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**Mini Project Report**

**Unmasking Illusion – AI Powered**

**Deepfake Video and Image Detection**

***Submitted by***

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***In partial fulfillment for the award of the degree of***

UNIVERSITY

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## BACHELOR OF ENGINEERING/ TECHNOLOGY

***in***

**Computer Science and Design**

**G H Patel College of Engineering and Technology**

## The Charutar Vidya Mandal (CVM) University, Vallabh Vidyanagar - 388120

**March, 2025**

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**B.Tech Computer Engineering**

**CERTIFICATE**

This is to certify that **Hitarth Soni (12202130501027)** and **Jayan Tandel (12202130501030)** have submitted the Mini Project report in partial fulfillment for the degree of B.Tech in **Computer Science and Design, G H Patel College of Engineering and Technology** at The Charutar Vidya Mandal (CVM) University, Vallabh Vidyanagar during the academic year 2024 - 25.

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**DECLARATION**

We, **Hitarth Soni (12202130501027)** and **Jayan Tandel (12202130501030),** hereby declare that the Mini Project report submitted in partial fulfillment for the degree of B.Tech in **Computer Science and Design, G H Patel College of Engineering and Technology**, The Charutar Vidya Mandal (CVM) University, Vallabh Vidyanagar, is a bonafide record of work carried out by us under the supervision of **Dr. Kinjal Joshi** (Internal Guide) and that no part of this report has been directly copied from any students' reports or taken from any other source, without providing due reference.

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**Abstract**

Over the last few decades, rapid progress in AI, machine learning, and deep learning has led to the development of various tools for manipulating multimedia. While these advancements have contributed to legitimate applications in entertainment, education, and research, they have also been misused for unethical and malicious activities. The rise of deepfake technology has resulted in the creation of highly realistic fake videos and images, which have been exploited for spreading misinformation, political manipulation, and cybercrimes. To counter the threats posed by deepfakes, researchers have proposed multiple detection techniques, including deep learning-based methods, classical machine learning approaches, statistical techniques, and blockchain-based solutions. Among these, deep learning-based methods, particularly convolutional neural networks (CNNs), have shown superior performance in identifying synthetic media. In this project, we develop a deepfake detection system utilizing a pretrained CNN model to analyze images and videos for inconsistencies in texture, facial artifacts, and motion distortions. By leveraging transfer learning, our approach enhances detection accuracy while optimizing computational efficiency. The system is trained on a dataset containing real and deepfake media, ensuring its effectiveness in identifying manipulated content. Our research contributes to the growing efforts in safeguarding digital media authenticity and mitigating the risks of AI-generated misinformation.

**Unit I**

**Introduction**

**1.1 Brief Discussion**

Deepfake technology is rapidly evolving, raising concerns in cybersecurity, media integrity, and personal privacy. These AI-generated synthetic images and videos can deceive audiences by portraying events or statements that never occurred. The growing sophistication of deepfake algorithms necessitates advanced detection mechanisms to safeguard authenticity in digital content.

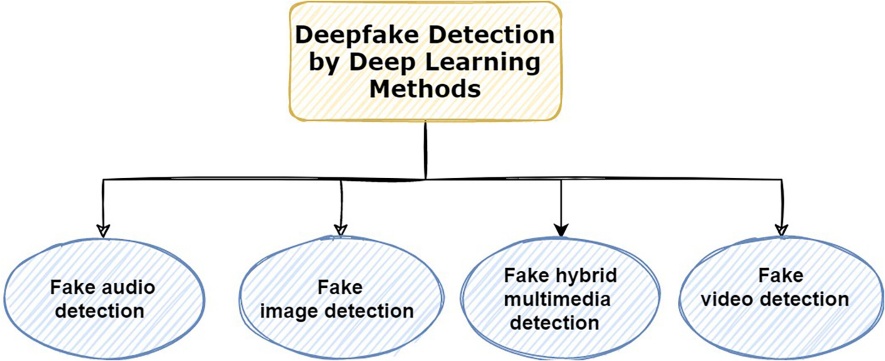


Figure 1.1: Different Types of Deepfake

Detection Techniques

Deepfake detection has become a critical area of research due to the increasing misuse of AI-generated media. The given image outlines the key categories of deepfake detection, highlighting four major approaches:

1. **Fake Audio Detection:** Deepfake audio detection focuses on identifying synthetic voices generated using AI-based models like WaveNet, Tacotron, and Voice Cloning. These models can replicate a person’s voice with high accuracy, making it essential to analyze speech patterns, voice modulations, and inconsistencies in audio signals.
2. **Fake Image Detection:** AI-generated images, such as deepfake faces and GAN-generated visuals, are detected by examining pixel-level anomalies, facial artifacts, and inconsistencies in textures. CNN-based models like XceptionNet and EfficientNet are commonly used to classify real vs. fake images.
3. **Fake Hybrid Multimedia Detection:** Some deepfake content consists of a mix of manipulated images, audio, and videos. Hybrid detection techniques leverage multimodal analysis, combining facial recognition, lip-sync analysis, and speech synthesis evaluation to identify inconsistencies in different media types.
4. **Fake Video Detection:** Video deepfakes often involve face swapping, motion inconsistencies, and unnatural facial expressions. Detection models analyze temporal and spatial inconsistencies across video frames, using techniques like recurrent neural networks (RNNs), optical flow analysis, and frame-by-frame CNN evaluations.

In this project, we focus on detecting **deepfake images and videos**. With the rapid advancement of AI-generated media, distinguishing between real and manipulated content has become increasingly important. Our system leverages pretrained convolutional neural networks (CNNs) to analyze patterns and inconsistencies in multimedia files. By identifying subtle artifacts and distortions, the model enhances the accuracy of deepfake detection. The project aims to contribute to the ongoing efforts in ensuring media authenticity and combating misinformation in the digital age.

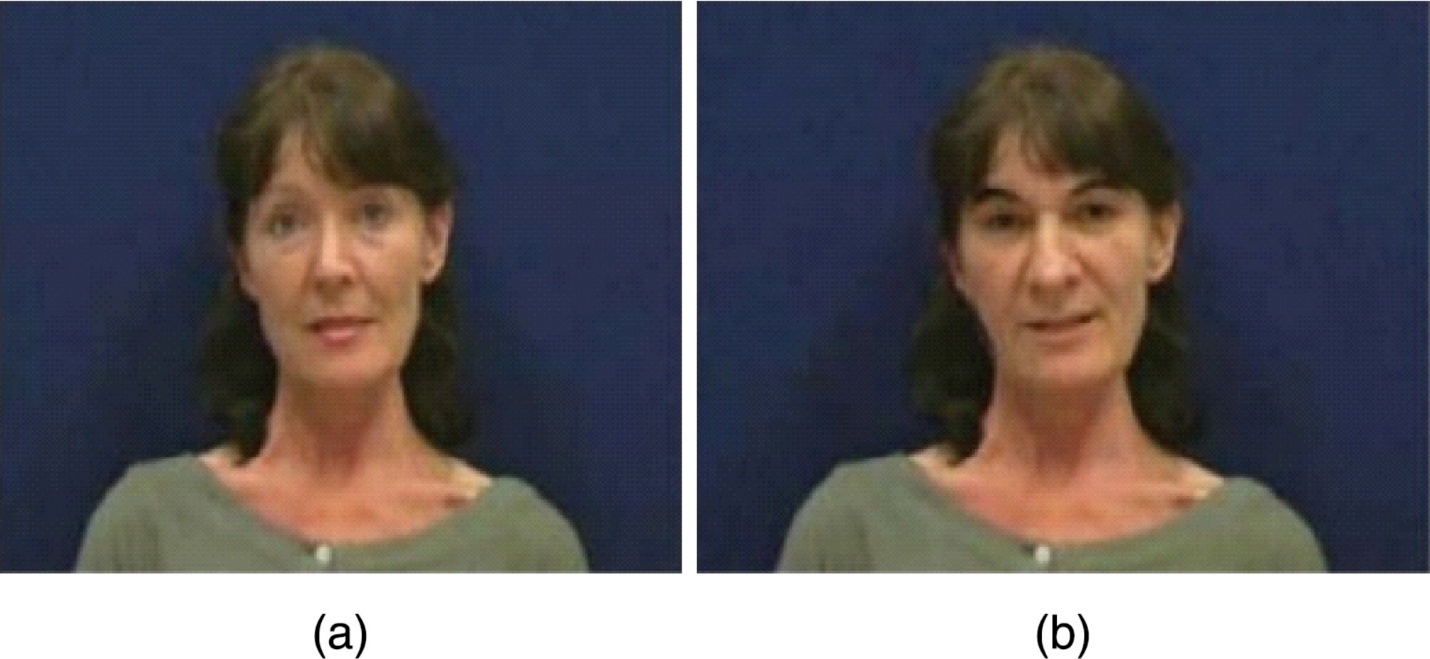


Figure 1.2: A person’s (a)real and (b)fake Image

Deepfake technology enables the manipulation of visual and auditory content using AI-based techniques such as Generative Adversarial Networks (GANs) and deep learning. Traditional editing techniques, such as splicing, inpainting, and copy-move, have been widely used to alter images and videos. However, deepfake technology advances these manipulations by achieving a higher level of realism, often making detection challenging. With the ability to synthesize entire media assets from scratch, deepfakes pose serious risks, including misinformation, identity fraud, and the spread of deceptive content. The increasing accessibility of deepfake tools highlights the urgent need for robust detection mechanisms to safeguard digital integrity.

**1.2 Objectives of the Project**

1. **Deepfake Image and Video Detection**

Develop a deep learning-based model to accurately detect deepfake images and videos by identifying inconsistencies in media.

1. **Enhanced Feature Extraction**

Utilize pretrained convolutional neural networks (CNNs) to improve feature extraction and classification accuracy for detecting synthetic content.

1. **Robust Model Performance**

Enhance detection capabilities through data augmentation, adversarial training, and optimization techniques to improve model generalization.

1. **User Friendly System**

Implement an intuitive and accessible interface for real-time deepfake analysis, ensuring ease of use for both technical and non-technical users.

1. **Evaluation and Performance Matrix**

Assess the model's effectiveness using standard evaluation metrics such as accuracy, precision, recall, and F1-score to ensure reliability.

**1.3 Scope and Significance of the Project**

* This project focuses on identifying manipulated images and videos using deep learning techniques, helping to differentiate between real and synthetic content.
* By leveraging pretrained CNN models, the system enhances the accuracy of detecting deepfake-specific artifacts such as texture inconsistencies and unnatural facial expressions.
* The system is designed to provide quick and accurate deepfake detection, making it suitable for media forensics, cybersecurity, and misinformation prevention.
* A well-designed interface ensures accessibility for researchers, security professionals, and general users to analyze media authenticity efficiently.
* By detecting AI-generated fake content, this project contributes to minimizing the spread of misinformation, identity fraud, and malicious manipulations.
* The deepfake detection system supports digital security efforts by identifying manipulated media in fraud cases, cybercrimes, and forensic investigations.
* This project aids in improving deepfake detection techniques, enhancing existing AI models, and supporting future research in artificial media detection.

**Unit 2**

**Background and Approach**

In this section, we have detailed about deepfake detection systems and its different approaches. Literature in the area is also reviewed.

**2.1 Background**

Deepfakes, synthetic media generated using deep learning techniques, have raised significant concerns due to their potential misuse in spreading misinformation, perpetrating fraud, and compromising personal privacy. The rapid advancement of deep learning has made it increasingly challenging to distinguish between authentic and manipulated content. To address these challenges, researchers have been developing various detection methods, with deep learning-based approaches showing promising results.

**2.2 Machine Learning Used**

In our project, we propose a deepfake detection system that leverages deep learning techniques to identify manipulated media content. The key components of our approach include:

1. **Model Selection**: We employ convolutional neural networks (CNNs), which are effective in capturing spatial features in images and videos. By utilizing pretrained models, we enhance the system's ability to detect subtle artifacts indicative of deepfakes.
2. **Data Preprocessing**: To improve the model's robustness, we perform data augmentation techniques such as rotation, flipping, and scaling. This ensures that the model generalizes well to various types of media manipulations.
3. **Feature Extraction**: The CNN model extracts intricate features from the input media, focusing on inconsistencies in texture, facial landmarks, and other anomalies that are characteristic of deepfakes.
4. **Classification**: The extracted features are fed into a classification layer that determines the likelihood of the media being a deepfake. We utilize metrics such as accuracy, precision, recall, and F1-score to evaluate the model's performance.

By integrating these components, our system aims to provide a reliable and efficient solution for detecting deepfakes, thereby contributing to the integrity and authenticity of digital media.

**2.3 Preprocessing**

To effectively detect deepfake images and videos, preprocessing plays a crucial role in preparing the input data for analysis. The preprocessing pipeline consists of the following steps:

Figure 2.1: Preprocessing

1. **Splitting Video into Frames**

The input video is divided into individual frames. This conversion allows the model to analyze each frame separately, improving the detection of inconsistencies that may not be noticeable in continuous motion.

1. **Face Detection**

A face detection algorithm, such as MTCNN, Haar cascades, or DLIB, is applied to each frame to identify human faces. Bounding boxes are drawn around detected faces to focus on the relevant regions..

1. **Cropping the Face**

Once the face is detected, it is cropped from the frame, removing unnecessary background details. This ensures that the model focuses exclusively on facial features, which are critical for deepfake detection.

1. **Creating a Face-Cropped Video**

The extracted face images from all frames are compiled into a new video. This transformation helps maintain consistency in face tracking and enhances the effectiveness of deepfake detection algorithms.

**2.4 Limitations**

Despite the advancements in our deepfake detection system, several limitations persist:

1. **Generalization to Unseen Deepfake Techniques:**

The system may struggle to detect deepfakes generated by novel methods not represented in the training data, limiting its adaptability to emerging manipulation techniques.

1. **Real-Time Processing Constraints:**

High computational demands can hinder real-time detection capabilities, making it challenging to analyze live video streams efficiently.

1. **Robustness to Adversarial Attacks:**

The system's susceptibility to adversarial attacks poses a significant challenge, as malicious actors can exploit these vulnerabilities to bypass detection mechanisms.

1. **Dependence on High-Quality Data:**

The accuracy of the detection system heavily relies on the quality and diversity of the training dataset. Insufficient or biased data can lead to reduced performance in real-world scenarios.

1. **Ethical and Privacy Considerations:**

The deployment of deepfake detection technologies must be balanced with ethical considerations, ensuring that such systems do not infringe upon individual privacy rights or lead to unintended consequences.

**Unit 3**

**Proposed Solution**

**3.1 Solution Discussion**

In this project, we focus on **image and video detection**. The system processes media content to identify inconsistencies by analyzing **spatial features, temporal artifacts, and deepfake-specific patterns**. Our approach leverages convolutional neural networks (CNNs) and transfer learning to **enhance detection accuracy**. The detection pipeline includes preprocessing input media, extracting essential features, applying classification models, and providing interpretability of detected fake regions. By integrating **state-of-the-art pretrained models**, we ensure robust performance in detecting manipulated images and videos while maintaining computational efficiency.

The **AI-Powered Deepfake** Video and Image Detection System is designed to analyze digital media for signs of manipulation using advanced deep learning techniques.

Below are the **key features** of the system:

1. **Deep Learning-Based Detection**:

* Utilizes the **DeepFake-Detector** model, a **CNN-based** deepfake detection architecture.
* Trained on diverse datasets, including **FaceForensics++, Celeb-DF, and DFDC**, to improve detection accuracy.

1. **Image and Video Analysis**:

* Processes both **images and video frames** to detect deepfake alterations.
* Extracts frames from videos for individual analysis before providing a final classification.

1. **Feature Extraction for Fake Detection**:

* Identifies **facial artifacts, texture inconsistencies, unnatural blurring, and manipulation patterns**.
* Uses deep learning to analyze spatial and temporal inconsistencies in media.

1. **Real-Time Processing**:

* Optimized for fast inference using **efficient CNN models**, making detection viable in real-world applications.
* Enables users to analyze media files within seconds.

1. **User-Friendly Interface**:

* **Simple UI** for uploading images or videos for analysis.
* Displays classification results with probability scores indicating the likelihood of manipulation.

1. **Transfer Learning for Improved Accuracy:**

* Fine-tunes a **pretrained deepfake detection model** using additional datasets to improve robustness.
* Uses transfer learning techniques to adapt to newer deepfake generation methods.

1. **Robust Evaluation Metrics:**

* Assesses performance using **accuracy**, **precision**, **recall,** and **F1-score.**
* Utilizes **AUC-ROC curve analysis** for model validation and fine-tuning.

1. **Scalability and Adaptability:**

* Can be integrated into cybersecurity, journalism, and forensic applications to detect media manipulation.
* Future improvements can include **real-time API integration** and **cloud-based deployment.**

**2.2 Model Selection and Training**

For this deepfake detection system, we have selected a pretrained deep learning-based model hosted on **Hugging Face**. The model was chosen for its robust performance in identifying manipulated media using advanced convolutional neural network (CNN) architectures.

Below are the key aspects of the model selection and training process:

Model Selection:

1. Pretrained Model:

* The **DeepFake-Detector is a transformer-based model** that leverages CNNs and deep learning techniques to identify manipulated media.
* It is trained on a diverse set of real and fake video datasets, ensuring its effectiveness in distinguishing between authentic and synthetic media.

1. Feature Extraction Capabilities:

* The model detects inconsistencies in facial artifacts, texture mismatches, and unnatural transitions in videos.
* It processes input frames using spatial and temporal feature analysis to enhance accuracy.

1. Efficiency and Performance:

* The model is optimized for **real-time inference**, making it suitable for online applications.
* It provides high precision and recall in detecting deepfakes across various datasets.

Training Process:

1. Dataset Used:

* The model was trained on **multiple deepfake datasets** such as **FaceForensics++, Celeb-DF, and DFDC (DeepFake Detection Challenge dataset)**.
* The dataset consists of labeled **real and fake videos**, allowing the model to learn critical features of deepfake content.

1. Preprocessing Steps:

* **Frame Extraction:** Videos are converted into individual frames for detailed analysis.
* **Face Detection and Cropping:** Faces are detected using **MTCNN or OpenCV** and then cropped for consistency.
* **Normalization:** Pixel values are scaled to a standard range to improve model efficiency.

1. Training Strategy:

* **Binary Classification Approach:** The model is trained to classify media as either **real or fake**.
* **Loss Function:** Uses **Binary Cross-Entropy Loss** to optimize classification accuracy.
* **Optimizer:** Utilizes **Adam optimizer** with learning rate scheduling for better convergence
* **Data Augmentation:** Techniques such as **rotation, blurring, noise injection, and color jittering** are used to enhance model robustness.

1. Evaluation Metrics:

* **Accuracy, Precision, Recall, F1-score**: Evaluates model performance in distinguishing real vs. fake media.
* AUC-ROC Curve**:** Measures the ability of the model to differentiate between real and fake instances.

**3.4 Literature Review**

The proliferation of deepfake technology has raised significant concerns regarding the authenticity of digital media. To address these challenges, researchers have developed various detection techniques, primarily focusing on deep learning-based methods. This literature review examines key studies in deepfake detection, highlighting their methodologies, datasets, and performance metrics.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Study** | |  | | --- | | **Methodology** |  |  | | --- | |  | | **Dataset** | | **Performance Metrics** | | --- |  |  | | --- | |  | |
| Rossler et al. (2019) | Introduced FaceForensics++, a dataset for detecting manipulated facial images using Convolutional Neural Networks (CNNs). | FaceForensics++ | Achieved 90.17% accuracy in detecting facial manipulations. |
| Nguyen et al. (2019) | Proposed Capsule Networks for deepfake detection, capturing spatial relationships between facial features. | Self-collected dataset | Demonstrated improved robustness against various manipulations. |
| Heidari et al. (2024) | Conducted a systematic review of deep learning methods for deepfake detection, categorizing techniques into image, video, audio, and multimodal approaches. | Various datasets | Provided a comprehensive analysis of advantages and challenges in existing methods. |
| Croitoru et al. (2024) | Surveyed deepfake generation and detection techniques, including recent developments like diffusion models and Neural Radiance Fields. | Multiple datasets | Identified limitations in current detectors and proposed future research directions. |
| Wang et al. (2022) | Reviewed deepfake detection studies from a reliability perspective, focusing on transferability, interpretability, and robustness. | Public benchmark datasets | Highlighted the need for reliable evidence in real-life applications. |

Table 3.1 Literature Review

**Unit 4**

**System Architecture & Flow**

The system architecture of our deepfake detection model follows a structured pipeline consisting of preprocessing, model training, and prediction phases. The workflow is divided into two major flows:

* **Training Flow** (black arrows)
* **Prediction Flow** (red arrows)

Fig 4.1 System Architecture

**4.1 Architecture:**

The architecture of the deepfake detection system is designed as a structured pipeline that integrates preprocessing, model training, and prediction phases to effectively identify manipulated video content. The system is divided into two primary workflows: the **Training Flow** (represented by black arrows) and the **Prediction Flow** (represented by red arrows). This modular design ensures scalability, efficiency, and adaptability to real-world applications.

The architecture begins with the **Upload Video** module, where users input video files for analysis. These videos are sourced from a dataset containing both real and fake (deepfake) videos.

The system then proceeds through the following key components:z

1. **Preprocessing Module:**

* **Splitting Video into Frames:** The uploaded video is decomposed into individual frames to enable frame-by-frame analysis.
* **Face Detection:** A face detection algorithm (e.g., MTCNN, Haar cascades, or DLIB) identifies human faces within each frame, drawing bounding boxes around them.
* **Face Cropping:** Detected faces are cropped to remove background noise, focusing the analysis on facial regions critical for deepfake detection.
* **Saving the Face-Cropped Video**: The cropped face images are compiled into a new video, ensuring consistency in face tracking across frames.

1. **Processed Dataset:**

* The output of the preprocessing module is a dataset containing only face-cropped videos. This dataset serves as the foundation for both training and prediction workflows.

1. **Data Splitting and Loading**

* **Data Splitting:** The processed dataset is split into training and test subsets to facilitate model training and evaluation.
* **Data Loader:** This component loads the training and test videos along with their corresponding labels (real or fake) for model processing.

1. **Deepfake Detection Model**:

* **LSTM (Long Short-Term Memory):** Employed for video classification, this recurrent neural network analyzes temporal dependencies across frames to detect motion distortions and unnatural transitions characteristic of deepfakes.

1. **Model Evaluation**:

* **Confusion Matrix:** Used to assess the model's performance by comparing predicted labels (real/fake) against actual labels, providing insights into accuracy, precision, recall, and F1-score.
* **Export Trained Model:** After evaluation, the trained model is saved for future use in the prediction phase

This architecture aligns with the objectives of your project by enhancing detection accuracy through feature extraction and temporal analysis, while optimizing computational efficiency using pretrained models like the **DeepFake-Detector** from Hugging Face

**4.2 Prediction Workflow:**

The prediction workflow (highlighted in red arrows) is a streamlined process for analyzing new video inputs:

Fig 4.2 Prediction Workflow

1. **Upload Video:** Users upload a video file to be analysed.
2. **Preprocessing:** The video undergoes the same preprocessing steps (splitting into frames, face detection, cropping, and saving as a face-cropped video) to prepare it for the model.
3. **Load Trained Model:** The pre-trained Deepfake Detection Model (LSTM for classification) is loaded.
4. **Classification:** The model processes the pre-processed video, classifying it as REAL or FAKE based on detected inconsistencies.
5. **Output**: The final result is presented to the user, indicating the likelihood of the video being a deepfake

This workflow ensures quick and accurate detection, making it user-friendly and suitable for real-time applications.

**4.3 Technology Stack**

* **Programming Language**: Python, React.
* **Backend**: Django(Framework), Supabase (for user authentication and database storage)
* **Machine Learning & NLP**: Python (for **image** and **video** detection)
* **Database**: Supabase (stores user data, interests, and news articles)

**Unit 5**

**Conclusion**

**Conclusion**

The "Unmasking Illusion – AI Powered Deepfake Video and Image Detection" project successfully developed an effective system to identify manipulated media using the pretrained DeepFake-Detector model from Hugging Face. By integrating feature extraction and LSTM for video classification, the system accurately detects deepfake artifacts through a streamlined pipeline of preprocessing, training, and prediction. It achieves its goals of robust performance, user-friendliness, and scalability for applications in media forensics and cybersecurity, contributing to the fight against AI-generated misinformation despite challenges like unseen deepfake techniques and real-time constraints.

**Future Scope**

Future enhancements for the deepfake detection system include integrating advanced AI techniques like diffusion models to counter evolving deepfake methods, deploying real-time APIs and cloud solutions for broader platform integration, and improving generalization with diverse datasets. Enhancing adversarial robustness, enabling multimodal detection for audio-video hybrids, and prioritizing ethical privacy measures will strengthen reliability. Additionally, adding multi-language support, optimizing for low-latency real-time processing, and incorporating accessibility features like voice commands can make the system more inclusive and efficient, ensuring its relevance in combating digital misinformation.

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