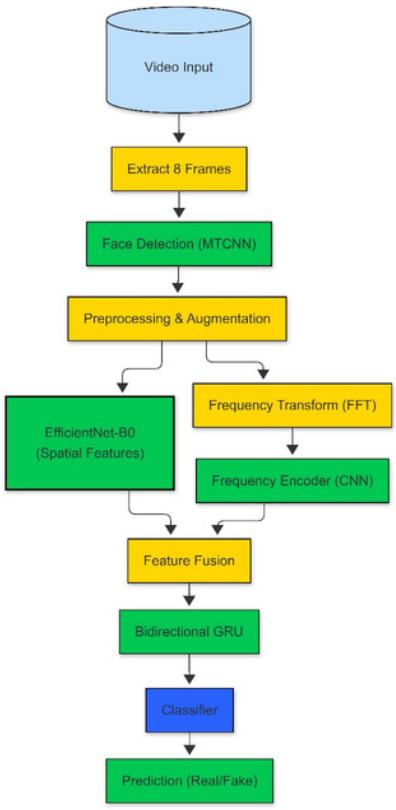

Fig. 1. Flow

TABLEI
DATASET STATISTICS

Subset	Total	Real	Fake
Training	4360	413	3947
Validation	934	88	846
Test	935	89	846
Total	6229	590	5639

B. Face Extraction Pipeline

We implemented a GPU-accelerated face extraction pipeline using OpenCV's DNN module and a ResNet-10 SSD face detector. For each video, we performed the following steps:

1) Sample 16 uniformly spaced frames.

2) Detectandextractfacesusingapre-trainedSSDmodel. Apply a confidence threshold of 0.5 to ensure accurate face detection.
3) Expand bounding boxes by 10% to include peripheral facial features.
4) Resize each cropped face image to 224 ×224 pixels.
5) If fewer than 16 faces are detected, duplicate the last available face frame.

The extracted faces are cached to avoid redundant computation during training. This pipeline ensures efficient GPU memory usage and preprocessing throughput.

C. Model Architecture

We developed the Enhanced EfficientFace model, a lightweight and efficient video-based deepfake detector. It builds on the EfficientNet-B0 backbone pretrained on Ima- geNet and incorporates temporal analysis components.

- FeatureExtraction:EfficientNet-B0extractsframe-wise 1280-dimensional features.
- Temporal Modeling: 3D convolutional layers capture inter-frame inconsistencies.
- TemporalAttention:Asoftattentionmechanismfocuses on the most informative frames.
- Classifier: A multi-layer perceptron with BatchNorm, ReLU, and dropout predicts real/fake.

TABLE II
LAYER-WISE DETAILS OF THE ENHANCED EFFICIENTFACEMODEL

Layer	Parameters	Output Shape
EfficientNet-B0	Pretrained on ImageNet	(batch, 1280)
3D Conv Layer 1	1280→512, k = (3, 1, 1)	(batch, 512, 16, 1, 1)
3D Conv Layer 2	512→512, k = (3, 1, 1)	(batch, 512, 16, 1, 1)
3D Conv Layer 3	512→512, k = (3, 1, 1)	(batch, 512, 16, 1, 1)
Attention	Sigmoid activation	(batch, 1, 16, 1, 1)
Global Pooling	Temporal averaging	(batch, 512)
Classifier	FC + BN + ReLU + Dropout	(batch, 1)

D. Training Strategy

To tackle class imbalance and enhance generalization, the following strategies were adopted during training:

- Weighted Sampling: Inverse class frequency weights of [1.81, 0.19] were used for the real and fake classes, respectively.
- Data Augmentation: Applied random horizontal flips, brightness/contrast shifts, and color jitter using Albumentations.
- Optimization: Used the Adam optimizer with a learning rate of 0.001.
- Scheduler: ReduceLROnPlateau dynamically reduced the learning rate based on validation AUC.
- Batch Size: Set to 8 to accommodate GPU memory constraints while maintaining efficiency.
- Early Stopping: Halted training when validation AUC did not improve for 3 consecutive epochs.

III. RESULTS

In this section, we present the evaluation metrics and performance analysis of the proposed deepfake detection system. The model was evaluated using the Celeb-DF v2 dataset, with the test set comprising 935 videos. The performance metrics, including Accuracy, AUC, F1 Score, Precision, Recall, and Equal Error Rate (EER), are reported below.

A. Performance Metrics

The evaluation metrics for the test set are summarized in Table III.

TABLE III
PERFORMANCEMETRICS ON TEST SET

Metric	Value
Accuracy	0.9733
AUC	0.9940
F1 Score	0.9851
Precision	0.9916
Recall	0.9787
Equal Error Rate (EER)	0.0337

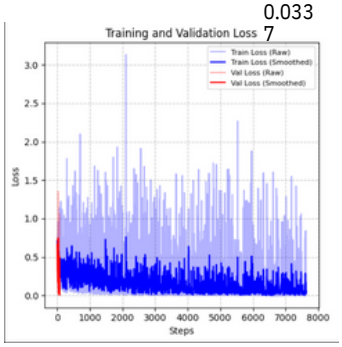

Fig. 2. Training v/s Validation Loss

B. Confusion Matrix

The confusion matrix, presented in Table IV, provides further insights into the classification performance. The matrix shows the number of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

TABLE IV
CONFUSIONMATRIX ON TEST SET

	Predicted Real	Predicted Fake
Actual Real	8	7
Actual Fake	21	828

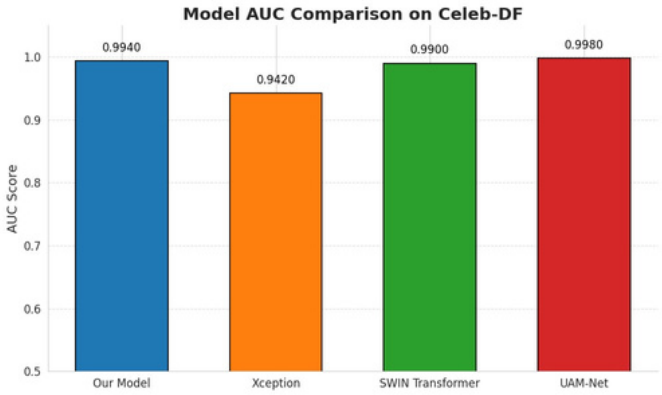

Fig. 3. Model AUC Comparison [1]

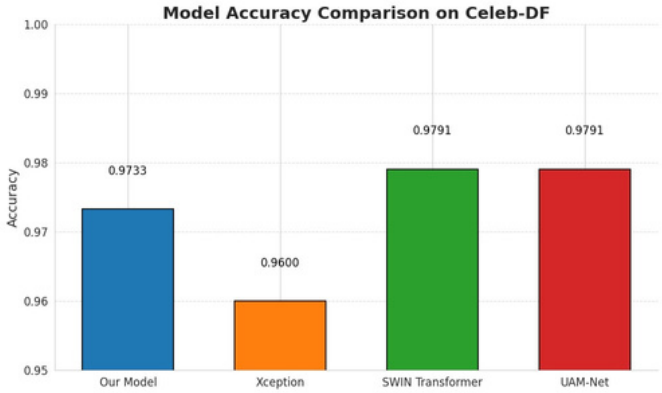

Fig. 4. Model Accuracy Comparison [2]

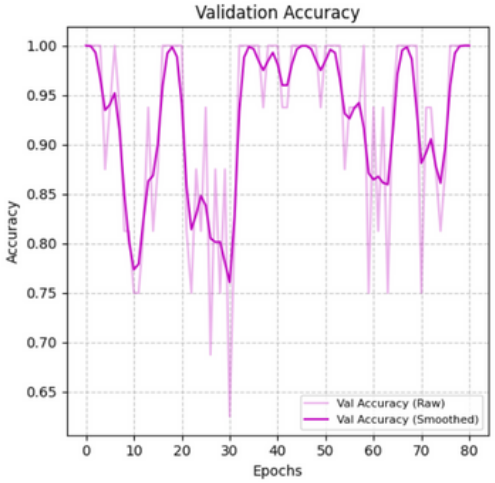

Fig.6. ValidationAccuracy

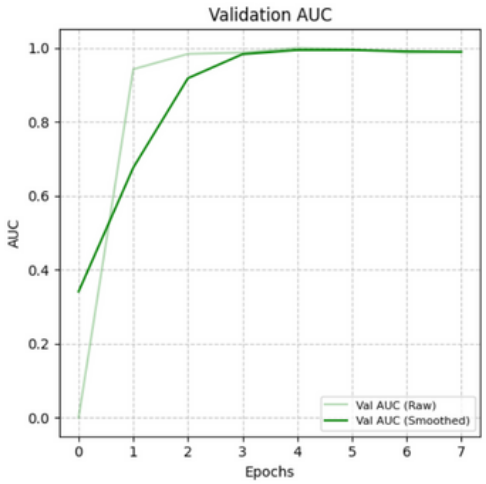

Fig. 5. Validation AUC

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