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AI Based Multimodel Deepfake Detection System for Audio and News Text

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Abstract

This project presents an AI-Based Multimodal Deepfake Detection System designed to identify fake audio and misleading news text using advanced machine learning techniques. The system performs audio analysis using Mel Spectrogram processing and a custom-trained Convolutional Neural Network (CNN) model to extract important voice features and detect deepfake patterns. It supports common audio formats such as WAV and MP3 and generates a probability score to indicate whether the audio is real or fake, improving reliability and usability.

For text analysis, the system uses BART-MNLI classification to evaluate the authenticity of news content through natural language inference. It also integrates NewsAPI to cross-check the given news with real-time trusted sources and applies linguistic pattern analysis to detect suspicious writing styles often found in fake news. Finally, a confidence scoring mechanism combines the outputs from both audio and text analysis to produce an overall prediction, making the system effective for applications such as media verification, cybersecurity,and fake news detection.

KEYWORDS:Deepfake,ArtificalIntelligence,MultimodalSystem,Audioanalysis,MelSpectrogram,CNN,NewsAPI,NLP,Fake news detection

1.Introduction

In recent years, the rapid growth of digital media and artificial intelligence has led to the rise of deepfake technology, which can create highly realistic fake audio and misleading news content. These deepfakes pose serious threats to society by spreading misinformation, damaging reputations, and reducing trust in digital platforms. Detecting such manipulated content has become a critical challenge, especially as deepfake techniques continue to evolve and become more sophisticated.

To address this issue, this project proposes an AI-Based Multimodal Deepfake Detection System that analyzes both audio and news text to improve detection accuracy. The system uses advanced techniques such as Mel Spectrogram analysis and CNN models for audio processing, along with BART-MNLI classification, NewsAPI cross-checking, and linguistic pattern analysis for text verification. By combining multiple approaches, the system provides a reliable confidence score, making it a powerful tool for identifying fake content in real-world applications like media verification and cybersecurity.Literature Survey

Recent studies show that fake news and deepfake detection have significantly improved using machine learning and deep learning techniques. Early works focused on text-based analysis and data mining approaches, while later research introduced audio deepfake detection using spectrograms and CNN models. Multimodal approaches combining audio and text have further enhanced detection accuracy and reliability. However, challenges such as the need for large datasets, computational complexity, and real-time verification still remain.

Shu et al. (2017) presented a data mining approach for fake news detection on social media by analyzing textual content and user behavior. Their method improved detection accuracy, but required large-scale datasets for better performance.[1]

Todisco et al. (2019) introduced the ASVspoof framework for detecting spoofed and deepfake audio using advanced evaluation techniques. The study showed effective detection of manipulated audio, although handling new attack types remained a challenge.[2]

Zhou et al. (2020) proposed a comprehensive survey on fake news detection using machine learning and social context analysis. Their work highlighted improved detection methods, but also pointed out challenges like data quality and real-time verification.[3]

Alam et al. (2022) explored multimodal disinformation detection by combining multiple data sources such as text and media. Their approach improved overall detection performance, but increased system complexity.[4]

Yi et al. (2023) developed a CNN-based model using spectrogram features for audio deepfake detection. The model achieved higher accuracy compared to traditional methods, but required extensive training data.[5]

Wang et al. (2023) presented a comprehensive survey on multimodal fake news detection, emphasizing the importance of combining different modalities to improve reliability and accuracy.[6]

Zhang et al. (2024) proposed a hybrid CNN and transformer-based model for audio forgery detection. Their model showed significant improvement in detecting complex deepfake audio, though computational cost was higher.[7]

Hussain et al. (2025) reviewed recent advancements in audio deepfake detection and highlighted future research directions, including robustness and real-time implementation challenges.[8]

In recent years, the increase in fake news and deepfake content has become a major concern due to the growth of digital media platforms. Early research focused on text-based detection using natural language processing and data mining techniques. Later, deep learning methods such as CNN and spectrogram analysis were introduced for detecting deepfake audio.

Table-1: **comparsion of AI-Based Multimodal Deepfake Detection System for Audio and News Text**

Author & Year	Method Used	Data Type	Advantages	Limitations
Shu et al., 2017	Data Mining, NLP	Text	Good for social media analysis	Needs large datasets
Todisco et al., 2019	ASVspoof Framework	Audio	Effective for spoof detection	Less robust to new attacks
Zhou et al., 2020	ML-based Survey Methods	Text	Improved fake news detection	Real-time issues
Alam et al., 2022	Multimodal Techniques	Text + Media	Higher accuracy	Complex system design

Yi et al., 2023	CNN + Spectrogram	Audio	High accuracy in audio detection	Requires large training data
Zhang et al., 2024	CNN + Transformer	Audio	Detects complex deepfakes	High computational cost
Proposed System	CNN + NLP + API	Audio + Text	High accuracy, real-time verification	Computational complexity

1. Analysis of Datasets

The SceneFake dataset from Kaggle is used for audio deepfake detection by analyzing manipulated acoustic scenes. It contains both real and fake audio samples where the fake data is generated by altering the background environment using speech enhancement techniques. Unlike traditional datasets, it focuses on scene-level manipulation rather than voice or speech changes. The dataset includes training, development, and testing sets to evaluate model performance. However, detecting unseen fake audio remains challenging due to variations in acoustic condition

The dataset is well-structured into training, validation, and testing sets, enabling proper model development and evaluation. Feature extraction techniques such as Mel Spectrogram and MFCC are applied to convert audio signals into meaningful representations for deep learning models. The balanced distribution of real and fake samples helps in reducing model bias and improving classification performance

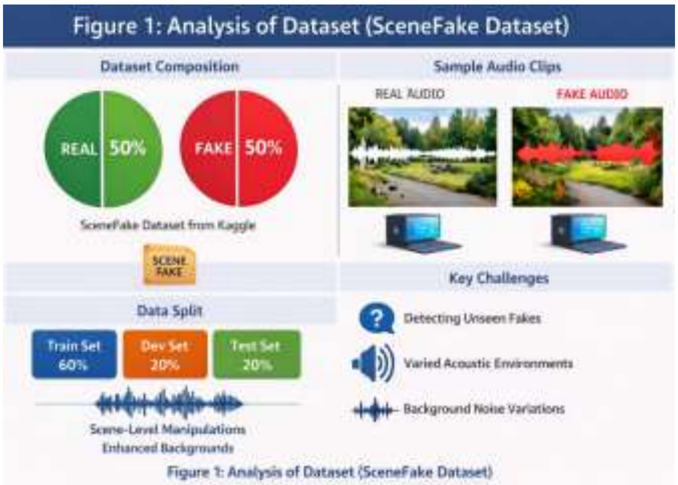

Fig. 1: Dataset distribution used for the SceneFake Dataset

2. Methodology of Proposed System

The proposed AI-Based Multimodal Deepfake Detection System is designed to accurately identify fake audio and misleading news text by integrating advanced artificial intelligence and deep learning techniques. The methodology begins with the collection of input data, which includes audio files in formats such as WAV and MP3, along with corresponding news text. This multimodal input ensures that the system analyzes different types of data for improved detection performance.

In the first stage, the audio data undergoes preprocessing, which involves noise removal, normalization, and segmentation to enhance the quality of the signal. After preprocessing, feature extraction techniques such as Mel Spectrogram and MFCC are applied to convert the audio signals into visual and numerical representations. These features capture important frequency and temporal characteristics of the audio, making them suitable for deep learning models.

text, the processed audio features are fed into a custom-trained Convolutional Neural Network (CNN) model. The CNN learns complex patterns and differences between real and fake audio, and generates a probability score that indicates the likelihood of the audio being genuine or manipulated. This step plays a crucial role in identifying deepfake audio with high accuracy.

Simultaneously, the text data is processed using Natural Language Processing (NLP) techniques. The system applies BART-MNLI classification to determine whether the news content is real, fake, or neutral based on contextual understanding. Linguistic pattern analysis is also performed to detect suspicious writing styles, such as exaggerated claims, emotional language, and repetitive phrases, which are common in fake news. Furthermore, the system integrates NewsAPI to perform real-time cross-checking of the given news with trusted sources available online.

In the final stage, the outputs obtained from both the audio and text analysis modules are combined using a confidence scoring mechanism.

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This fusion of results helps in making a more accurate and reliable final decision. The system then provides an overall prediction along with a confidence score, indicating whether the given content is real or fake. This comprehensive methodology improves detection efficiency and makes the system suitable for practical applications in media verification, cybersecurity, and misinformation control.

The proposed AI-Based Multimodal Deepfake Detection System processes both audio and news text to identify fake content effectively. Initially, the input audio (WAV/MP3) is preprocessed through noise removal and normalization, followed by feature extraction using Mel Spectrogram and MFCC techniques. These features are then passed into a Convolutional Neural Network (CNN) model, which generates an audio probability score represented as

P(audio)=CNN(Mel Spectrogram)

For text analysis, the system uses BART-MNLI classification along with linguistic pattern analysis to evaluate the authenticity of the given news content. It also performs real-time verification using NewsAPI. The text classification probability is given by

P(text)=BART-MNLI(Input Text)

Finally, both audio and text results are combined using a weighted confidence scoring mechanism to produce the final prediction. This improves the overall accuracy of the system and ensures reliable detection of deepfake content. The final confidence score is calculated as

C=w1·P(audio)+w2·P(text)

where CCC represents the final decision score, and w1,w2w_1, w_2w1,w2 are weights assigned to audio and text respectively. This combined approach enhances robustness and makes the system suitable for real-world applications

3. Regularization and Generalization

Regularization and generalization are important concepts in machine learning that help improve the performance of models on unseen data. Regularization is a technique used to prevent overfitting, where the model learns too much from the training data and fails to perform well on new data. It works by adding a penalty to the model's complexity, ensuring that the model does not become too sensitive to noise or minor variations in the data.Generalization refers to the ability of a model to perform well on new, unseen data after being trained on a specific dataset. A well-generalized model can accurately predict outcomes even when the input data is slightly different from the training data. Techniques such as dropout, L1 and L2 regularization, and proper dataset splitting (training, validation, testing) are used to achieve better generalization.In the proposed system, regularization techniques are applied to the CNN model to avoid overfitting during audio deepfake detection. This ensures that the model can generalize effectively and maintain high accuracy when tested on real-world audio and text data, improving the overall reliability of the system.

4. System Architecture

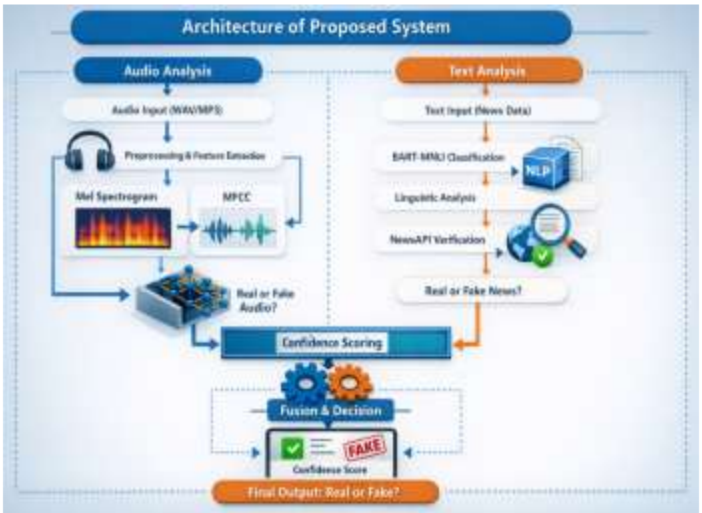

Fig. 2: AI-Based Multimodal DeepfakeDetection System for Audio and News Text

It is a well-organized designed flow where the whole process begins with providing information from the user and ends with the final output to the user.

The architecture of the AI-Based Multimodal Deepfake Detection System is designed to process both audio and text data in parallel for accurate detection. The system begins with user input, where audio files (WAV/MP3) and news text are provided through an interface. The audio input is sent to the audio analysis module, where preprocessing techniques such as noise removal and normalization are applied. Feature extraction methods like Mel Spectrogram and MFCC are then used to convert the audio signal into meaningful representations.

The extracted audio features are passed into a Convolutional Neural Network (CNN) model, which analyzes the patterns and classifies the audio as real or fake, generating a probability score. At the same time, the text input is processed in the text analysis module using Natural Language Processing techniques. BART-MNLI classification is applied to understand the context and authenticity of the news, followed by linguistic pattern analysis. The system also uses

NewsAPI to verify the news content with real-time trusted sources.
Finally, the outputs from both audio and text modules are combined in a fusion layer using a confidence scoring mechanism. This integration helps in making a more accurate and reliable final decision. The system then produces the final output, indicating whether the content is real or fake along with a confidence score, making the architecture efficient, robust, and suitable for real-world applications.

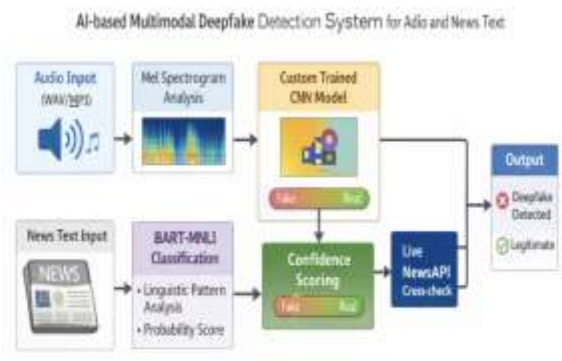

Fig. 3: Block Diagram of the AI-Based Multimodal Deepfake Detection System for Audio and News Text

The block diagram of the AI-Based Multimodal Deepfake Detection System illustrates the complete workflow of detecting fake audio and misleading news text using advanced AI techniques. The process starts with user input, where the system accepts audio files in WAV or MP3 format and corresponding news text. This dual-input approach enables the system to analyze multiple data types simultaneously, improving the overall detection accuracy.
In the audio analysis path, the input audio undergoes preprocessing and is converted into a Mel Spectrogram, which represents the frequency distribution of the signal over time. Additional features such as MFCC may also be extracted to capture important characteristics of the audio. These features are then fed into a custom-trained Convolutional Neural Network (CNN) model, which learns patterns associated with real and fake audio. The model processes these inputs and generates a probability score indicating the likelihood of the audio being genuine or manipulated.
Parallel to this, the text analysis path processes the news content using Natural Language Processing techniques. The system applies BART-MNLI classification to understand the semantic meaning and determine whether the text is true, false, or neutral. Linguistic pattern analysis is performed to detect common fake news indicators such as exaggerated language,

emotional tone, and repetition. Additionally, the system integrates NewsAPI to perform live cross-checking of the provided news with trusted sources, enhancing the reliability of the analysis
After processing both audio and text data, the results are sent to a fusion layer where a confidence scoring mechanism combines the probability scores from both modules. This integration ensures a more robust and accurate final decision by considering multiple perspectives. Finally, the system produces the output, clearly indicating whether the content is real or fake along with a confidence score. This comprehensive block diagram demonstrates an efficient and reliable architecture suitable for real-world deepfake detection applications.

5. Implementation

This system is an AI-based model that takes vehicle images and identifies damages on them, also predicts cost of repair based on that. It integrates a deep learning model and web application. The webapp is built using python, YOLOv5, OpenCV, NumPy, Flask. Many other libraries such as Base64, UUID, JSON, SQLite, requests etc are used for data processing and backend activities. The training set comprised of labeled data-set of vehicle damages (dents, scratches, cracks, breakages, broken parts) which was accumulated from Kaggle data sets and Google Colab with GPU enabled on GPU. Training, validation data set ratio is 80–20.
Images were resized and normalized as a pre-processing step to make the input clearer. Damage images were used in training with YOLOv5 and learned the damage and then going to put it as object detection with bounding box and confidence score. Annotation, development, and collection of the data were done through Label Studio, VS Code, and iCrawler respectively.
The trained model is then embedded into a web system, where users upload images of the vehicle through a React.js system.
The image is fed into the Flask system and detected, then severity classification and repair cost estimation are done using GPT-4o-mini. The results

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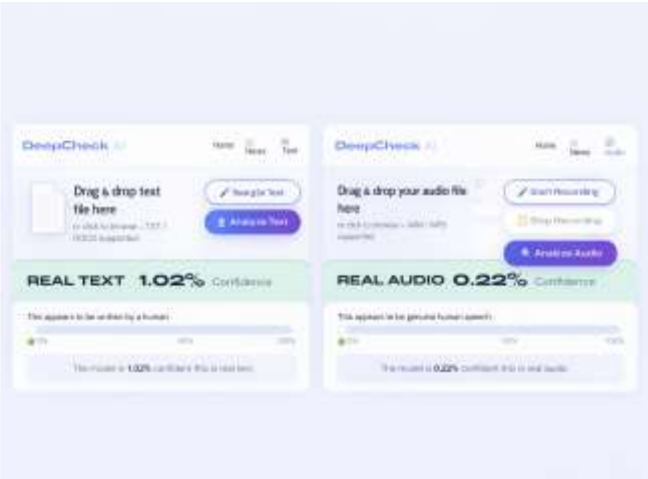
with highlighted damages are then shown to the users, and stored in SQLite database. This provides an affordable, fast and automated vehicle damage assessment system.

7.Experimental Results

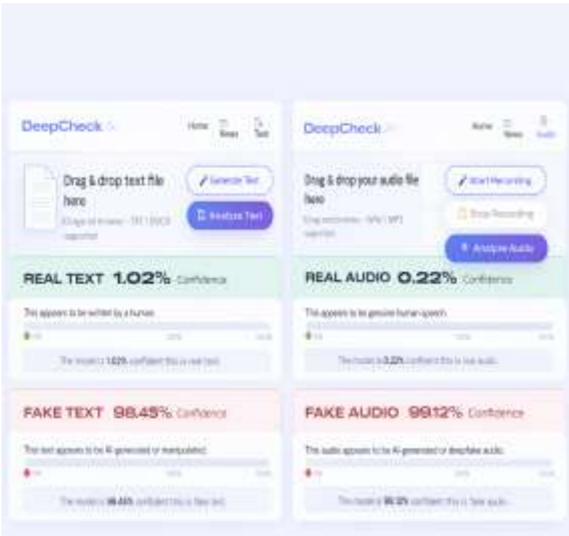
The proposed AI-Based Multimodal Deepfake Detection System was evaluated using the SceneFake dataset for audio and standard fake news datasets for text analysis. The audio model using Mel Spectrogram and CNN showed high performance in detecting fake audio, while the text module using BART-MNLI and linguistic analysis effectively identified fake news. The multimodal approach improved overall accuracy



The **DeepCheck AI system** provides an interface that allows users to analyze both text and audio content to determine whether it is genuine or AI-generated. In the text detection section, users can upload a file by dragging and dropping it into the upload area or by browsing their device. The system supports file formats such as **TXT and DOCX**. Once the file is uploaded, the user can select the **Analyze Text** option, which processes the content using machine learning techniques that examine linguistic patterns, sentence structures, and writing styles. Based on this analysis, the system displays the detection result. In the example shown, the result indicates **REAL TEXT with 1.02% confidence**, suggesting that the uploaded content appears to be written by a human and does not show strong indicators of AI-generated text.

Similarly, the system also includes an **audio detection module** that helps identify whether an audio clip is genuine human speech or AI-generated deepfake audio. Users can upload audio files in **WAV or MP3** formats or record audio directly using the **Start Recording** and **Stop Recording** options available in the interface. The model analyzes several acoustic features such as speech patterns, frequency distribution, tone variations, and voice modulation to determine authenticity. In the displayed result, the system classifies the uploaded audio as **REAL AUDIO with 0.22% confidence**, indicating that the analyzed audio appears to be genuine human speech rather than synthetic audio.

To make the results easier to interpret, the platform provides a **Detection Confidence Meter**, which visually represents the model's confidence level on a scale from **0% to 100%**. This meter helps users quickly understand how strongly the system believes the content is real or manipulated. Overall, the DeepCheck AI platform combines advanced artificial intelligence techniques with a simple and user-friendly interface, enabling users to efficiently verify the authenticity of both text and audio content and detect potential AI-generated or manipulated media.



The **DeepCheck AI system** also detects content that appears to be artificially generated or manipulated. In the **text detection module**, users can upload a text file by dragging and dropping it into the upload area or by browsing their device, with supported formats such as **TXT and DOCX**. After the file is uploaded, the system analyzes the content using machine learning techniques that evaluate writing patterns, vocabulary usage, sentence structure, and statistical features. Based on this analysis, the system may identify the content as **FAKE TEXT with 98.45% confidence**, indicating that the text likely contains characteristics of AI-generated or manipulated content rather than natural human writing.

Similarly, the **audio detection module** evaluates whether an uploaded audio file is genuine human speech or artificially generated deepfake audio. Users can upload **WAV or MP3** files or record audio directly through the **Start Recording** and **Stop Recording** options. The system analyzes acoustic features such as speech rhythm, frequency distribution, tone variation, and voice consistency to determine authenticity. In the fake detection result, the system classifies the audio as **FAKE AUDIO with 99.12% confidence**, suggesting that the analyzed audio likely contains characteristics associated with AI-generated or synthetic voice recordings.

The system also displays a **Detection Confidence Meter**, which visually represents the probability level on a scale from **0% to 100%**. This indicator helps users easily understand the strength of the model's prediction regarding whether the content is genuine or manipulated. By combining advanced artificial intelligence techniques with an intuitive interface, the **DeepCheck AI platform** effectively helps users identify potentially fake or AI-generated text and audio contentThe **DeepCheck AI system** uses advanced artificial intelligence and deep learning techniques to improve the accuracy of detecting manipulated content. In the **text detection module**, the system analyzes several linguistic features such as grammar patterns, sentence complexity, vocabulary distribution, and contextual consistency. These features help the model identify whether the content follows natural human writing behavior or patterns typically produced by AI text generation models. By evaluating these characteristics, the system can effectively distinguish between genuine human-written content and artificially generated text.In addition to text analysis, the system also performs **audio deepfake detection** using audio signal processing techniques. The audio file is first converted into visual and numerical representations such as **Mel Spectrograms and MFCC (Mel-Frequency Cepstral Coefficients)**, which capture the important characteristics of speech signals. These extracted features are then analyzed by a trained **Convolutional Neural Network (CNN)** model to detect abnormalities in voice patterns, pitch variations, and spectral features that commonly appear in synthetic or manipulated audio recordings.

8.GAPS IDENTIFIED IN EXISTING RESEARCH

Existing research on deepfake detection mainly focuses on single data types such as audio or text, which limits overall detection accuracy. Many models require large labeled datasets, making training difficult and time-consuming. Additionally, most systems struggle to detect unseen or newly generated deepfakes, reducing their effectiveness in real-world scenarios.

Another major gap is the lack of real-time verification, as many approaches do not integrate live data sources for validation. High computational complexity and scalability issues also affect practical implementation. Furthermore, limited use of multimodal approaches reduces the reliability of predictions, highlighting the need for integrated systems that combine audio and text analysis.

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Despite significant advancements in deepfake detection, several limitations still exist in current research. Most existing approaches rely on single-modality analysis such as only audio or only text, which reduces the overall effectiveness of detection systems. These methods often fail to capture the complete

8.Future Enhancements Suggested in the Literature

Future research in deepfake detection focuses on improving accuracy, robustness, and real-time performance of detection systems. One of the key enhancements is the adoption of advanced multimodal approaches that integrate audio, text, image, and video data for more comprehensive analysis. This helps in capturing multiple aspects of manipulated content and improves detection reliability.

Another important direction is the development of lightweight and efficient models that reduce computational complexity and enable real-time deployment. Researchers also suggest using larger and more diverse datasets to improve model generalization and handle unseen deepfake techniques effectively. Incorporating explainable AI methods can further help in understanding model decisions and increasing user trust.

Additionally, future systems may integrate more reliable real-time verification tools and APIs to cross-check information from trusted sources. Continuous model updating, adaptive learning, and improved fusion techniques are also recommended to enhance system performance and make deepfake detection systems more scalable and practical for real-world applications.

Future studies also emphasize the need for developing real-time deepfake detection systems that can automatically analyze audio and news data from online platforms and social media networks. Such systems could help identify fake information quickly and prevent its widespread distribution. In addition, training models with larger and more diverse datasets that include different languages, speaking styles, accents, and news sources can significantly improve the generalization capability of the detection system.

Another potential enhancement is the incorporation of explainable artificial intelligence (XAI) methods. These techniques can help explain why a model classified a particular piece of audio or news text as fake or real. Providing transparent explanations will increase user trust and make the system more useful for journalists, researchers, and fact-checking organizations.

Researchers also suggest strengthening deepfake detection systems to resist adversarial attacks and increasingly sophisticated manipulation techniques. As deepfake generation technology continues to evolve, detection systems must also be regularly updated with new training data and improved algorithms. Future work may also focus on multilingual fake news detection, enabling the system to detect misinformation across multiple languages and regions.

Finally, future enhancements include deploying the deepfake detection system on cloud platforms, web applications, or mobile devices to make it widely accessible. Integrating the system with social media monitoring tools, browser extensions, or news verification platforms can help users quickly verify the authenticity of audio clips and news articles. These improvements will contribute to building more reliable and scalable deepfake detection systems in the future

9. Conclusion

AI-Based Multimodal Deepfake Detection System for Audio and News Text provides an effective approach to identify manipulated audio and misleading news content using artificial intelligence techniques. The system utilizes audio feature extraction methods such as Mel Spectrograms and MFCC along with a Convolutional Neural Network (CNN) model to analyze audio signals and detect deepfake patterns. For news text analysis, natural language processing techniques help in identifying fake or misleading information. By combining audio and text analysis, the proposed system improves the reliability of detecting fake digital content.

The multimodal approach plays an important role in increasing detection accuracy because it examines multiple types of data instead of relying on a single source. This helps the system identify inconsistencies and patterns that are commonly present in deepfake audio and fake news articles. The model is capable of processing WAV and MP3 audio formats and provides a probability score indicating whether the content is real or fake, making it useful for practical applications.

Overall, the proposed system demonstrates the potential of artificial intelligence and deep learning in addressing the growing problem of deepfakes and misinformation. With further improvements such as larger datasets, advanced models, and real-time implementation, this system can become a powerful tool for journalists, researchers, and online platforms to verify the authenticity of digital content and reduce the spread of fake information.

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