DeepGuard: Fake Video Detention

Dr P Sumalatha, Saisree Kalyankar, Sharvani Nimmakanti
[1] Assistant Professor, Department Of Cse, Bhoj Reddy Engineering College For Women, India.
[2,3]B. Tech Students, Department Of Cse, Bhoj Reddy Engineering College For Women, India.

ABSTRACT
The proliferation of deepfake technology has raised serious concerns across various domains, from political misinformation to personal defamation. Deepfakes—AI-generated synthetic videos—can closely mimic real individuals, making them a powerful tool for deception. The increasing realism and accessibility of deepfake generation tools have created an urgent need for reliable detection mechanisms. To address this challenge, this project proposes DeepGuard, a hybrid deep learning-based system that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for effective fake video detection. The proposed system utilizes a ResNeXt-based CNN for spatial feature extraction from individual video frames and an LSTM-based Recurrent Neural Network to analyze temporal inconsistencies across frames. By training on a diverse set of benchmark datasets such as FaceForensics++, Celeb-DF, and the DeepFake Detection Challenge (DFDC), DeepGuard demonstrates strong generalization capabilities. This dual approach ensures accurate detection of both replacement and reenactment deepfakes. The system also supports real-time analysis, enabling its deployment in live video environments such as social media platforms. Compared to traditional methods, DeepGuard achieves higher detection accuracy, better scalability, and lower computational overhead, making it suitable for real-world applications. Through comprehensive evaluation, DeepGuard has proven effective in identifying subtle artifacts and unnatural motion patterns typical in manipulated videos, offering a robust and scalable solution to combat the evolving threat of deepfakes.

1-INTRODUCTION

The advent of deepfake technology, enabled by significant advancements in computational power and deep learning, has revolutionized the creation of AI-synthesized videos. Deepfakes—manipulated videos that are nearly indistinguishable from authentic footage—pose a growing threat across multiple sectors, from political manipulation and misinformation to personal exploitation and defamation. These AI-generated videos can easily be weaponized to spread false information, stage fake events, or even blackmail individuals. The sophistication and realism of deepfakes make them a serious concern for both individuals and society as a whole, necessitating the development of effective detection systems.This project presents a novel deep learning-based approach to detect AI-generated fake videos, using the combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks.

Existing System

Current deepfake detection techniques have made significant strides, yet many of them face limitations in detecting complex manipulations or subtle differences between real and fake videos. Existing systems generally focus on one of two detection methods: frame-level analysis or temporal inconsistency analysis. However, combining both spatial and temporal features in a unified model remains an ongoing challenge

Proposed System

The proposed system **Deep Learning-Based Fake Video Detection Using CNN-LSTM Architectures**, seeks to address the limitations of existing methods by leveraging a combination of advanced deep learning techniques, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. This approach is designed to overcome the challenges of detecting both replacement and reenactment deep fakes with higher accuracy and efficiency.

2-REQUIREMENT ANALYSIS

Functional Requirements

User Module

The User Module allows end-users to interact with the DeepGuard system for fake video detection.

Login/Logout: Users must log in to gain access to the system and log out securely after use.

Video/Image Submission: Users can upload media files (video or image) to be analyzed by the deepfake detection system.

Result Reporting: After analysis, users receive a binary classification output (Real or Fake) along with a confidence percentage, indicating the likelihood of manipulation.

Non-Functional Requirements

Portability: The system must be capable of running on various platforms with minimal configuration, ensuring accessibility across devices.

Reliability: DeepGuard must maintain high accuracy across different media formats and datasets, ensuring consistent results.

Performance: The system should perform predictions efficiently to support real-time or near real-time detection, especially for social media or live applications.

Security: All data, especially user-uploaded content, must be handled securely. Access control mechanisms should be implemented to prevent misuse or manipulation of the system.

Software Requirements

The software environment used to build and deploy the fake video detection system includes:

Operating System: Windows 10

Programming Language: Python

IDE: PyCharm / Jupyter Notebook

Frameworks and Libraries:

Flask (for web frontend)

Bootstrap (for UI responsiveness)

TensorFlow and Keras (for building and running deep learning models)

Hardware Requirements

Minimum hardware resources required to develop and run the system:

Processor: Intel i3 or higher

RAM: 4 GB minimum (8 GB recommended for training models)

Hard Disk: 500 GB (including space for datasets and temporary video storage)

3.DESIGN

Project architecture represents number of components we are using as a part of our project and the flow of request processing i.e. what components in processing the request and in which order. An architecture description is a formal description and representation of a system organized in a way that supports reasoning about the structure of the system. Architecture is of two types. They are

Software Architecture

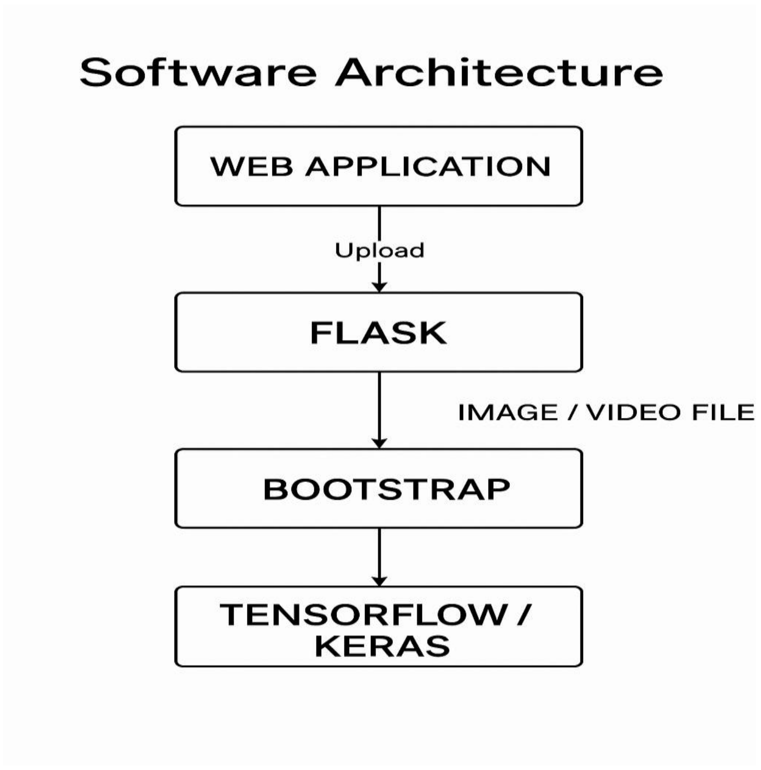


Fig.3.1 Software Architecture

Technical Architecture

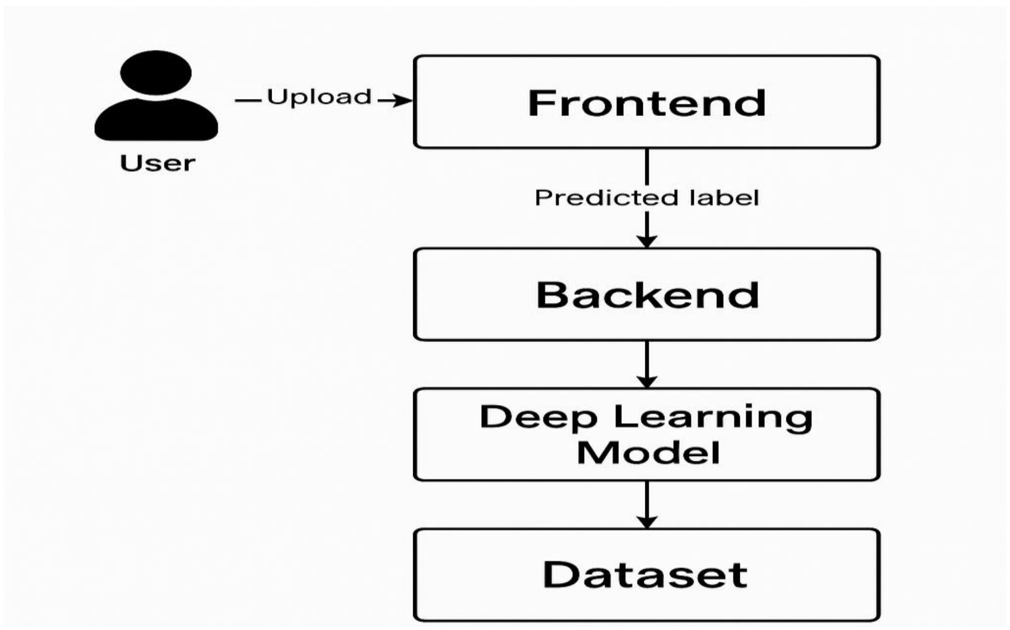


Fig.3.2 Technical Architecture

4-IMPLEMENTATION

HTML

HTML (HyperText Markup Language) is used to create the structure of the DeepFake Detector web interface. It defines the layout and content for user registration, login, and video/image upload forms. HTML tags are used to structure elements like buttons, text fields, and headings, ensuring a clear and intuitive interface for users. This forms the backbone of the frontend, enabling users to interact with the system.

CSS

CSS (Cascading Style Sheets) is used to style the HTML content and enhance the visual appearance of the web application. It is responsible for creating a responsive and user-friendly design through the use of Bootstrap. CSS handles layout structuring, color schemes, font styles, spacing, and animations, ensuring that the application looks modern and is easily navigable on various devices.

JavaScript

JavaScript is used to add interactivity and dynamic behavior to the web pages. It handles client-side validations, real-time feedback, form controls, and user interaction events. JavaScript ensures smooth transitions, loading indicators, and dynamic content rendering, improving the user experience during media uploads and result displays.

Python

Python is the core programming language used for building the backend and implementing the deep learning models. It provides the infrastructure to process user-uploaded media files, perform preprocessing, and pass them to the detection models. Python's simplicity and extensive libraries make it ideal for tasks such as file handling, image/video processing, model prediction, and system integration.

Flask

Flask is a lightweight Python web framework used to build the backend of the application. It acts as the bridge between the frontend and the deep learning models. Flask handles HTTP requests, routes them to the appropriate processing functions, and returns the prediction results to the user interface. It also integrates seamlessly with TensorFlow/Keras and supports secure file uploads and session management.

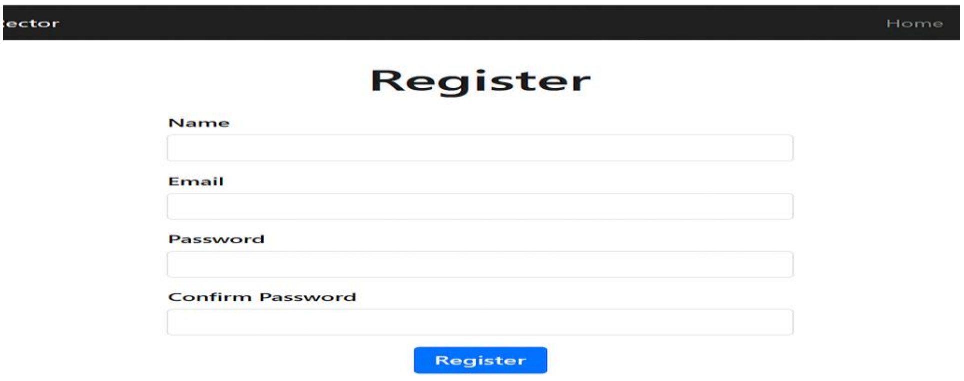
TensorFlow / Keras

TensorFlow and Keras are used for building and running the deep learning models—specifically CNN for spatial analysis and CNN-LSTM for temporal video frame analysis. The models process each uploaded media file and return a binary classification (Real or Fake) along with a confidence percentage. These frameworks provide high-level APIs and tools for training, evaluating, and deploying machine learning models efficiently.

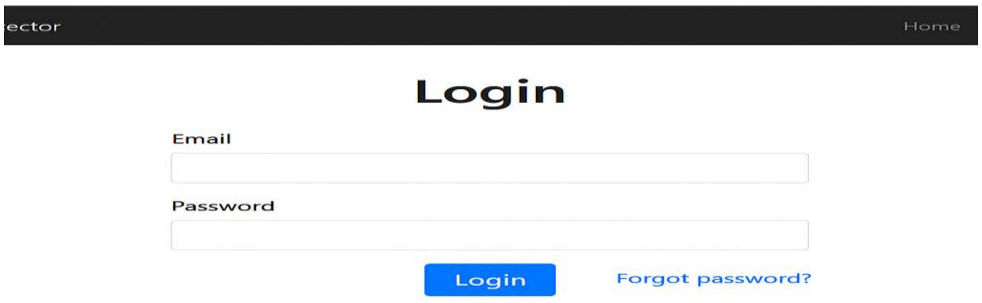
SQLite

SQLite is a lightweight, serverless database used for storing user information, upload history, and model prediction logs. It supports fast, reliable local storage of data and is well-suited for small-scale applications. Flask integrates easily with SQLite for performing CRUD operations like user login, storing file metadata, and tracking prediction results.

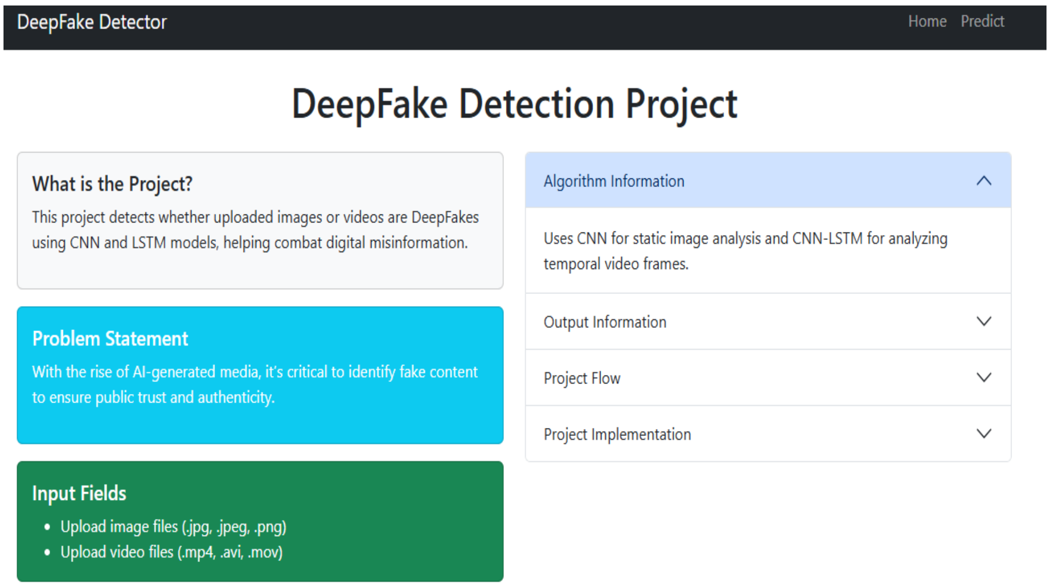
5-SCREENSHOTS


ector
Home
Register
Name
Email
Password
Confirm Password
Register

Screenshot 1 Registration


ector
Home
Login
Email
Password
Login
Forgot password?

Screenshot 2 Login


DeepFake Detector
Home Predict

DeepFake Detection Project

What is the Project?
This project detects whether uploaded images or videos are DeepFakes using CNN and LSTM models, helping combat digital misinformation.

Problem Statement
With the rise of AI-generated media, it's critical to identify fake content to ensure public trust and authenticity.

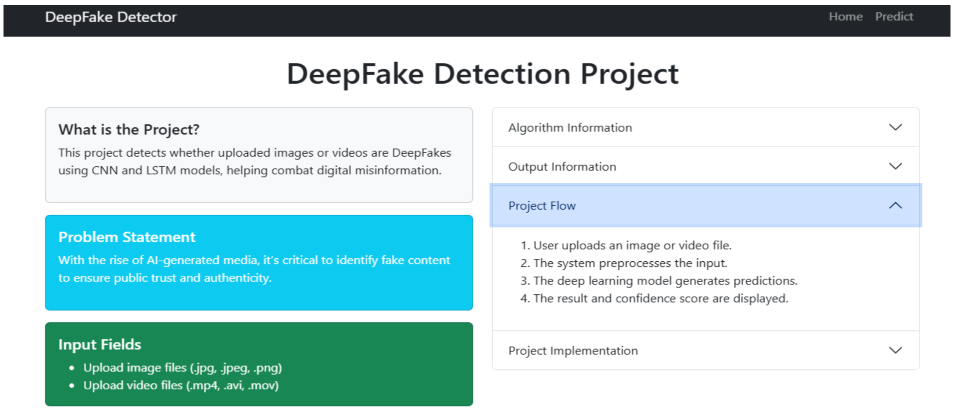
Input Fields
- Upload image files (.jpg, .jpeg, .png)
- Upload video files (.mp4, .avi, .mov)

Algorithm Information
Uses CNN for static image analysis and CNN-LSTM for analyzing temporal video frames.

Output Information

Project Flow

Project Implementation


DeepFake Detector — Home Predict

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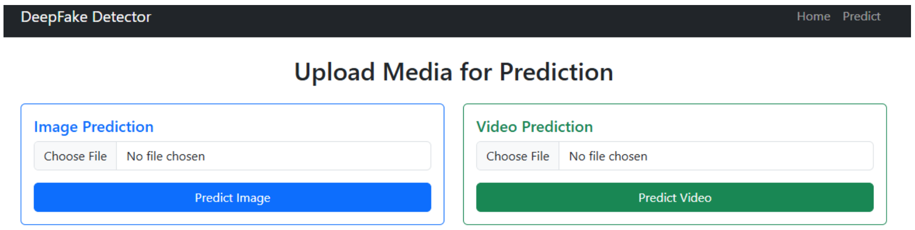
Algorithm Information
Output Information
Project Flow
1. User uploads an image or video file.
2. The system preprocesses the input.
3. The deep learning model generates predictions.
4. The result and confidence score are displayed.

Project Implementation


DeepFake Detector — Home Predict

Upload Media for Prediction

Image Prediction — Choose File: No file chosen — Predict Image

Video Prediction — Choose File: No file chosen — Predict Video

I

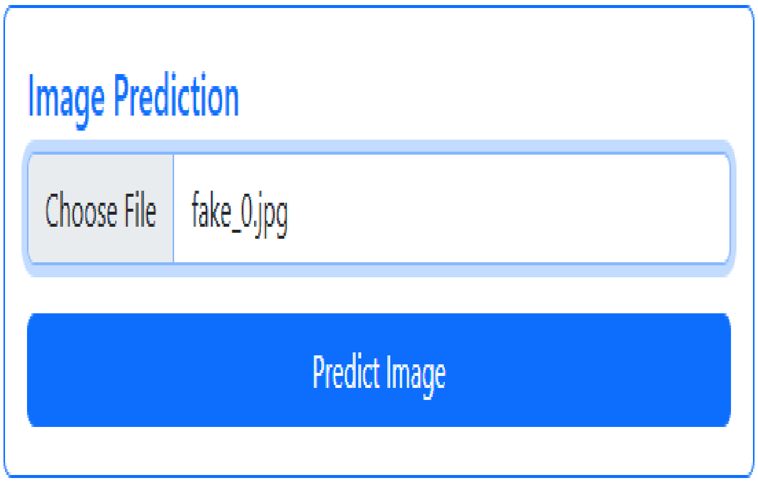
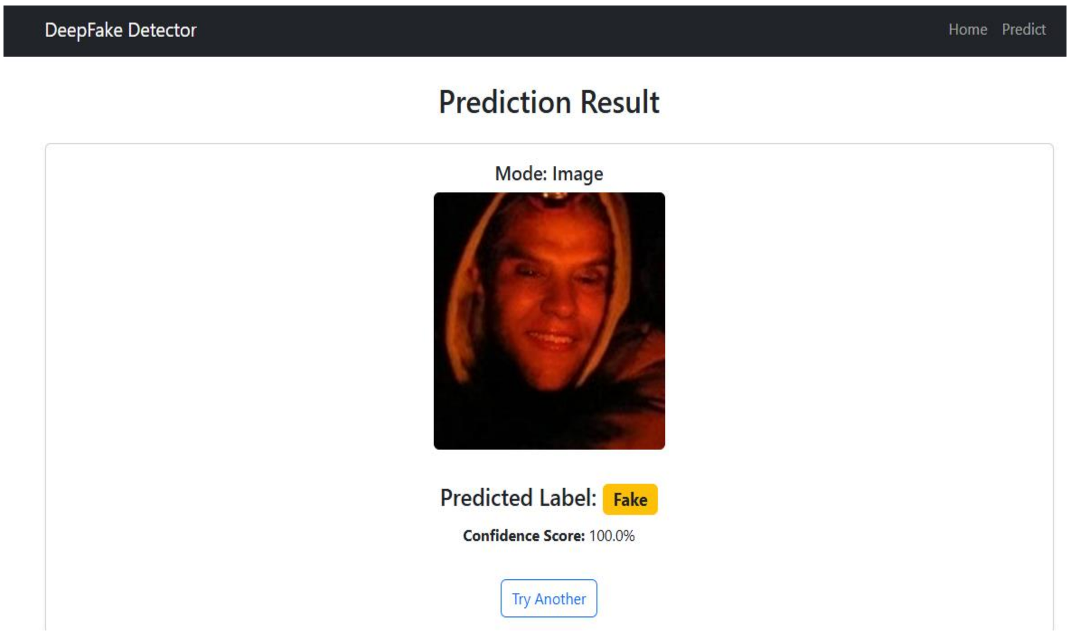
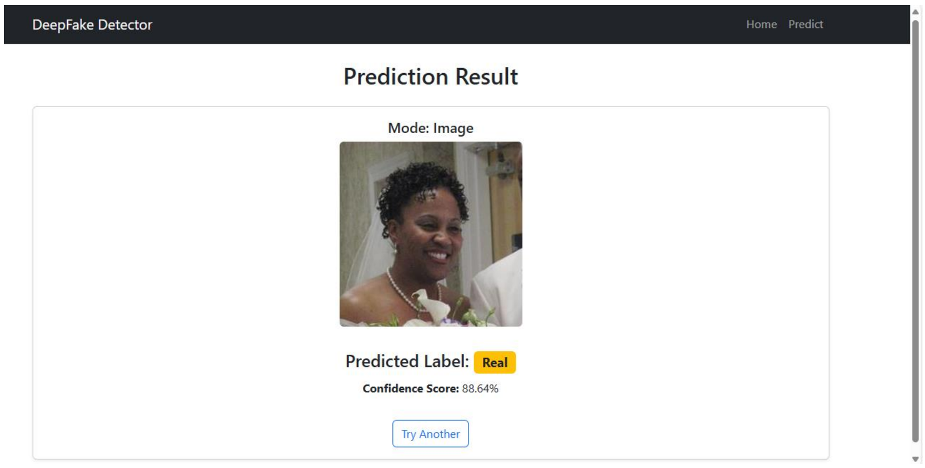


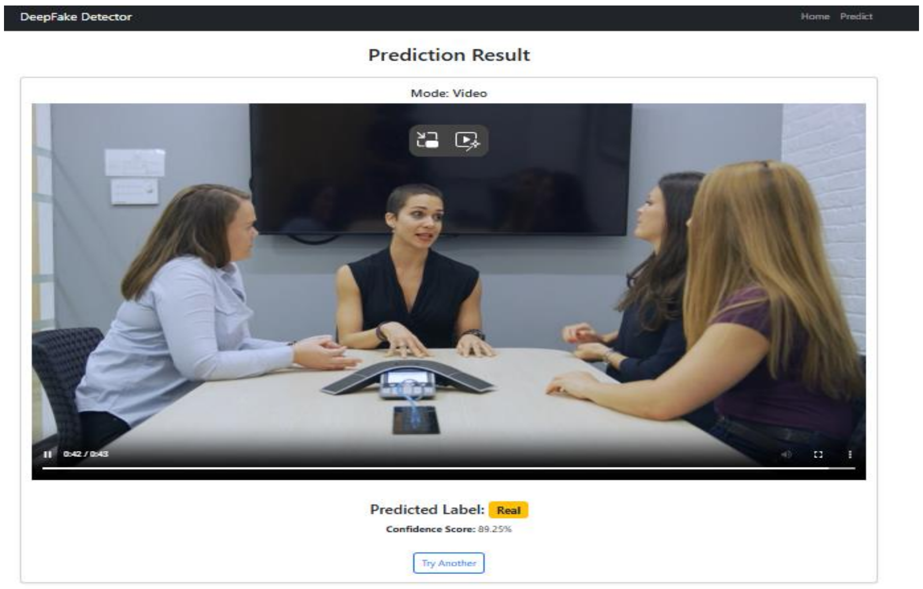
Image Prediction

Choose File: fake_0.jpg

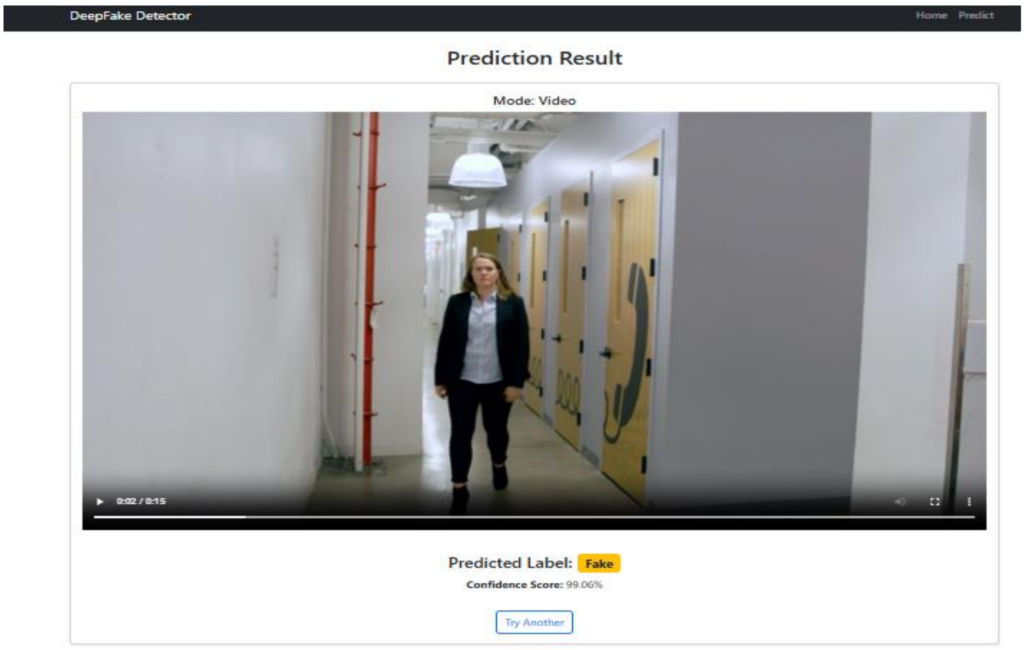
Predict Image


DeepFake Detector
Home Predict
Prediction Result
Mode: Image
Predicted Label: Fake
Confidence Score: 100.0%
Try Another


DeepFake Detector
Home Predict
Prediction Result
Mode: Image
Predicted Label: Real
Confidence Score: 88.64%
Try Another


DeepFake Detector
Home Predict
Prediction Result
Mode: Video

Predicted Label: Real
Confidence Score: 89.25%
Try Another



Predicted Label: Fake
Confidence Score: 99.06%

6-CONCLUSION

The increasing sophistication of deepfake technology poses a significant threat to digital authenticity and trust. The proposed system, **DeepGuard**, effectively addresses this challenge by leveraging a hybrid deep learning architecture combining **ResNeXt Convolutional Neural Networks (CNNs)** and **Long Short-Term Memory (LSTM)** networks to detect both spatial and temporal inconsistencies in manipulated videos. By integrating this model with a Flask-based web application and using real-world datasets like **FaceForensics++, Celeb-DF,** and **DFDC**, the system achieves accurate and real-time detection of deepfake content.

The user-friendly interface enables seamless media uploads, prediction viewing, and confidence scoring, while the admin module supports dataset management and system monitoring. Extensive testing at unit, integration, and system levels confirms the system's reliability, scalability, and robustness. Overall, DeepGuard successfully demonstrates how AI can counteract malicious uses of AI, helping restore trust in digital media.

7-REFERENCES

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