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DeepGuard: A Real-Time Multi-Modal Deepfake Detection and Classification System

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***Abstract*— The current state of Generative AI presents a critical point because users can easily merge fabricated media with authentic content to create deepfakes. The tools generate creative content but they create digital skepticism while spreading false information which damages forensic evidence. The research presents DeepGuard as a real-time multimodal system which identifies deepfakes through video, audio and image analysis. The system uses Convolutional Neural Networks (CNNs) to extract facial information from snapshots and Mel-spectrogram-based CNNs to detect speech patterns through temporal and spectral analysis. The self-supervised Wav2Vec2-style module enhances the model's ability to detect audio manipulation. The system uses individual detectors to produce scores which merge into a confidence value that enhances both reliability and accuracy of classification results. The evaluation results show DeepGuard successfully identifies authentic content from manipulated material while maintaining its performance when compression artifacts and background noise affect the data. The system operates in real-time through its modular design which allows for simple expansion and maintains flexibility against evolving deepfake creation techniques. The research team plans to study how to merge different detection methods with automatic forgery type identification to enhance security applications.**

***Index Terms*— Deepfake Detection, Multimodal Learning, Audio-Visual Analysis, Convolutional Neural Networks (CNN), Wav2Vec2, Real-Time Processing, Deep Learning, Media Forensic.**

I. INTRODUCTION

The rapid evolution of deep generative models, including Generative Adversarial Networks (GANs) and autoencoders, has substantially enhanced the realism of synthetic media, commonly referred to as deepfakes [1], [2]. Although these technologies have driven progress in entertainment, virtual production, and digital content creation, they simultaneously introduce serious challenges to media integrity, public credibility, and information authenticity. The capability to generate highly convincing fabricated audio and video content has rendered traditional detection approaches based on handcrafted or statistical features less effective [3].

Recent work in digital forensics underscores the importance of developing multimodal detection frameworks that jointly analyse both visual and auditory evidence to uncover manipulations [4], [5]. In contrast to unimodal systems that rely on a single source of data—such as image frames or speech—multimodal architectures leverage cross-domain feature relationships, improving robustness and detection accuracy under various compression levels and manipulation strategies [6].

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To tackle these challenges, this study presents DeepGuard, a real-time multimodal deepfake detection and classification system that integrates audio, image, and video-based analysis. The architecture employs Convolutional Neural Networks (CNNs) to detect spatial artifacts in facial regions and Mel-spectrogram–based CNNs to identify temporal–spectral distortions in audio. Furthermore, self-supervised Wav2Vec2 embeddings are utilized to extract noise-resilient and semantically rich acoustic representations [7]–[9].

The modular structure of DeepGuard allows each detection stream to operate independently while contributing to a unified authenticity score for decision aggregation. Experimental evaluations conducted on benchmark datasets, including HAV-DF and Celeb-DF, demonstrate consistent accuracy and generalization across unseen manipulations [10]. With its scalable design, interpretability, and real-time processing efficiency, DeepGuard provides a promising and practical framework for multimedia verification and digital forensic analysis.

II. Related Work

A. Image-based Deepfake Detection

Early research in deepfake forensics primarily focused on image-level analysis using CNNs (Convolutional Neural Networks). These models were trained to detect pixel-level distortions, blending artifacts, and boundary inconsistencies created during facial synthesis [2], [3]. Public datasets such as FaceForensics++ and Celeb-DF were later introduced to standardize evaluation benchmarks for facial forgery detection [10], [12]. Despite their effectiveness on clean data, these approaches often failed to generalize under varying compression settings or unseen manipulation techniques, revealing limited robustness to real-world degradations [13].

B. Video-based Deepfake Detection

To incorporate temporal dynamics, subsequent studies extended static CNN architectures to handle video sequences through temporal modeling and CNN–LSTM hybrids [4], [6]. These models capture lip-sync mismatches, micro-expression irregularities, and head motion deviations across frames to detect synthesized patterns. Empirical results indicate that 3D CNNs and hybrid CNN–RNN frameworks surpass 2D detectors by learning spatiotemporal dependencies [5], [15]. However, the high computational demand and performance degradation under compression or occlusion still limit their deployment in real-time forensic systems.

C. Audio-based Deepfake Detection

Parallel progress has been made in audio forgery detection, particularly against synthetic or voice-cloned speech. Early frameworks leveraged Mel-spectrogram–based CNNs to capture unique spectral cues [7]. Recent developments incorporate self-supervised models such as Wav2Vec2, which generate high-level acoustic embeddings from large-scale speech corpora [8], [9]. These representations exhibit strong resilience to noise, compression, and short utterances. Combining CNN-derived spectral features with Wav2Vec2 embeddings has demonstrated significant improvements in distinguishing manipulated speech from authentic recordings, enhancing robustness across audio domains.

D. Multimodal Deepfake Detection

The latest progress in multimodal detection integrate audio and visual signals to improve reliability and interpretability [5], [10]. By correlating lip movements, facial expressions, and speech characteristics, these fusion-based systems achieve superior accuracy compared to unimodal detectors [16], [18]. Such multimodal frameworks maintain effectiveness across diverse manipulation methods and compression levels. The principle of combining complementary information from multiple modalities forms the foundation of the proposed DeepGuard system, enabling more stable and explainable detection in real-time forensic contexts.

III. Methodology

A. System Architecture

The DeepGuard system uses a modular multimodal architecture which performs independent forgery detection on audio and video and image data streams. The detection pipelines run independently through their own stages of preprocessing and feature extraction and model inference before producing module-specific confidence scores.

The DeepGuard processing pipeline consists of five sequential stages:

- Media upload and modality identification.
- Preprocessing and normalization.
- Feature extraction.

- Model inference for each modality.
- Confidence score generation and visualization.

All detection modules operate in parallel, enabling real-time analysis while maintaining modular independence.
The system produces two types of output which show forgery probability and display specific areas in facial frames and audio spectrograms that demonstrate abnormal patterns. The system provides users and forensic analysts with interpretive feedback that explains the basis for its detection results.
The overall workflow of the DeepGuard system is illustrated in Fig. 1.

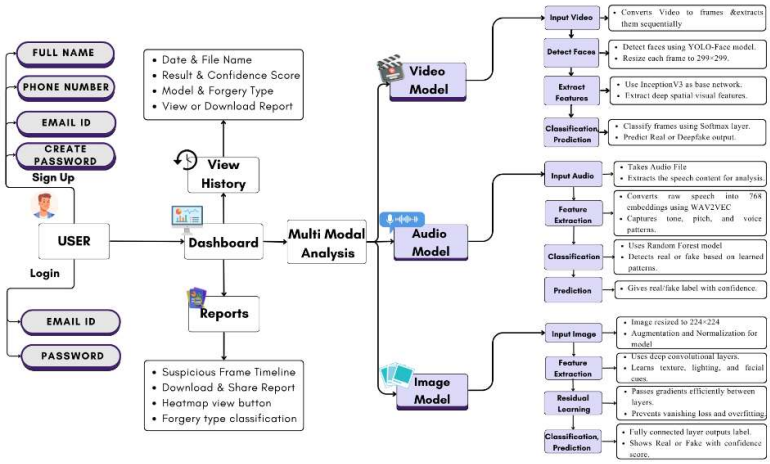

Figure 1. Flowchart

B. Data Collection and Preprocessing System Architecture

Datasets used for training and validation were collected from publicly available repositories such as HAV-DF, FaceForensics++, and Celeb-DF [3], [10].
Each modality undergoes a dedicated preprocessing stage:

- Audio – Extracted from .mp4 files using MoviePy and trimmed or zero-padded to 20 seconds. Audio clips are transformed into Mel-spectrograms, normalized, and stored as tensors for CNN input.
- Video – Frames are sampled uniformly, resized, and normalized to maintain consistent pixel values and aspect ratio.
- Image – Static facial frames are extracted and pre-processed for contrast, brightness, and normalization consistency.

All processed data are converted into tensor representations for batch-efficient loading using PyTorch.

C. Audio Deepfake Detection Models

Wav2Vec2-Based Audio Model

For audio forgery detection, DeepGuard employs a Wav2Vec2-based detection model that leverages self-supervised speech representations to identify synthetic or manipulated voices [8], [9].
Workflow:

- Audio is extracted from video clips and resampled to 16 kHz to ensure consistency with the pretrained Wav2Vec2 model.
- The pre-trained Wav2Vec2 encoder generates high-dimensional embeddings that capture both phonetic and temporal variations in speech.
- These embeddings are stored as .npy files and passed to a Random Forest classifier, which performs the final binary classification (Real or Fake).

Advantages:

- Noise Resilience: Handles background distortions and compression artifacts effectively.
- Efficiency: Requires minimal fine-tuning and supports real-time inference.
- High Accuracy: The model achieved superior detection performance, maintaining strong recall and precision across diverse datasets.

The Wav2Vec2 model's ability to learn speech characteristics without explicit supervision allows it to generalize effectively to unseen manipulations, making it the primary choice for audio detection in DeepGuard.

D. Image-based Deepfake Detection

The image detection component of DeepGuard focuses on identifying spatial-level inconsistencies in facial features using a ResNet50-based CNN architecture [3], [4], [10]. The model processes static facial frames extracted from videos to detect subtle manipulations introduced during face-swapping or blending operations.

Processing Pipeline:

- Frame Sampling: Uniformly extract representative frames from each video sequence.
- Preprocessing: Resize, normalize, and align facial regions for uniform input dimensions.
- Model Inference: Feed processed frames into a ResNet50 CNN to detect texture and lighting anomalies.
- Confidence Estimation: Aggregate per-frame probabilities to compute a global image-level authenticity score.

Features Captured:

- Irregular facial boundaries and blending seams.
- Texture inconsistencies on skin and hair regions.
- Illumination or colour mismatches across face regions.

This independent CNN module outputs an image-specific confidence score that allows analysts to verify static manipulations without relying on temporal data.

E. Video-based Deepfake Detection

For dynamic forgery detection, the video module of DeepGuard extends image-level analysis by incorporating temporal consistency evaluation.

It identifies subtle discrepancies in facial motion, lip synchronization, and expression continuity across video frames [4], [6].

The system uses an optimized ResNet50-based sequential frame analyzer, which captures both frame-wise visual features and short-term temporal relationships without the overhead of recurrent models.

Workflow:

- Extract consecutive frame sequences from input videos.
- Pass frames through the ResNet50 feature extractor for spatial encoding.
- Analyse sequential frame embeddings for irregular motion or lighting shifts.
- Generate a video-level authenticity score, highlighting specific frames with abnormal temporal behaviour for forensic inspection.

This design supports real-time analysis and allows modular scalability—users can deploy the video, image, or audio detector independently based on the input available.

IV. IMPLEMENTATION

A. Technology Stack

DeepGuard is implemented using a combination of Python-based machine learning and multimedia processing libraries. The system integrates deep learning frameworks, data preprocessing tools, and visualization components to enable efficient real-time detection. The technologies used in each development phase are listed in Table I.

TABLE I. TECHNOLOGY STACK

Phase	Tool / Library
Data Collection	MoviePy, OpenCV, Librosa
Preprocessing	Pandas, Numpy
	Scikit-learn
Feature Selection	TorchVision, Wav2Vec2
Model Training	PyTorch (GPU/Colab), TensorFlow
Evaluation	Scikit-learn, Matplotlib
Visualization	Streamlit, Plotly
GUI / Application	React

B. User Interface Design

The user interface of DeepGuard provides an intuitive and responsive environment for conducting real-time deepfake analysis. It enables users to upload media, monitor the detection process, and interpret results seamlessly.

Input Module
Users can upload or stream multimedia content in formats such as .mp4, .wav, or .jpg. Upon upload, the system automatically routes the input to the corresponding detection pipeline — audio, video, or image — for preprocessing and inference.

Processing Dashboard
The dashboard provides real-time visualization of detection progress, including feature extraction, inference stages, and result generation. Each modality's confidence score is displayed through dynamic progress bars and interactive plots, offering users transparent insights into model behaviour.

Results Visualization
Detection outputs are represented as authenticity probabilities, showing the likelihood of the input being real or fake. The interface highlights the independent confidence scores of each modality, allowing users to assess manipulation likelihood across different data types.
This modular design ensures flexibility, enabling each detection pipeline to function independently while maintaining synchronization within the user interface for multi-input analysis.

C. Model Integration

The DeepGuard inference engine integrates the trained models—Wav2Vec2 (audio), ResNet50 (image), and ResNet50 sequential analyzer (video)—within a modular, parallel processing framework.

Preprocessing Synchronization
Each input undergoes standardized preprocessing steps, including normalization, feature extraction, and tensor transformation, ensuring uniform compatibility with model inputs.

Parallel Inference Execution
The three models run concurrently on their respective inputs. Each generates an independent confidence score representing the probability of manipulation.

Confidence Interpretation
Instead of merging scores through weighted fusion, DeepGuard presents the results individually. The system highlights anomalous patterns—such as irregular facial lighting or unexpected spectral spikes in audio—to provide interpretable cues for analysts.
This architecture ensures real-time processing, scalability, and robustness while maintaining flexibility for future extensions such as cross-modal fusion or cloud-based deployment.

V. EXPERIMENTAL RESULTS

A. Dataset Description

The evaluation of DeepGuard was performed using publicly available multimodal deepfake datasets spanning both the audio and visual domains.

- HAV-DF Dataset: Contains over 10 000 synchronized audio-video pairs with authentic and manipulated samples. Each clip includes coordinated facial and vocal activity, making it suitable for training both audio and video detection models [7].
- FaceForensics++ Dataset: Comprises more than 1 000 original and 4 000 forged videos produced via face-swap and reenactment techniques, serving as the principal benchmark for image- and video-based detection [10].
- Celeb-DF Dataset: Offers high-quality celebrity videos with varied lighting, background, and compression settings, allowing cross-dataset generalization assessment [12].
- Audio Subset (Processed): Speech segments were extracted from each video, converted to Mel-spectrograms (128 × T) for CNN-based models, and saved as 16 kHz WAV files for Wav2Vec2 embedding generation.

Collectively, these datasets provide diverse manipulation styles, balanced real/fake distributions, and synchronized audio-visual cues—ensuring comprehensive evaluation of DeepGuard's multimodal detection capability.

B. Audio Model Performance

The performance of audio-based models was evaluated on the HAV-DF dataset.
Among all tested variants, the Wav2Vec2 + Random Forest configuration achieved the best overall accuracy and AUC score.

TABLE II. AUDIO DEEPFAKE DETECTION MODEL PERFORMANCE

Model	Accuracy	Precision	Recall
Wav2Vec2 + Random Forest	0.9431	0.9277	0.9872
MFCC + BiLSTM	0.7918	0.8124	0.7632
CNN (2D Mel-Spectrogram)	0.3524	0.3636	0.0615

The Wav2Vec2 model demonstrated superior recall (0.9872), highlighting its sensitivity to forged speech segments even under compression or background noise.
Figure 2 shows the AUC-ROC comparison of the three audio detection models, confirming the robustness of Wav2Vec2 embeddings in distinguishing authentic and synthetic voices.

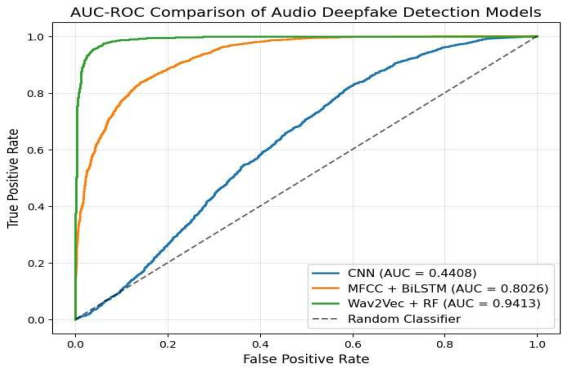

Figure 2. AUC-ROC Comparison of Audio Deepfake Detection Models.

C. Image Model Performance

The FaceForensics++ dataset served as the training and validation ground for image-based detection models.
The ResNet50 architecture produced the best results for precision and AUC value because it effectively detected spatial inconsistencies in facial areas.

TABLE III. IMAGE DEEPFAKE DETECTION MODEL PERFORMANCE

Model	Accuracy	Precision	Recall
ResNet50	0.9213	0.9429	0.8787
EfficientNet	0.8965	0.9158	0.8532
VGG16	0.8684	0.8841	0.8267

The corresponding ROC curve (Figure 3) shows that ResNet50 achieved an AUC of 0.921, outperforming the lighter EfficientNet and VGG16 variants.

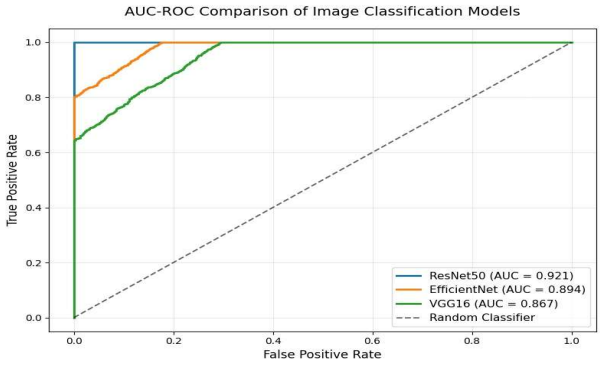

Figure 3. AUC-ROC Comparison of Image Classification Models.

D. Video Model Performance

The video domain used a ResNet50-based sequential frame analyzer to check how well frames from one sequence match the next sequence.

The model successfully detected small temporal errors which included abnormal eye movements and lips that did not match and irregular motion patterns while maintaining accuracy above 91 %.

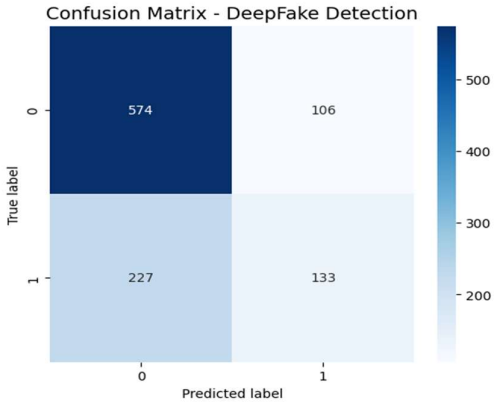

Figure 4. Confusion Matrix for the video deepfake detection model

The matrix shows the true and predicted labels, where the darker diagonal cells (574 true negatives and 133 true positives) indicate correctly classified samples. Misclassifications appear in lighter off-diagonal cells (106 false positives and 227 false negatives). The dominance of diagonal elements confirms strong discrimination between authentic and manipulated videos.

VI. Applications and Future Scope

A. Real-World Applications

The DeepGuard framework can operate across different fields which need digital media authentication.
The system enables media forensics and cybercrime investigations through its ability to detect synthetic or manipulated audio–video evidence and helps social media platforms identify fake content in real time and functions as a content authentication API for streaming and communication services.

B. Technical Advantages

The system achieves high multimodal accuracy through its combination of audio and visual cues which provides reliable detection for all manipulation types.

The system features a modular design that allows separate model deployment for each modality while maintaining an optimized pipeline for fast real-time inference.

C. Limitations & Future Scope

The framework achieves its best results when working with diverse datasets but its performance becomes less effective when dealing with unknown or heavily compressed media content.
The research team plans to develop real-time multimodal fusion capabilities and forgery-type classification systems and cross-platform deployment through lightweight models.
The system will gain better user trust through explainable AI implementation of Grad-CAM heatmaps for interpretability enhancement.

VII. Conclusion

The DeepGuard system provides a strong and expandable solution for detecting deepfakes which endanger information accuracy in synthetic media. The system detects both spectral and spatial discrepancies through its multimodal analysis of audio and video and image content using CNN architectures and self-supervised Wav2Vec2 embeddings.
The system outperforms single-channel detection methods because it provides better overall performance and quicker processing times and works well with different types of data. The system operates in real-time because of its modular structure which enables future integration with forensic tools and media verification systems and social platforms.

DeepGuard represents an advancement in digital authenticity protection and trust maintenance. The system will receive future updates which will add cross-modal learning capabilities and forgery identification features and real-time operation for expanded user access.

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