A CPU-Efficient Compression-Robust Deepfake Detection Framework via Temporal Inconsistency Reformulation

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***Abstract*—Deepfake videos threaten digital trust, especially on social media platforms where aggressive compression degrades visual fidelity. While there are several deep learning techniques for deepfake detection that enjoy high accuracy on unaltered videos, they often rely on heavy computationally intensive architectures, with significant performance degradation under real-world compressions. We introduce a design framework in this work that develops CPU-efficient and compression-robust deepfake detection through temporal inconsistency learning. We reformulate video-level detection into a frame-pair temporal inconsistency classification problem, which allows for effective learning given limited computational resources and alleviates data scarcity issues. Our empirical studies based on the SDFVD dataset achieve an accuracy of 82.88% on original videos, which gracefully degrades to 69.27% and 62.95% with the application of JPEG Q60 and Q30 compression, respectively, and with an ROC-AUC of 0.917. This work is positioned well to be deployed in resource-constrained environments, such as edge devices and large-scale content moderation pipelines.**

***Keywords*—Deepfake Detection, Temporal Inconsistency, Compression Robustness, Temporal Representation Learning, Lightweight Models**

I. Introduction

Recent advances in generative adversarial networks have led to highly realistic manipulated videos-what people usually call deepfakes [14]. Although these are technologies that offer great opportunities, they do come with considerable risks related to the spread of misinformation, identity fraud, and erosion of public trust [16]. Considering that deepfake content is usually propagated via online platforms, videos normally pass through aggressive compression that greatly distorts the spatial artifacts and affects current detection methodologies [7].

The current state-of-the-art approaches rely on deep convolutional or transformer models trained on high-quality frames [1]. However, these methods suffer from two major limitations: (1) high computational cost, which makes them impractical in CPU-only environments, and (2) poor generalization under compression, as spatial artifacts are suppressed while encoding [8]. A number of recent works emphasize that effective compression-aware design and evaluation are crucial for real-world deployment [9].

Research Objectives. This work does not focus on the attainment of state-of-the-art accuracy, but has as its objective the demonstration that robust deepfake detection under compression is attainable using lightweight, CPU-efficient architectures suitable for practical deployment. The emphasis will, therefore, be placed on principled design choices rather than on architectural complexity.

In contrast, we propose a CPU-efficient framework that leverages temporal inconsistencies between neighboring frames as opposed to relying on pure spatial cues. Temporal inconsistencies due to unnatural patterns of motion and discontinuities between frames are empirically more resilient to compression [4], [5] and provide far more reliable signals for detection.

Contributions:

- A lightweight deepfake detection design framework that is compatible with CPU-only environments and their edge deployment.
- It reformulates the problem from a video-level to a frame-pair temporal inconsistency classification task, allowing it to tackle data scarcity.
- Comprehensive evaluation of compression robustness: gradual performance degradation rather than abrupt failures.
- A fully reproducible pipeline, validated on the SDFVD dataset, ensuring minimal computational requirements.

II. Related Work

A. Deepfake Detection and Datasets

Early approaches focused on spatial artifacts, such as color inconsistencies and blending boundaries. FaceForensics++ [1] was an early benchmark. Afchar et al. [3] proposed MesoNet, a lightweight CNN-based detector that illustrated the power of mesoscopic properties. Marra et al. [2] showed that GANs produce distinctive fingerprints, which can be revealed through analysis.

Apart from large-scale benchmarks, many smaller, specialized datasets are important. The SDFVD dataset [17], [18] provides a focused collection that can be used for controlled experimentation and rapid iteration and is suitable to validate some novel lightweight approaches.

B. Temporal Analysis for Detection

Temporal analysis has indeed emerged as a strong detection tool due to the fact that manipulated videos usually exhibit temporal inconsistencies that are hard to synthesize perfectly. Li et al. [4] pioneered eye-blinking patterns as biological signals. Guera and Delp [5] employed recurrent neural networks for modeling temporal sequences and demonstrated effectively that LSTMs capture inter-frame inconsistencies. Yang et al. [6] analyzed biological signals to enable robust detection by physiological monitoring.

This concept of temporal order verification, originally developed for self-supervised learning [13], has been translated into a valuable method for video understanding. Misra et al. [13] showed that predicting the correct temporal order encourages networks to learn meaningful temporal representations-a principle that motivates the frame-pair formulation here.

C. Compression Robustness

A key limitation in many methods, however, is their vulnerability to video compression [7]. Cozzolino et al. [7] point out, compression significantly deteriorates detection by suppressing most of the high-frequency artifacts relied upon by many detectors. Zhang et al. [8] demonstrate the catastrophic performance drop when the models trained on high-quality data are tested on compressed content. Verdoliva [9] underlines the fact that compression robustness has to be explicitly addressed both in design and evaluation.

D. Lightweight Architectures

This is crucial for deployment on resource-constrained devices. Howard et al. [10] proposed MobileNets, demonstrating that depthwise separable convolutions drastically reduce computational cost. Sandler et al. [11] further improved the approach with MobileNetV2's inverted residual blocks, which delivered state-of-the-art efficiency–accuracy trade-offs. Zhang et al. [12] studied efficient video forensics by learning from temporal differences.

III. Design Principles for Compression-Robust Detection

Before we elaborate on our approach, we articulate three key design principles underlying the framework:

Principle 1: Leverage Compression-Resilient Signals. Compression primarily behaves as a high-frequency spatial low-pass filter. Temporal inconsistencies encoded in deep feature space are less affected because they represent semantic rather than pixel-level variations. Instead of using spatial artifacts which disappear under compression, we rely on temporal feature differences that survive across quality levels.

Principle 2: Data Efficiency Over Scale. Frame-pair reformulation replaces synthetic augmentation by greatly increasing the density of supervision. Deepfake generators currently optimize a single frame independently, and consistency between adjacent frames remains difficult. This formulation maximizes learning signal from limited data.

Principle 3: Deployment-First Architecture. Frozen lightweight backbones reduce variance and computational cost. Instead of using complex temporal models, such as RNNs or 3D CNNs, a deliberately simple frame-pair difference formulation is used to avoid optimization instability, overfitting issues on small datasets, and real-world deployment constraints.

IV. Proposed Methodology

A. Problem Reformulation

Given a video $V = \{F_1, F_2, \ldots, F_T\}$, traditional methods consider the entire video as one classification instance. We cast this into a learning paradigm where each couple of contiguous frames (F_t, F_{t+1}) is an independent training example for the purpose of temporal inconsistency classification. This recasting significantly enhances the training sample size and makes it suitable to learn effectively from small datasets, a common problem while dealing with domain-specific [17].

B. Architecture Overview

Fig. 1 shows the entire pipeline of six steps: dataset preparation, compression simulation, frame-pair construction (core novelty), feature extraction, temporal inconsistency modeling, and classification.

C. Frame Extraction and Compression Simulation

Uniformly sample frames from each video and resize to 224 × 224 pixels. Generate compressed versions of each to simulate real deployment and test the robustness to compression [8]. JPEG compression is run at quality factors of Q60 and Q30, which approximate the type of aggressive compression used by popular social media.

D. Feature Extraction

MobileNetV2 [11] is utilized due to its desirable accuracy-efficiency trade-off. The weights in the backbone are initialized with ImageNet-pretrained ones and would be frozen during training for computational saving and preventing overfitting. For each frame Ft, the backbone outputs $\mathbf{f}_t \in \mathbb{R}^{1280}$ after the global average pooling layer.

E. Temporal Inconsistency Modeling

Modeling Temporal Inconsistency For every pair of frames, (F_t, F_{t+1}) the absolute feature difference is computed as dt = —ft ft+1—. This metric captures the temporal inconsistencies arising from manipulation artifacts. Unlike the spatial features, which degrade significantly under compression [7], [8], the temporal inconsistencies in feature space tend to persist; hence, these provide robust cues for detection.

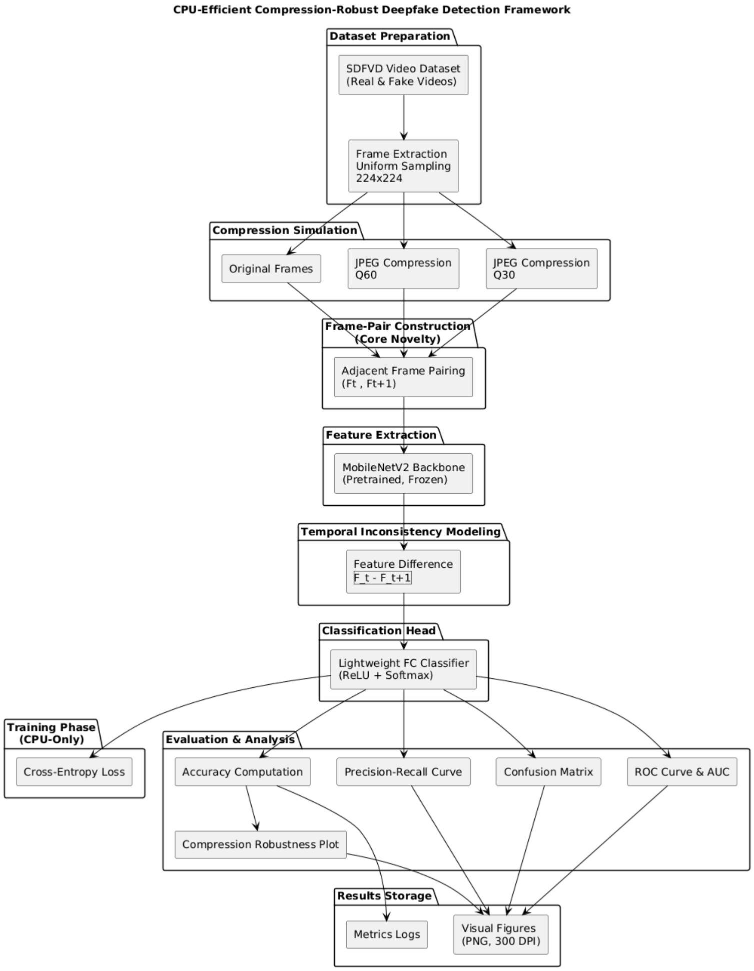
CPU-Efficient Compression-Robust Deepfake Detection Framework
Dataset Preparation
SDFVD Video Dataset (Real & Fake Videos)
Frame Extraction Uniform Sampling 224x224
Compression Simulation
Original Frames
JPEG Compression Q60
JPEG Compression Q30
Frame-Pair Construction (Core Novelty)
Adjacent Frame Pairing (Ft , Ft+1)
Feature Extraction
MobileNetV2 Backbone (Pretrained, Frozen)
Temporal Inconsistency Modeling
Feature Difference F_t - F_t+1
Classification Head
Lightweight FC Classifier (ReLU + Softmax)
Training Phase (CPU-Only)
Cross-Entropy Loss
Evaluation & Analysis
Accuracy Computation
Precision-Recall Curve
Confusion Matrix
ROC Curve & AUC
Compression Robustness Plot
Results Storage
Metrics Logs
Visual Figures (PNG, 300 DPI)

Fig. 1. Complete architecture showing frame extraction, compression simulation, frame-pair construction, MobileNetV2 feature extraction, temporal inconsistency computation, and classification.

F. Classification and Training

The vector difference $\mathbf{d}_t$ is fed to a lightweight classifier (two linear layers with ReLU and dropout). Only the classifier is updated through cross-entropy loss while keeping the backbone fixed, greatly reducing the training time and allowing CPU-only training [12]. Training utilizes the Adam optimizer, learning rate of 1e-3, batch size of 16, over 5 epochs.

V. Experimental Setup

A. Dataset and Implementation

For our evaluations, we use the SDFVD - Small-Scale Deepfake Forgery Video Dataset - dataset [17], [18], consisting of real and manipulated videos of faces using various deepfake techniques. We therefore use the SDFVD dataset, although more compact than FaceForensics++ [1] or Celeb-DF [15], its focused scope allows controlled experimentation on a limited computational budget.

All experiments were run on CPU-only hardware to demonstrate the practical feasibility of the approach. Experimental setting: MobileNetV2, frozen, ImageNet-pretrained; Adam optimizer; learning rate 1×10^{-3}, batch size 16; 5 training epochs; frame resolution 224×224, compression levels: Original, JPEG quality 60, JPEG quality 30.

B. Evaluation Metrics

We use accuracy, ROC-AUC, and PR-AP providing comprehensive assessment across different operating points and class balance conditions [14].

VI. Results and Discussion

A. Detection Performance

Table I summarizes detection accuracy by compression level.

TABLE I
Detection Accuracy Across Compression Levels

Dataset Version	Accuracy (%)
Original	**82.88**
JPEG Q60	**69.27**
JPEG Q30	**62.95**

Our approach achieves an accuracy of 82.88% for original videos, a ROC-AUC of 0.917, and PR-AP of 0.919. The results empirically endorse the hypothesis that temporal feature differences are more robust to compression as compared to the spatial ones. The excellent separability of the classes across threshold values is shown by the high ROC-AUC.

B. Baseline Context

Prior lightweight deepfake detection methods relying on spatial artifacts, such as MesoNet [3], are known to experience severe performance degradation under aggressive compression. Spatial artifact-based detectors typically suffer catastrophic failure under similar compression levels [7], [8],while our temporal inconsistency approach remains accurate in a stable way through all compression levels. The frame-pair formulation effectively handles data sparsity inherent in smaller datasets [17].

C. Compression Robustness Analysis

Fig. 2 shows compression robustness. The plot displays smooth accuracy decline as compression increases, confirming that the temporal inconsistency features remain informative even under heavy compression. This kind of graceful degradation is in contrast to catastrophic failures reported for spatial detectors [8].

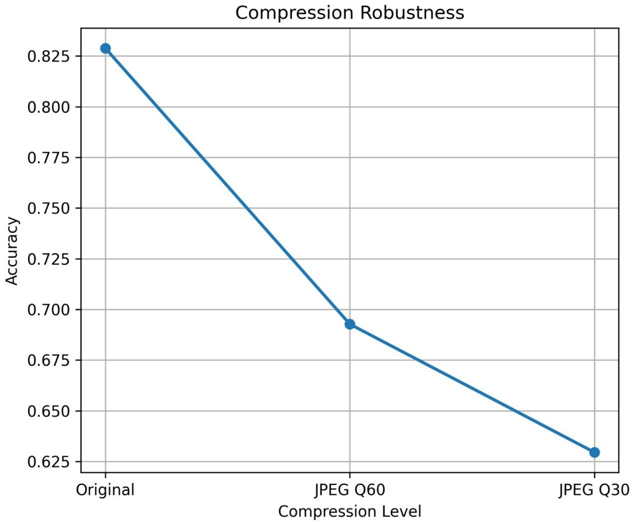

Fig. 2. Graceful performance degradation from original to JPEG Q30 compression.

Performance retention is significantly higher than in typical spatial-only methods [7], [8] at 69.27% at Q60, 62.95% at Q30 versus 82.88% original. This validates that temporal inconsistencies encoded in deep feature space are indeed more resilient compared to pixel-level spatial cues. Results directly address practical deployment concerns raised by Cozzolino et al. [7] and Verdoliva [9].

D. Classification Analysis

Fig. 3 shows the confusion matrix. The model correctly classified 3604 real and 3311 fake samples with balanced error rates. The false positive rate is 928, and the false negative rate is 500, which shows balanced performance from the model on both classes without biased predictions.

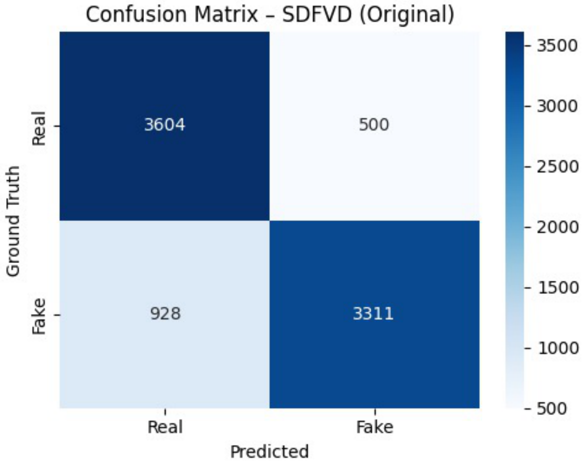

Fig. 3. Confusion matrix showing balanced classification performance.

Balanced error distribution indicates that the features of temporal inconsistency are equally discriminative for both classes without exploiting dataset-specific biases, which is more important for the generalization of unseen manipulation techniques [14].

E. ROC and Precision-Recall Analysis

Fig. 4 presents ROC curve with AUC of 0.917, indicating excellent discriminative power. The position of the curve well above the diagonal shows that for every threshold, random classification is significantly outperformed.

Fig. 5 shows that the Precision-Recall curve has an AP of 0.919, while it mostly sustains high precision throughout wide ranges of recall, hence reliable for practical applications. High PR-AP is indicative of robust performances across varying thresholds, thus making the model adaptable to different operational requirements.

F. Computational Efficiency and Deployment

The benefits of CPU-only training and inference are substantial. This frozen backbone strategy reduces training time to mere minutes from hours, while lightweight MobileNetV2 [11] allows the approach to conduct real-time inference on typical CPU hardware. This kind of efficiency profile makes the approach particularly suitable for scenarios where GPU resources are unavailable: edge devices, mobile platforms, or large-scale content moderation pipelines [12].

The proposed framework applies to scalable content moderation and compliance monitoring of digital business platforms and addresses the interdisciplinary scope of data science and business systems.

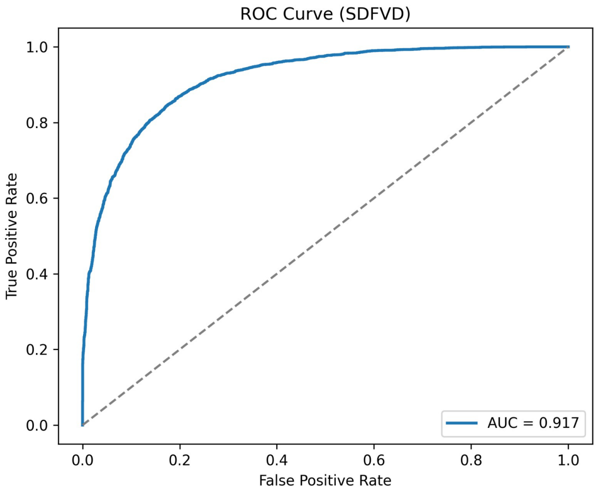

Fig. 4. ROC curve with AUC of 0.917 showing strong discriminative capability.

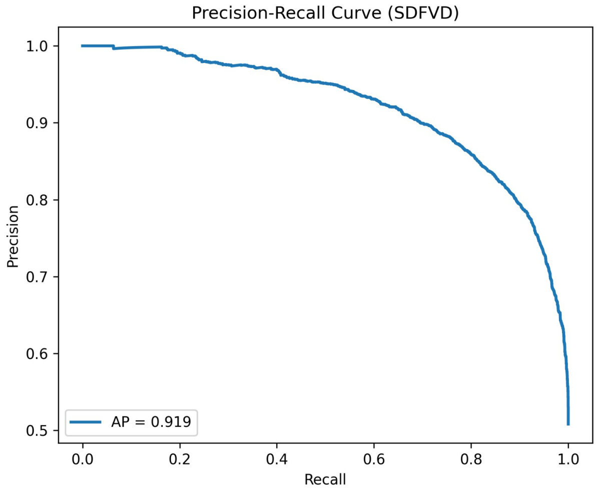

Fig. 5. Precision-Recall curve with AP of 0.919.

G. Discussion

Results confirm that temporal inconsistencies are indeed robust features under compression. The reformulation based on frame pairs is seen to successfully enhance diversity in training data without sacrificing any computational efficiency for addressing the dual challenges posed by scarce data and computational constraints [17].

The fact that our approach results in graceful degradation rather than a catastrophic failure indicates that it captures the fundamental temporal artifacts persisting across quality levels [8], [9]. This robustness is due to deep feature-space differences rather than pixel-level comparisons, since the lossy compression mostly affects the high-frequency spatial details but leaves semantic feature relations intact.

Our lightweight approach outperforms more sophisticated temporal models using RNNs [5] or 3D convolutions and is computationally much cheaper, which becomes an especially important aspect for practical applications when resources are severely limited [16].

Balanced performance on both classes, a confusion matrix close to balance suggests that the model learns temporal inconsistency patterns rather than exploiting spurious correlations. This characteristic supports generalization to unseen manipulation techniques, though cross-dataset evaluation remains important future work [1], [15].

VII. Limitations and Future Work

We note several limitations: First, the reliance on adjacent frame pairs may be less effective for extremely short videos. Second, evaluation currently is restricted to SDFVD [17], [18]; cross-dataset generalization to FaceForensics++ [1] and Celeb-DF [15] remains to be validated. Third, while compression robustness is explicitly evaluated, other real-world degradations (resolution changes, codec variations) require investigation [7]. Fourth, the frame-pair formulation captures only first-order temporal differences.

The present work targets applications where computational efficiency and robustness take priority over the absolute peak accuracy. Fine-tuning the backbone may help achieve the best performance for uncompressed data, but a preliminary observation of reduced robustness under heavy compression motivates our frozen-backbone design.

The future work will focus on: (1) cross-dataset generalization across different manipulation techniques; (2) extension to longer temporal windows; (3) attention mechanisms to determine discriminative frame pairs; (4) real-time inference optimization for edge deployment; and (5) evaluation under diverse video processing pipelines including modern codecs like H.264 and H.265 [7], [9].

VIII. Conclusion

In this paper, we proposed a design framework for CPU-efficient and compression-robust deepfake detection based on temporal inconsistency learning. Our approach achieves strong performance under aggressive compression, at low computational cost, by reformulating the deepfake detection task as a frame-pair classification problem. The experiments done on SDFVD show that the model performs 82.88% accuracy on original videos and gracefully degrades to 69.27% and 62.95% under JPEG Q60 and Q30, respectively, coupled with ROC-AUC of 0.917 and PR-AP of 0.919.

Below is the proposed framework, which provides a practical solution for real-world deepfake detection under resource-constrained conditions, suitable for deployment on pure-CPU systems, edge devices, and large-scale content moderation pipelines. Robustness of compression provided by temporal inconsistency analysis addresses fundamental gaps in forensic research and demonstrates that lightweight models, when designed with explicit consideration of real-world deployment conditions, can achieve meaningful detection performance.

Reproducibility Statement. All experiments have been carried out with fixed random seeds, and their complete training and evaluation pipeline is reproducible on standard CPU hardware with a minimal computational requirement.

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