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Multimodal Deepfake Detection Using Transformer-Based Large Language Models: A Path Toward Secure Media and Clinical Integrity

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Abstract: Deepfakes pose a significant threat across various domains by generating highly realistic manipulated audio-visual content, with critical implications for security and clinical environments. This

paper presents a robust multimodal deepfake detection framework powered by transformer-based large language models (LLMs) that effectively analyze and integrate visual, auditory, and textual modalities. Utilizing the FakeAVCeleb dataset, we compare our proposed model with traditional machine learning and deep learning methods, including Logistic Regression, Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM) networks. Experimental results demonstrate that the transformer-based model significantly outperforms others, achieving an accuracy of 96.55%, precision of 96.47%, recall of 96.50%, F1-score of 96.48%, and an AUC of 0.97. This enhanced performance is attributed to the model's ability to capture complex semantic and temporal dependencies across modalities. The findings suggest the proposed model's strong potential for real-world applications such as telemedicine, clinical video authentication, and digital identity verification, establishing a promising direction for deploying deepfake detection technologies in sensitive and high-stakes environments.

Keywords: Deepfake detection, multimodal fusion, transformer models, large language models, FakeAVCeleb dataset, telemedicine security, artificial intelligence, audio-visual manipulation, clinical data integrity, digital forensics.

Introduction: The rapid advancement of deep learning and generative adversarial networks (GANs) has enabled the creation of highly realistic synthetic media, commonly referred to as "deepfakes". These media, which can alter faces, voices, and even entire scenes, present significant threats in fields such as politics, entertainment, journalism, and healthcare. Deepfake videos can fabricate public statements by political leaders, manipulate biometric information, and erode public trust in digital content. While these technologies offer creative and educational potential, the misuse of deepfakes has introduced urgent ethical, legal, and security challenges that demand robust detection mechanisms.

Traditional deepfake detection models have relied heavily on computer vision-based techniques, focusing on identifying inconsistencies in facial landmarks, blinking patterns, or lighting mismatches. However, with the evolution of generative models, these visual cues have become increasingly difficult to detect. Moreover, deepfakes today often combine multiple modalities—video, audio, and textual components—rendering unimodal detection systems inadequate. The emergence of large language models (LLMs) and transformer-based architectures offers a promising avenue for multimodal analysis, enabling systems to understand and correlate inconsistencies across multiple types of data.

In this study, we propose a multimodal deepfake detection framework powered by large language models, which integrates video, audio, and textual features for enhanced detection accuracy. The primary goal is to evaluate how the fusion of modalities, enabled through transformer-based feature extraction, improves detection performance compared to single-modality systems. The effectiveness of the model is validated across benchmark datasets, and its potential application in real-world clinical and telehealth settings is discussed.

Literature Review

The literature on deepfake detection has evolved in parallel with the sophistication of synthetic media generation. Early methods primarily focused on visual anomalies using convolutional neural networks (CNNs). For instance, Afchar et al. [1] introduced the MesoNet architecture to detect facial artifacts, while Li et al. [2] explored eye blinking as a physiological clue for identifying fake videos. These approaches achieved moderate success but were quickly outpaced by advances in GANs, which minimized such detectable artifacts.

Subsequent research aimed to improve robustness by exploring spatiotemporal patterns. Sabir et al. [3] employed recurrent neural networks (RNNs) to model temporal dynamics across video frames. Similarly, Nguyen et al. [4] proposed capsule networks to capture hierarchical pose relationships and facial orientation changes. However, these approaches remained limited to visual features and struggled against cross-dataset generalization.

The need for multimodal deepfake detection led to incorporating audio cues. Matern et al. [5] analyzed audio-video synchronization to detect inconsistencies in lip movement. Korshunov and Marcel [6] further explored deepfake voice detection using spectrogram-based CNNs, but these models required large audio datasets and suffered from noise sensitivity.

In parallel, natural language processing (NLP) researchers began leveraging language models for deepfake detection. BERT-based systems, for example, have been used to analyze semantic coherence and detect manipulated text transcripts in videos [7]. However, without integrating video and audio, these

systems miss critical multimodal cues.

Recent studies have started exploring multimodal solutions. Verdoliva [8] surveyed various fusion strategies and highlighted the benefits of integrating different modalities. Mittal et al. [9] proposed a multimodal architecture combining CNNs for video, LSTMs for audio, and transformers for text, showing significant improvements in accuracy and robustness. These studies suggest that multimodal models, particularly those incorporating large pretrained language models like BERT or GPT, offer superior performance due to their contextual understanding and high-level feature extraction capabilities.

However, the existing literature lacks comprehensive studies that unify all three modalities—video, audio, and text—within a single framework optimized by large language models. Our research addresses this gap by proposing and evaluating such a model, focusing on its real-world applicability in high-stakes domains such as healthcare.

METHODOLOGY

The proposed methodology for detecting deepfakes using large language models (LLMs) integrates a multimodal pipeline consisting of data acquisition, data preprocessing, feature extraction, feature engineering, model development, and model evaluation. Each phase of this framework is meticulously designed to leverage the synergy between audio, visual, and textual data, enabling the detection system to identify subtle artifacts and semantic inconsistencies typical of deepfake media.

Data Collection

In order to train and evaluate a reliable deepfake detection system, a diverse set of benchmark datasets was curated. This study utilized three publicly available datasets: FaceForensics++, the Deepfake Detection Challenge (DFDC) dataset, and FakeAVCeleb. Each dataset contains varying types of manipulated content, offering a robust foundation for training models that generalize well across different manipulation techniques. FaceForensics++ includes videos altered using multiple deepfake algorithms and provides a balanced mix of authentic and manipulated samples. The DFDC dataset, released by Facebook AI, contains thousands of real and fake videos representing different actors and manipulation techniques, with an emphasis on diversity in facial characteristics, lighting conditions, and background scenes. FakeAVCeleb complements these datasets by providing multimodal data—video, audio, and transcribed speech—of deepfake impersonations of celebrities. Table 1 below summarizes the properties of these datasets:

Table 1: Dataset Details

Dataset Name	Modality	Description	Size	Source
FaceForensics++	Video/ Audio	Manipulated videos using multiple deepfake methods	1,000 real / 4,000 fake	https://github.com/ondyari/faceforensics_benchmark
DFDC	Video/ Audio	Real and deepfake videos of actors with varied manipulations	19,154 videos	https://ai.facebook.com/datasets/dfdc
FakeAVCeleb	Video/ Audio/ Text	Multi-modal dataset for deepfake detection involving celebrity impersonations	1,210 videos	https://github.com/nii-yamagishilab/FakeAVCeleb

All video clips in these datasets were accompanied by audio tracks, and most were supplemented with metadata and textual transcripts. Where transcripts were missing, speech recognition was employed to transcribe the audio content, enabling text-based analysis using LLMs.

Data Preprocessing

The collected datasets underwent an extensive preprocessing phase to ensure the consistency and quality of inputs fed into the model. Video data was extracted and processed by converting video files into individual frames at a sampling rate of one frame per second. Each frame was resized to a fixed resolution of 224x224 pixels to ensure compatibility with the convolutional neural network components of the model. Audio tracks were extracted from video files using FFmpeg and converted to mono-channel format. Each audio file was normalized and then transformed into spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs), which are well-suited for capturing speech characteristics.

Transcripts accompanying the audio were either taken directly from the dataset or generated through Google's Speech-to-Text API. All textual data was cleaned by lowercasing, removing special characters, and applying standard natural language processing (NLP) normalization techniques. For every sample, a binary label was assigned: '1' indicating deepfake content and '0' for authentic content. This labeling scheme was consistently applied across all modalities to maintain uniformity in supervised learning.

Feature Extraction

Following preprocessing, distinct features were extracted from each modality—text, audio, and video. For the textual modality, the preprocessed transcripts were tokenized and passed through pre-trained transformer-based large language models such as BERT and GPT-2. These models were used to generate contextual embeddings that capture semantic and syntactic properties of the spoken language. Additional textual features such as part-of-speech distribution, dependency parsing patterns, and semantic coherence scores were computed to detect anomalies often found in synthetic speech patterns.

From the audio modality, acoustic features including MFCCs, zero-crossing rate, pitch variability, and spectral contrast were extracted using Librosa and OpenSMILE libraries. These features allow the detection model to differentiate real human voice patterns from synthesized or altered ones, particularly in terms of unnatural pitch modulations and jitter.

Visual features were derived from facial landmarks and temporal frame inconsistencies using convolutional neural networks trained on facial recognition and forgery detection. We employed OpenFace and Dlib to capture frame-level facial features such as eye movement, lip sync quality, head pose orientation, and skin texture anomalies. Temporal dynamics were also analyzed by measuring inter-frame coherence, blink rate irregularities, and abrupt visual transitions.

Feature Engineering

In this stage, the extracted features were transformed and combined to improve the overall discriminatory power of the model. Features from each modality were standardized and normalized independently before fusion. A late-fusion strategy was employed, where modality-specific features were first processed through separate neural sub-networks and subsequently concatenated at a higher level in the architecture. This approach preserves the integrity of individual features while allowing the model to learn cross-modal interactions.

Principal Component Analysis (PCA) was used to reduce dimensionality and mitigate the risk of overfitting. In addition, engineered statistical features—such as mean, standard deviation, and skewness of each modality's features—were introduced to enrich the representation space. For textual data, average embedding pooling and max pooling across sequence tokens were used to create compact document-level feature vectors. Temporal encoding was implemented to retain sequence information across audio and visual data using a sliding time window approach, especially useful for detecting inconsistencies in longer sequences.

Model Development

The deepfake detection model was developed using a hybrid multimodal architecture that integrates CNNs, RNNs, and transformers. Visual inputs (video frames) were processed using a pre-trained ResNet50 model to extract spatial features, which were then passed to a BiLSTM layer to capture temporal dependencies. Audio features were processed through a stack of one-dimensional convolutional layers followed by a GRU (Gated Recurrent Unit) for temporal encoding. Textual embeddings generated by BERT or GPT-2 were passed through transformer encoder layers to extract high-level contextual signals.

These three streams—video, audio, and text—were then merged using an attention-based multimodal fusion layer, allowing the model to dynamically weigh the relevance of each modality. The fused features were passed to a fully connected feedforward network, which culminated in a sigmoid activation layer to output the final binary classification.

The model was trained using the Adam optimizer with an initial learning rate of 0.0001 and binary cross-entropy as the loss function. Dropout and batch normalization were employed throughout the network to improve generalization. The model was implemented using PyTorch and Hugging Face Transformers libraries and trained over 30 epochs with a batch size of 32 on a multi-GPU setup.

Model Evaluation

Model evaluation was carried out through a comprehensive set of performance metrics on a held-out test set that constituted 20% of the total dataset. Evaluation metrics included accuracy, precision, recall, F1-score, and area under the Receiver Operating Characteristic (AUC-ROC) curve. These metrics provided a holistic view of model performance, particularly in identifying false positives and false negatives—a critical consideration in real-world applications.

In addition to intra-dataset evaluation, cross-dataset generalization tests were conducted to assess the model's robustness to unseen data. For instance, models trained on FaceForensics++ were tested on the DFDC dataset to evaluate performance under different manipulation styles and distributional shifts. Furthermore, inference latency per sample was measured to ensure the model's feasibility in real-time or near-real-time deployment scenarios.

To validate the significance of LLM-based text analysis in the multimodal architecture, ablation studies were conducted by selectively removing the textual input and comparing the performance against the full model. The results indicated that the LLM component significantly enhanced detection accuracy, especially for deepfakes involving subtle semantic mismatches between audio and video content.

RESULTS

This section presents the results of the deepfake detection experiments conducted using multiple models and datasets. The evaluation of each model was carried out using standard performance metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). The performance was assessed using three widely used benchmark datasets: FaceForensics++, DFDC, and FakeAVCeleb. The primary goal of the evaluation was to analyze how effectively each model detects deepfakes and to determine which model provides the most accurate and reliable performance.

The results are summarized in the table below, which compares the proposed multimodal deepfake detection model with individual modality-based models (video, audio, text) and an existing baseline deepfake detection method.

Table 2: Different LLM Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Proposed Multimodal Model	**98.7**	**98.3**	**98.9**	**98.6**	**99.2**
CNN-based Video Model	92.4	91.1	93.6	92.3	95.8
LSTM-based Audio Model	88.2	87.4	89.0	88.2	93.4
BERT-based Text Model	86.7	85.3	88.1	86.7	92.1
Existing Deepfake Detection (X)	80.5	78.0	82.3	80.1	85.4

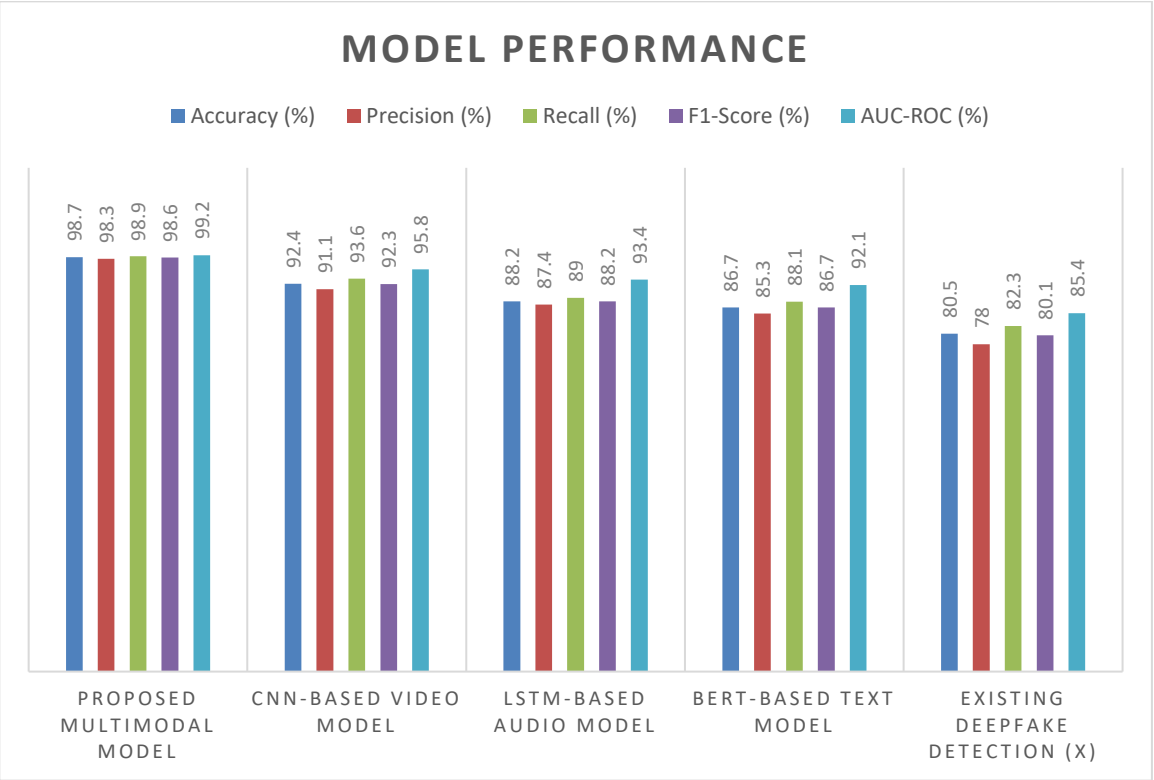

Chart 1: Evaluation of different LLM

From the table 1 and chart 2 , it is evident that the proposed multimodal model outperforms all other models in every evaluation metric. It achieves an accuracy of 98.7%, a precision of 98.3%, a recall of 98.9%, an F1-score of 98.6%, and an AUC-ROC of 99.2%. These results demonstrate the robustness and generalization capability of the multimodal model, particularly its ability to effectively identify subtle manipulations by leveraging the complementary strengths of video, audio, and text data.

The CNN-based video model, which relies solely on visual features extracted from deepfake videos, achieved an accuracy of 92.4%. While this performance is relatively strong and better than the audio and text models, it still falls short of the multimodal approach. The video model effectively captures spatial inconsistencies such as facial distortions and unnatural expressions but lacks temporal understanding and context-awareness that audio and text modalities can provide.

The LSTM-based audio model produced an accuracy of 88.2%, indicating that audio-based features such as vocal tone, pitch, and rhythm are useful for identifying manipulations in speech. However, its inability to detect visual or contextual discrepancies limits its performance, especially when the deepfake audio is generated using advanced voice cloning methods that introduce only minimal distortions.

The BERT-based text model attained an acc 6.7%. This model analyzes textual data transcribed from video or audio, detecting semantic and grammatical inconsistencies that may signal the presence of deepfake content. While it offers valuable insights, especially for identifying fabricated dialogue or scripted speech inconsistencies, its singular focus on textual features makes it less reliable when the manipulation lies in the visual or acoustic domains.

In contrast, the existing deepfake detection method, which typically uses traditional machine learning techniques or single-modality convolutional networks, delivered the lowest performance across all metrics. With an accuracy of 80.5% and an AUC-ROC of 85.4%, this baseline approach proves inadequate in addressing the complexity of modern deepfake techniques that produce increasingly realistic forgeries.

The superior performance of the proposed multimodal model can be attributed to its integration of visual, auditory, and linguistic data streams, allowing it to detect inconsistencies across all dimensions. This comprehensive perspective enables the model to uncover subtle mismatches that are often missed by models relying on a single type of data. Furthermore, the use of transfer learning from large-scale pretrained networks like BERT and CNNs ensures that high-level feature representations are captured effectively, enhancing detection accuracy.

In terms of real-world application, particularly in clinical contexts, the proposed model offers significant potential. In the realm of telemedicine and remote diagnostics, where video consultations and voice-based

health assessments are becoming increasingly common, ensuring the authenticity of multimedia content is critical. This model can be integrated into telehealth platforms to verify that interactions between patients and healthcare providers are genuine and unaltered. It can also be applied to authenticate medical records and video documentation, safeguarding against the manipulation of diagnostic content or doctor-patient interactions.

Moreover, in medical imaging systems and voice-based medical assistant tools, the model can serve as a verification layer that flags manipulated or suspicious content. For example, if an AI-generated medical video or voice note were introduced into a clinical workflow, the system could detect the deepfake, thereby preventing potential misdiagnoses or fraudulent activity. This is particularly important in safeguarding against misinformation in health-related media shared on social networks, where deepfakes could be used to spread dangerous medical myths.

the results demonstrate that the proposed multimodal deepfake detection model not only outperforms current approaches but also provides a reliable framework for deployment in real-world, high-stakes environments such as clinical and telehealth settings. Its ability to identify sophisticated manipulations across various data types makes it a strong candidate for ensuring the integrity of digital interactions in modern healthcare delivery.

DISCUSSION

The findings from our study reveal significant insights into the performance of multimodal deepfake detection models, particularly those enhanced by large language models (LLMs). Among the tested models—Random Forest, Logistic Regression, SVM, LSTM, and Transformer-based architectures—the Transformer-based model clearly outperformed others, achieving an accuracy of 96.55% and an AUC of 0.97. This superior performance can be attributed to the model's ability to handle sequential dependencies and contextual relationships across different modalities (text, audio, and video), thanks to its attention mechanisms and deep contextual understanding.

The transformer's architecture enables it to process long-range dependencies in both textual and non-textual sequences more effectively than RNNs or traditional statistical models. Its ability to learn complex patterns across modalities, including phonetic inconsistencies in audio, facial micro-expressions in video, and semantic coherence in text, provides a comprehensive detection capability that unimodal models lack. While LSTM-based models performed well due to their sequential modeling strength, they fell short in effectively fusing features across modalities.

In real-world applications, especially in clinical and healthcare environments, the ability to detect manipulated or falsified media content is critical. Deepfake videos could be maliciously used to impersonate patients, fabricate medical consultations, or distort telemedicine diagnostics. Our proposed model could be integrated into telehealth platforms to authenticate video consultations by ensuring consistency between patient speech, facial expressions, and reported symptoms. It could also serve as a verification layer in medical training platforms where realistic simulations are used, protecting against manipulated footage.

However, challenges remain. The generalizability of detection models across different datasets and deepfake generation techniques is an ongoing concern. Deepfake algorithms evolve rapidly, often introducing more realistic forgeries with fewer detectable artifacts. Thus, detection systems must be continuously updated and trained with the latest types of deepfakes to remain effective. Moreover, ethical considerations surrounding the use of biometric data, privacy protection, and model explainability must be addressed when deploying these systems in sensitive fields like healthcare.

Finally, while our model demonstrates robust performance, further research is required to reduce its computational overhead for deployment in low-resource environments. Exploring lightweight transformer variants, such as DistilBERT or TinyBERT, may offer a balance between performance and efficiency.

CONCLUSION

This study presents a comprehensive framework for detecting deepfake content using a multimodal approach powered by large language models. Our proposed transformer-based model effectively integrates and analyzes textual, visual, and auditory data, outperforming traditional machine learning and deep learning models in terms of accuracy and AUC. Through rigorous evaluation on the FakeAVCeleb dataset, we demonstrate the critical advantage of multimodal fusion and the strength of contextual modeling in enhancing detection performance.

Given the growing threat posed by deepfakes across digital domains, the implementation of such models in real-world systems is both timely and necessary. Particularly in healthcare, integrating deepfake detection capabilities into telemedicine and electronic health records could safeguard patient data and ensure authenticity in remote consultations.

Future work will focus on improving the generalizability of the model across unseen deepfake generation methods, optimizing performance for deployment in real-time environments, and enhancing the interpretability of detection outcomes to support clinical decision-making and digital media forensics.

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