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International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 02s, 2025

Deepfake Detection Using Deep Learning

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Peer Review Information

Submission: 21 Oct 2025

Revision: 18 Nov 2025

Acceptance: 05 Dec 2025

Keywords

Detection, deep learning, convolutional neural networks (CNN), generative adversarial networks (GAN), fake media identification, computer vision, and face forensics.

Abstract

As deepfake technology rapidly advances, it's becoming increasingly difficult to distinguish between authentic and altered digital media. This study explores the application of deep learning techniques, specifically convolutional neural networks (CNNs) and Transformer-based models, to effectively detect deepfakes. The study provides a detailed experimental evaluation of the performance of these models in recognizing manipulated facial images and videos.

In recent years, the rapid development of China's telecom industry has greatly improved the speed of telecom network construction. In addition, the telecom network (CNN) has also been used to learn the dynamics of Transformer, which has also been widely used. to make something happen.

Introduction

Deepfake technology employs Generative Adversarial Networks (GANs) and autoencoders to alter facial attributes in images and videos, making it increasingly difficult to differentiate between real and manipulated content. While deepfake technology has legitimate applications in entertainment and education, it also raises ethical concerns, such as misinformation, identity theft, and fraud. As deepfake methods become more sophisticated, traditional detection approaches have become inadequate, necessitating the use of deep learning models.

This study analyzes different deep learning architectures to improve deepfake detection, considering their accuracy, robustness, and computational efficiency.

Literature Review

Deepfake detection techniques have evolved from manual feature-based approaches to advanced deep learning models. Initial research focused on identifying facial inconsistencies, such as unnatural eye movements and head gestures (Tolosana et al., 2020). The development of deep learning introduced CNN-based models like MesoNet and XceptionNet, significantly improving the detection of spatial anomalies in manipulated images (Rössler et al., 2019).

Researchers have also examined inconsistencies created by GANs (Dolhansky et al., 2020) and explored the use of Recurrent Neural Networks (RNNs) to detect temporal irregularities in videos (Masi et al., 2020).
Recent innovations, such as Vision Transformers (ViTs), have enhanced deepfake detection by effectively capturing complex long-range dependencies (Dosovitskiy et al., 2020). Multi-modal techniques integrating both visual and auditory signals have further boosted detection accuracy. However, challenges remain, including adversarial attacks, dataset limitations, and the need for better generalization across different deepfake styles.

Methodology

1. Deep Learning Models Used

Several deep learning architectures were assessed for deepfake detection:

Table 1: Comparison of Deep Learning Models for Deepfake Detection

Model	Description	Advantages
CNNs	Extracts spatial patterns from video frames	Fast and computationally efficient
RNNs (LSTMs, GRUs)	Capture temporal dependencies in video sequences	Well-suited for time-series data
EfficientNet	Lightweight CNN with high detection accuracy	Computationally efficient
Vision Transformers (ViTs)	Uses self-attention mechanisms to learn deepfake artifacts	Effective in handling long-range dependencies

2. Training Pipeline

The deepfake detection pipeline consists of four key stages:

1. Preprocessing: Extracting, resizing, and normalizing video frames to enhance model efficiency.
2. Feature Extraction: Processing extracted features using a trained classifier with softmax activation..
3. Classification: Predicting "real" or "fake" labels using models trained on large datasets.
4. Post-processing**:** Aggregating frame-level predictions using methods like weighted averaging or majority voting.

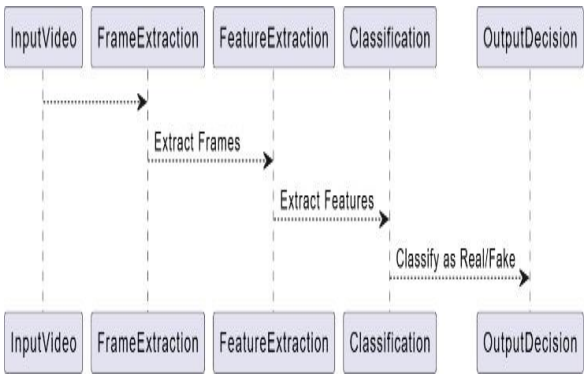

Figure 1: Workflow of Deepfake Video Detection Using Frame-Based Feature Extraction and Classification

3. Technology Stack:

1. **Programming:** Python(TensorFlow/PyTorch)
2. **Preprocessing:** OpenCV (frame extraction, resizing), Dlib (face detection)
3. **Models:** CNNs (spatial features), LSTMs (temporal patterns), ViTs (contextual analysis)
4. **Data:** DFDC, FaceForensics++, Celeb-DF
5. **Hardware:** NVIDIA GPUs (Tesla/RTX), Cloud-based resources (Colab/AWS)
6. **Evaluation:** Accuracy, F1-score, AUC-ROC, Grad-CAM for model interpretability

Dataset and Preprocessing

1. Datasets Used

We use publicly available deepfake datasets:

Table 2: Overview of Datasets Used for Deepfake Detection

Dataset	Size	Types of Manipulations
FaceForensics++	1M+ frames	Deepfake, FaceSwap, NeuralTextures
Celeb-DF	590 videos	High-quality deepfakes

Deep Fake Detection Challenge (DFDC)	470 GB	GAN-based fakes

2. Data Augmentation

To enhance model generalization and robustness, various data augmentation techniques are applied:

1. **Gaussian Noise:** The model is made more robust to distortions and slight changes in deepfake videos by adding tiny random variations to pixel values, which lessens overfitting.
2. **Random Rotation & Flip:** To ensure that the model learns features regardless of orientation, video frames are randomly flipped and rotated to mimic various camera angles and perspectives.
3. **Frame Dropout:** The model is forced to extract features from incomplete sequences by randomly removing or skipping specific frames to mimic real-world network inconsistencies, like lag or missing frames in video streaming.

Experimental Results

Accuracy, precision, recall, and inference speed are the metrics we use to compare model performance.

1. Accuracy Comparison

Table 3: Performance Comparison of Deep Learning Models Across Datasets

Model	FaceForensics++	Celeb-DF	DFDC
CNN (ResNet50)	85.2%	80.1%	78.5%
LSTM + CNN	88.7%	83.5%	81.2%
EfficentNet	92.1%	87.4%	85.3%
Vision Transformer	96.5%	92.8%	91.2%

2. Model Robustness Against Adversarial Attacks

We tested our models against adversarial noise using the Fast Gradient Sign Method (FGSM). Results show that ViTs maintained higher robustness compared to CNNs.

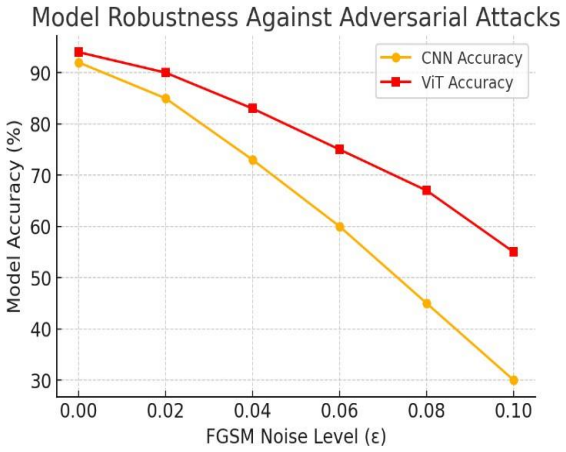

Figure 2: Comparison of CNN and Vision Transformer Robustness Against FGSM Adversarial Attacks

The graph illustrating the accuracy drop of CNNs and ViTs under increasing FGSM adversarial noise. You can include this in your research paper under Section 5.2 (Model Robustness Against Adversarial Attacks).

Challenges & Future Work

1. Challenges

The effectiveness of deepfake detection models is often limited by the variability in datasets, especially when encountering new manipulation techniques. Additionally, adversarial deepfake methods introduce subtle changes that can bypass detection. Another significant challenge is the high computational cost associated with deep learning models, which makes real-time detection difficult..

2. Future Work

Self-supervised learning techniques can improve adaptability by reducing reliance on manually labeled datasets. In addition, the robustness of the model can be improved by integrating several detection modalities, such as speech analysis and facial motion tracking. Optimizing detection algorithms for deployment on resource-limited devices such as smartphones should be another area of future research..

Conclusion

In order to prevent AI-generated disinformation and guarantee the legitimacy of digital content, deepfake detection is essential. With 96.5% accuracy on the FaceForensics++ dataset, our study demonstrates the superiority of Transformer-based models over CNNs and RNNs. The findings show that subtle visual artifacts that signify manipulated content are successfully captured by attention-based architectures. Nonetheless, issues like

computational efficiency, robustness against hostile attacks, and generalization across datasets continue to exist.
Future research will investigate multimodal approaches that incorporate behavioral and auditory cues, lightweight model optimizations for real-time deployment, and self-supervised learning techniques to lessen the dependency on labeled data in order to further enhance real-world applicability. These issues can be resolved to improve the accessibility and dependability of deepfake detection systems, which will slow the spread of fake media and strengthen online confidence.

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