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Deepfake Video Detection Using Spatial and Temporal Feature Learning

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***Abstract*—Deepfake technology has rapidly evolved due to advancements in generative adversarial networks and diffusion models, enabling the creation of highly realistic synthetic media. The misuse of such manipulated content poses significant threats to digital trust, national security, and personal identity protection, as these videos can be misused for spreading fake news, online fraud, and creating false information about individuals [2]. As these videos become more realistic, it is difficult to detect them using human observation or simple image-based methods. This research addresses the problem by analyzing both spatial features from individual video frames and temporal features across consecutive frames. Faces are detected using a Multi-Task Cascaded Convolutional Neural Network, spatial features are extracted using the EfficientNet-B0 architecture, and motion inconsistencies are analyzed using a Bidirectional Long Short-Term Memory network [11], [15]. By combining spatial and temporal learning frameworks, the proposed system accurately classifies videos as real or fake with low computational complexity, achieving an optimized F1-score of 0.98 upon threshold tuning. The experimental findings confirm that incorporating temporal sequence modeling into spatial feature extraction substantially enhances detection generalization capability against unseen manipulations.**

***Index Terms*—Deepfake Detection, EfficientNetB0, Bidirectional LSTM, Spatial-Temporal Features, Synthetic Media, Video Forensics.**

I. Introduction

The rapid proliferation of artificial intelligence technologies has enabled the creation of highly realistic synthetic media known as deepfakes. Deepfakes are generated using deep neural networks that manipulate facial identity, expressions, or speech while preserving natural appearance and continuity. The accessibility of open-source deep learning frameworks and large-scale datasets has significantly lowered the barrier for generating forged multimedia content. Although deepfake technology has legitimate applications such as virtual avatars, film production, and accessibility tools, its misuse has led to the spread of fake news, political propaganda, identity theft, financial fraud, and cyber harassment.

The increasing realism of generated content has rendered traditional forensic detection methods ineffective. Early detection systems relied on handcrafted visual cues such as blinking frequency or head pose inconsistencies, but as generative models improved, these artifacts became less noticeable. Consequently, researchers have shifted toward deep learning-based detection systems capable of learning discriminative representations directly from raw data [9].

Most existing systems analyze videos frame by frame, focusing mainly on spatial image-based features, and do not effectively capture temporal inconsistencies [5]. This limitation results in lower accuracy for video deepfakes, an inability to detect unnatural facial movements, and limited real-world reliability [9]. To overcome these challenges, this paper proposes a hybrid spatial-temporal deep learning framework. The primary objectives of this research are to detect deepfake videos using deep learning techniques, analyze facial features from individual video frames, capture temporal inconsistencies across video frames, and classify videos as real or fake while building an efficient and easy-to-deploy detection system [6]. The proposed system aims to mitigate misinformation and propaganda, contributing to reliable information systems and strengthening institutional credibility [10].

II. Literature Survey

Understanding deepfake generation techniques is critical for designing effective detection models. Early detection methods relied on handcrafted features utilizing classifiers like Support Vector Machines (SVM). However, these approaches lack robustness against evolving generative models and suffer from poor cross-dataset generalization [13].

Recent advancements have shifted focus toward spatial and temporal deep learning methods. Patel et al. [11] emphasized the efficacy of utilizing Convolutional Neural Networks (CNNs) at the frame level to extract visual features, coupled with Recurrent Neural Networks (RNNs) to classify temporal manipulations in video sequences. This foundational approach aligns with the findings of Jbara et al. [6], whose comprehensive survey highlighted that integrating CNN and Long Short-Term Memory (LSTM) architectures provides a superior defense against the rapid evolution of deepfake generation compared to standalone methods.

Furthermore, Jain et al. [5] explored various machine learning models across audio, video, and image domains. Their research concluded that while traditional deep learning models offer strong spatial analysis, hybrid and ensemble learning strategies are necessary to construct robust countermeasures against manipulated media.

Generalization across unseen datasets remains a critical hurdle in video forensics. Yermakov et al. [17] recently demonstrated that cross-dataset generalization could be significantly

improved through parameter-efficient adaptation of foundational vision encoders, proving that maintaining a robust feature manifold is essential for detecting novel manipulation techniques.

TABLE I
COMPARISON OF EXISTING DEEPFAKE DETECTION APPROACHES

Techniques	Advantages	Limitations
Standalone CNN [5]	High accuracy on spatial frame-level artifacts	Fails to detect sequential/motion anomalies
Parameter-Efficient Encoders [17]	Excellent cross-dataset generalization	High initial dependency on foundational models
Multimodal Analysis [8]	Correlates audio-visual inconsistencies	High computational overhead
Hybrid CNN-RNN (Proposed, [6], [11])	Captures both motion and fine spatial artifacts	Requires careful hyperparameter and threshold tuning

Additionally, the emergence of advanced impersonation attacks has necessitated the development of multimodal datasets. Khalid et al. [8] introduced the FakeAVCeleb dataset, illustrating that modern detection systems must eventually transition from purely visual analysis to incorporating audio-visual synchrony to effectively combat comprehensive deepfakes. Despite these advancements, robust generalization across different manipulation types and the high computational cost of hybrid models remain open research problems that the proposed architecture seeks to optimize [15].

III. PROPOSED METHODOLOGY

The proposed methodology leverages a hybrid spatial-temporal architecture designed to extract discriminative features from both the visual appearance of individual frames and the sequential flow of motion across multiple frames.

A. Data Collection and Preprocessing

The initial phase of the pipeline involves rigorous data collection and preprocessing to prepare high-quality facial frame sequences from real and fake videos. The video input undergoes uniform frame sampling, where exactly 25 frames are extracted from each video to ensure a consistent temporal window for the sequence model. Face detection is performed using a Multi-Task Cascaded Convolutional Neural Network (MTCNN), which identifies and aligns facial landmarks to crop the region of interest effectively.

The cropped facial images are then resized to a standardized dimension of 224×224 pixels and normalized before being grouped into sequential formatted batches of shape $(25, 224, 224, 3)$. Frame-level augmentation is applied identically to every frame within a single sequence, utilizing random left-right flipping, brightness adjustments, contrast variations, and saturation scaling to improve model robustness [3].

B. Spatial Feature Extraction

Spatial feature extraction is conducted using the EfficientNet-B0 architecture, which serves as the visual backbone. EfficientNet-B0 utilizes dynamic input scaling, squeeze-and-excitation blocks, and multi-scale feature fusion through depthwise convolutions to extract hierarchical feature representations [14]. The spatial extraction mathematically operates as a standard convolution applied across the input tensor:

$$F = \sigma(W * X + b) \quad (1)$$

where X represents the input image, W is the convolution kernel, and σ denotes the activation function. Global Average Pooling (GAP) reduces the spatial dimensions, outputting a 1024-dimensional discriminative feature vector for each individual frame.

C. Temporal Feature Learning

To capture frame-to-frame temporal inconsistencies, the extracted spatial features are passed into a Bidirectional Long Short-Term Memory (BiLSTM) network. Temporal models effectively model blinking frequency anomalies, lip synchronization mismatches, irregular motion transitions, and flickering artifacts [7], [10]. The LSTM network maintains hidden states computed at each time step:

$$h_t = f(W_h h_{t-1} + W_x x_t + b) \quad (2)$$

By processing the sequence in both forward and backward directions, the Bidirectional architecture captures temporal context in both directions, yielding a comprehensive understanding of the video's motion dynamics. The output of the temporal model is routed through a fully connected classification head with dropout regularization, culminating in a single sigmoid activation node [6].

IV. SYSTEM ARCHITECTURE

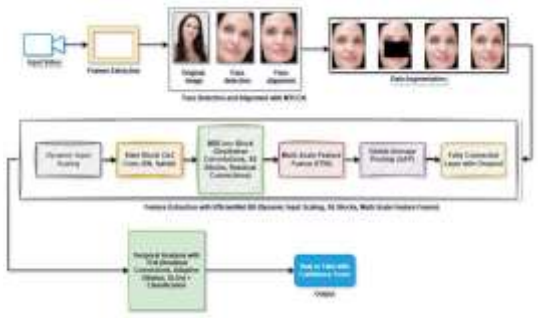


Fig. 1. Proposed Hybrid Spatial-Temporal System Architecture.

The system architecture integrates the data preprocessing, spatial extraction, and temporal analysis components into a unified pipeline. The raw input video is first parsed by a frame extraction module [4]. The MTCNN processes these frames to perform face detection and alignment, isolating the subject's face from the background to minimize environmental noise [12]. Data augmentation layers introduce variability during the training phase, making the network resilient to diverse lighting and resolution conditions.

Following preprocessing, the frames are sequentially fed into the EfficientNet-B0 backbone. This network begins with a stem block comprising a 3×3 convolution with batch normalization and Swish activation. The core processing occurs within mobile inverted bottleneck convolution (MBConv) blocks, which integrate depthwise convolutions, squeeze-and-excitation layers, and residual connections to optimize feature maps efficiently.

These frame-level embeddings are subsequently distributed across the temporal dimension using a `TimeDistributed` wrapper, effectively transforming the spatial features into a temporal sequence. The sequential data is processed by two stacked BiLSTM layers [15]. The temporal features are finally flattened and passed through dense layers equipped with dropout mechanisms to prevent overfitting.

V. Implementation Details

The implementation utilizes the Celeb-DF dataset, a high-quality repository of real and synthesized videos. The dataset is processed to generate structured numerical arrays, saving the extracted and normalized face sequences as `.npy` files [4]. The dataset is partitioned into a training set (70%), a validation set (15%), and a hold-out test set (15%) [8].

The optimization process employs the Adam optimizer coupled with a Binary Crossentropy loss function incorporating a label smoothing factor of 0.05 [16]. Label smoothing is explicitly utilized to prevent the model from making overly confident predictions, thereby improving generalization.

The training is executed in two distinct phases:

- **Phase 1 (Frozen Backbone):** The EfficientNet-B0 backbone weights are frozen, and only the temporal LSTM layers and dense classification head are trained. This uses an initial learning rate of 3×10^{-4} with a cosine learning rate decay scheduler [3].
- **Phase 2 (Fine-Tuning):** The top 30 layers of the EfficientNet-B0 backbone are unfrozen to adapt spatial filters specifically to deepfake-related artifacts [1]. This phase operates at a reduced learning rate of 1×10^{-5} [14].

Both phases employ gradient clipping with a maximum norm of 1.0 to stabilize the recurrent gradient updates.

VI. Results and Discussion

The evaluation of the hybrid model on the held-out test dataset demonstrates its efficacy in distinguishing between authentic and synthetically generated content. Performance is quantified using standard evaluation metrics, including Accuracy, Precision, Recall, and the F1-Score [5]. The mathematical formulations are:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

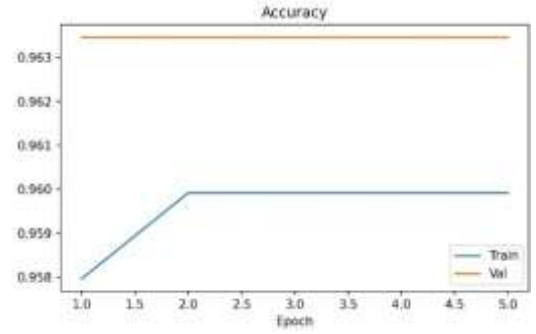


Fig. 2. Model Accuracy across training epochs (Train vs. Validation).

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

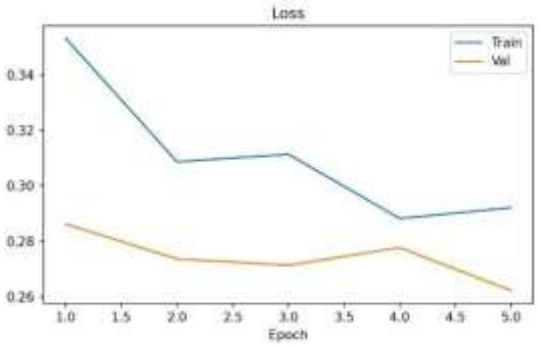


Fig. 3. Model loss across training epochs (Train vs. Validation).

The training progression is visualized through learning curves tracking accuracy, loss, and the Area Under the Curve (AUC) across epochs. The validation accuracy curve closely follows the training accuracy, plateauing at a high level, which indicates that the model successfully learns the discriminative features without succumbing to severe overfitting.

TABLE II
Result Comparison by Classification Threshold

Threshold	Accuracy	Precision	Recall	F1-Score
Default (0.50)	0.88	0.89	0.87	0.88
Optimal (0.10)	0.96	0.96	1.00	0.98

Testing the model against unseen data yields a confusion matrix highlighting the classification distribution. Optimization of the decision boundary using Youden's J statistic reveals that a lower threshold significantly maximizes the balance between sensitivity and specificity [13]. By adjusting the threshold to an optimal value of 0.10, the model achieves a peak F1-Score of 0.98 [11]. This threshold tuning is particularly vital in deepfake detection, where the cost of false negatives is substantially higher than false positives.

VII. Conclusion and Future Work

This research addresses the critical challenge of synthetic media identification by proposing a robust hybrid spatial-temporal deep learning framework. By combining the feature extraction prowess of EfficientNet-B0 with the sequential modeling capabilities of Bidirectional LSTM networks, the system successfully detects deepfake videos by analyzing both spatial artifacts and temporal motion inconsistencies [10], [15]. The two-phase training methodology, combined with rigorous data augmentation and hyperparameter tuning, yields a highly accurate model capable of generalizing to unseen data, ultimately achieving an optimized F1-score of 0.98.

Future advancements should focus on domain adaptation techniques to improve cross-dataset reliability [17], the integration of Explainable Artificial Intelligence (XAI) to provide interpretability for the model's decisions [7], and the development of lightweight mobile deployment models for real-time analysis. Additionally, exploring multimodal detection systems that combine visual features with audio and physiological signals [8] will provide a more comprehensive defense against increasingly sophisticated generative models.

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