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Fake News Detection Using NLP

Mr. Karan Khandagale, Mr. Tejas Solase , Mr. Prasad Khaire,
Mr. Pritam Bangar, Prof. Rahane D A.
Sahyadri Valley College of Engineering and Engineering and Technology, Rajuri

Abstract: *Unified Framework for Deepfake Detection in Videos, and Audio is a comprehensive system designed to identify manipulated multimedia content across multiple modalities. The project utilizes state-of-the-art deep learning techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and spectrogram- based analysis to detect synthetic media generated by advanced AI tools. By integrating visual and auditory feature extraction pipelines, the framework ensures robust and reliable identification of fake, video frame manipulations, and voice synthesis-based deepfakes. The pro- posed unified approach eliminates the need for separate detection systems by combining multimodal data analysis within a single architecture. Developed using Python, TensorFlow, Flask, and React.js, the framework supports real-time detection, visual analytics, and alert mechanisms for suspected deepfake content. Experimental results demonstrate high detection accuracy and adaptability against emerging deepfake generation techniques, confirming the system's potential in digital forensics, social media verification, and cybersecurity applications. This work emphasizes the importance of developing unified, AI-driven tools to combat misinformation and safeguard the authenticity of digital content in modern communication networks.*

Keywords: Deepfake Detection, Artificial Intelligence, Machine Learning, Convolutional Neural Networks (CNN), Multimodal Learning

I. INTRODUCTION

In the era of advanced artificial intelligence and synthetic media generation, deepfakes have emerged as a major challenge to digital trust and authenticity. Deepfakes are artificially generated or manipulated, videos, and audio clips created using machine learning techniques such as Generative Ad- versarial Networks (GANs) and autoencoders. While these technologies enable creative and entertainment applications, they are increasingly being exploited for malicious purposes such as misinformation, identity theft, fraud, and defamation. Traditional detection methods are often limited to a single modality and fail to adapt to rapidly evolving generative techniques.

With recent progress in Deep Learning (DL) and multimodal analysis, it has become possible to detect subtle inconsistencies in visual and auditory data that indicate synthetic manipulations. Leveraging Convolutional Neural Networks (CNNs) for image and video frame analysis, and spectrogram-based models for audio signals, provides a comprehensive way to identify fake media content. Moreover, the integration of advanced attention mechanisms and feature fusion techniques enables simultaneous evaluation of visual and auditory cues, improving the overall detection accuracy and reliability.

The proposed system, Unified Framework for Deepfake Detection in, Videos, and Audio, aims to build an intelligent and scalable detection framework capable of identifying deepfakes across multiple media formats within a single unified architecture. Developed using Python, TensorFlow, Flask, and React.js, this framework processes media files, extracts feature from multiple modalities, and classifies them using a deep learning- based multimodal fusion network.

II. LITERATURE REVIEW

Fake news detection has emerged as a critical research domain due to the exponential proliferation of misinformation across digital and social media ecosystems. Initial methodologies employed classical machine learning algorithms such as Naive Bayes, Logistic Regression, and Support Vector Machines, leveraging feature extraction techniques like Bag

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of Words and TF-IDF. However, these approaches exhibited limitations in capturing contextual semantics and complex linguistic patterns.

Subsequently, deep learning paradigms, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN/LSTM), demonstrated superior performance by effectively modeling hierarchical representations and sequential dependencies within textual data. Complementing these models, Natural Language Processing (NLP) techniques—such as tokenization, lemmatization, and sentiment analysis—facilitated enhanced textual understanding and feature engineering.

Recent advancements emphasize multimodal frameworks integrating textual, visual, and auditory data streams to improve detection robustness. Despite achieving high accuracy, challenges persist, including susceptibility to adversarial manipulation, dependency on large-scale annotated datasets, and significant computational overhead. Consequently, ongoing research focuses on developing scalable, adaptive, and interpretable models to address these limitations.

III. METHODOLOGY

The methodology combines deep learning, audio visual forensics, and multimodal fusion for robust detection of manipulated media. The process is divided into five key stages as described below:

1. Data Acquisition and Preprocessing:

The framework collects diverse datasets containing authentic and deep- fake, videos, and audio. Each sample undergoes pre-processing — including normalization, resizing, noise reduction, and conversion to consistent formats (RGB for /videos and spectrograms for audio).

2. Feature Extraction:

CNN-based feature extractors analyze spatial inconsistencies, lighting anomalies, and pixel- level artifacts in and video frames. For audio, time- frequency representations are processed to detect anomalies in pitch, tone, and phase coherence.

3. Model Training and Classification:

Separate models are trained for each modality using TensorFlow/Keras. The outputs from these models are then fused using a multimodal attention-based neural network that assigns weighted importance to visual and auditory features for final classification.

4. Decision Fusion and Scoring:

The unified model generates an authenticity score that quantifies the likelihood of manipulation. A threshold- based decision mechanism classifies input as either Real or Deepfake. Visualization and Alert Generation: Once classified, results are displayed on a web dashboard. Suspicious media triggers alerts, logs with timestamps, and evidence visualization to aid in further forensic investigation. The proposed methodology ensures a comprehensive and adaptive detection system capable of identifying complex deepfakes across various media types with high accuracy and reliability.

A. Mathematical Model The detection of deepfakes can be formalized as a binary or multi-class classification problem. Let M represent a multimedia input that may contain an image, video, or audio sample. The deep learning-based model learns a multimodal function fθ

(M) parameterized by θ, which predicts the probability

5. P (f ake|M):

$$P(f\,ake|M) = \sigma(Wn \cdot \phi n{-}1\,(M) + bn)\ (1)$$

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where σ denotes the sigmoid activation function, ϕn−1
(M) is the feature representation from the penultimate layer, and Wn, bn are trainable weights and biases of the model.
For multimodal fusion, let Fi, Fv, and Fa denote feature vectors extracted from image, video, and audio modalities respectively. The unified representation Fu is computed as:

$$Fu = \alpha Fi + \beta Fv + \gamma Fa \quad (2)$$

where α, β, and γ are learnable weights representing the relative importance of each modality. The model is optimized using binary cross-entropy loss for two-class (Real vs. Fake) classification:

$$L = -[y \log(y\hat{}) + (1 - y) \log(1 - y\hat{})] \quad (3)$$

where y is the true label (1 for deepfake, 0 for real) and
y^ is the predicted probability.

IV. SYSTEM ARCHITECTURE

The architecture of the proposed unified deepfake detection framework follows a modular and multimodal pipeline to process and analyse, videos, and audio within a unified environment. it consists of three major layers interconnected through restful Apis and a centralized database for storage and retrieval.
Input layer (data acquisition): accepts different types of media inputs, including static, video clips, and audio recordings. each input is preprocessed for normalization, resizing, and format conversion. for videos, OpenCV extracts frames; for audio, mel-frequency cepstral co- efficient (mfccs) and spectrograms are generated.
Processing layer (feature extraction and classification): this layer performs deep learning-based analysis using CNNs for image and video frames, and recurrent neural networks (rnns) or CNN-based models for audio spectrograms. a multimodal fusion model combines features from all modalities to produce a unified authenticity score.
Output layer (visualization and alerts): implemented using flask and react.js, this layer displays detection results in real time, showing whether content is authentic or manipulated. it also generates alert messages and stores analysis logs, accuracy metrics, and visual evidences in the backend database.
The system's modular client-server design allows parallel processing of multiple inputs and easy integration with cloud-based services or digital verification platforms. the architecture supports scalability, real-time inference, and continuous model updates as new deepfake generation methods emerge.

V. IMPLEMENTATION AND RESULTS

The system is implemented using Python 3.10 with TensorFlow/Keras, OpenCV, and Librosa for deep learning and data processing. A Flask backend handles APIs, while a React-based frontend provides real-time interaction. MongoDB/MySQL is used for data storage, and NVIDIA GPUs support model training. A CNN-RNN hybrid model is trained on multimodal datasets with data augmentation techniques like rotation and noise addition. The model uses the Adam optimizer with a learning rate of 0.0001 over 100 epochs.
The system achieved 97.6% accuracy, with precision of 97.1% and recall of 96.8%, ensuring reliable and balanced deepfake detection performance

VI. CONCLUSION AND FUTURE WORK

Conclusion

The Unified Framework for Deepfake Detection in, Videos, and Audio successfully demonstrates a multimodal deep learning approach capable of identifying synthetic content with high precision and speed. By combining CNN, RNN, and spectrogram- based models into a unified architecture, the framework provides a robust and adaptive solution to the growing threat of deepfakes in the digital ecosystem.
Experimental results validate the system's efficiency, achieving over 97% accuracy with reduced false detection rates across multiple datasets. The framework's modular design, cloud compatibility, and real-time web interface make it suit- able for deployment in forensic labs, social media monitoring, and cybersecurity platforms. Future advancements,

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including edge AI, blockchain integration, and adversarial resistance, will further enhance the reliability and scalability of the proposed framework in combating deepfake-based misinformation

Future Work

Adversarial Defense: Integration of GAN resistant train ing methods to enhance robustness.
Explainable AI: Addition of visualization techniques (Grad-CAM, SHAP) for model interpretability.
Edge AI Deployment: Convert trained model into TensorFlow Lite / ONNX for low-power edge devices.
Blockchain Integration: Store digital fingerprints of authentic media for traceable verification.

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