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Detection of Face-Swap based on DeepFake Videos

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ABSTRACT: The Audio to Sign Language Converter is an innovative Python-based system designed to bridge the communication gap between the hearing and hearing-impaired communities. It facilitates real-time translation of spoken language into sign language using a combination of Natural Language Processing (NLP), computer vision, and advanced machine learning techniques. The system leverages Google Speech Recognition to transcribe audio input with high accuracy, which is then processed for sign language translation. To visually represent sign language, the system employs 3D animated avatars that perform corresponding sign gestures. This approach ensures more natural, expressive, and easily understandable visual feedback for users who rely on sign language. OpenCV is integrated for gesture mapping and processing, enhancing the system's ability to interact in real-time. One of the key features of this solution is its support for multiple regional languages, enabling accessibility across diverse linguistic populations. This multilingual capability makes the system inclusive and practical for use in multicultural environments.

KEYWORDS: Deepfake Detection, AI-generated Video Identification, ResNeXt CNN, LSTM RNN, Video Forgery Classification, Face Manipulation Detection, Synthetic Media Analysis, Frame-level Feature Extraction, Temporal Sequence Analysis, Real vs Fake Video Classification.

I. INTRODUCTION

Deepfakes have emerged as a serious threat in today's digital age, often used to spread misinformation, create fake events, or harm individuals. To address this challenge, our project leverages artificial intelligence to detect deepfake videos. We use a ResNeXt CNN to extract frame-level features and an LSTM network to analyze temporal patterns across frames. Trained on a combination of major datasets like FaceForensics++, Celeb-DF, and the Deepfake Detection Challenge, our model delivers accurate results.

We've also built a user-friendly application that allows anyone to upload a video and instantly check its authenticity with a confidence score. This integration of deep learning and usability makes the system suitable for both research and public use. The model has been optimized for real-world performance by accounting for different video qualities and manipulation types. With the growing accessibility of deepfake tools, such detection systems are essential for preserving media trust. Our solution represents a step toward safeguarding digital content using the same technology that threatens it.

II. LITERATURE SURVEY

1. Implicit Identity Driven Deepfake Face Swapping Detection" Authors: Huang, Y., Li, Y., & Lyu, S. 2023

This study introduces a deepfake detection method based on identity-driven features rather than just visual artifacts. It focuses on subtle personal traits like facial expressions and movement patterns that are hard for deepfake models to replicate. The approach is especially effective in detecting face-swapping manipulations and enhances detection robustness against high-quality fakes.

2. Unmasking Deepfake Faces from Videos Using An Explainable Cost-Sensitive Deep Learning Approach" Authors: Mahmud, F., Abdullah, Y., Islam, M., & Aziz, T. 2023

This paper presents a deepfake detection method that uses a **cost-sensitive learning model** to handle class imbalance in real vs. fake video data. It also focuses on **explainability**, helping users understand why a video was flagged as fake. The model improves both accuracy and transparency, making it suitable for practical and ethical AI applications.

3. FaceForensics++: Learning to Detect Manipulated Facial Images – Rossler et al. (2019)

This research introduced FaceForensics++, a large-scale dataset containing manipulated facial videos created using various deepfake generation techniques. The authors evaluated several CNN-based models, such as XceptionNet, for their ability to detect tampered content. Their findings showed that models trained on high-quality, diverse datasets could generalize better to unseen manipulations. This work is highly relevant to our project as it provides one of the key datasets we used and highlights the significance of data diversity and quality in training effective deepfake detection models.

4. Exploiting Visual Artifacts to Expose Deepfakes – Matern et al. (2019)

Matern and his team explored how simple visual artifacts, such as inconsistent blinking, unnatural facial symmetry, and misaligned facial features, can be clues to detect deepfakes. Rather than relying solely on deep learning, this approach leveraged human-perceptible flaws in AI-generated content. The study's insights help us understand the types of anomalies a CNN might learn to recognize during training. It supports the idea that visual inconsistencies at the frame level are key indicators in distinguishing real from fake content.

III. METHODOLOGY

Deepfakes pose a growing threat in the digital age, often used to spread misinformation, manipulate media, and harm individuals. Our project aims to detect deepfake videos using a deep learning-based approach that combines spatial and temporal analysis. A pre-trained ResNeXt CNN is used to extract frame-level features, while an LSTM network captures temporal patterns across frames. The model is trained on a diverse and balanced dataset that includes FaceForensics++, Celeb-DF, and the Deepfake Detection Challenge. This improves its generalization across various manipulation techniques. We also developed a simple, user-friendly web interface where users can upload videos and receive real-time results with a confidence score. The system helps users identify manipulated videos effectively, contributing to media security and public awareness. By using AI to fight AI, the project offers a practical solution to combat deepfake threats.

Architecture:

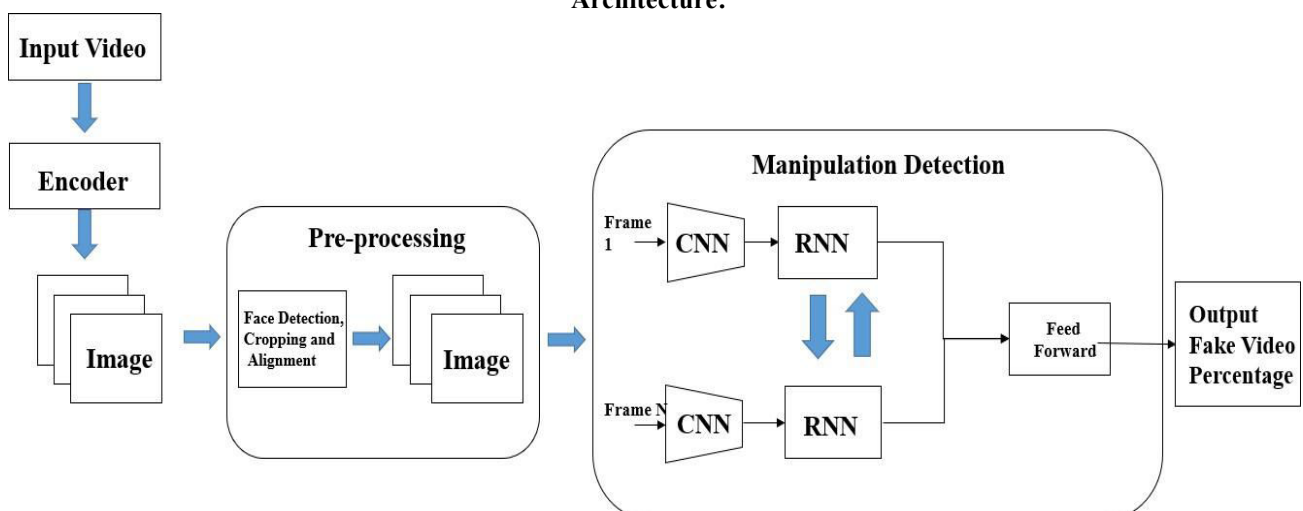


Fig.1 Architecture

IV. EXPERIMENTAL RESULTS

Welcome Interface :

The main GUI welcome screen of the application displays the title and provides an option to proceed, allowing users to initiate the deepfake detection process. It acts as the launch point for uploading video content and viewing results.

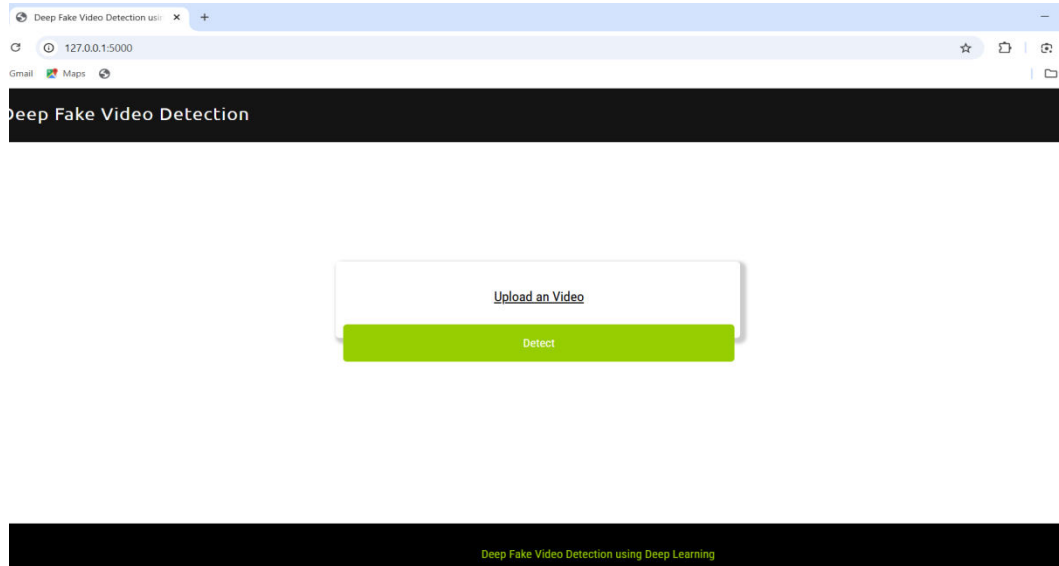


Fig 2. Home Page

1.prediction Phase:

In this phase, the uploaded video is processed frame by frame . Based on the model's output, the system classifies the video as either **Real** or **Fake**. The result is displayed along with a confidence score, helping users interpret the model's decision.

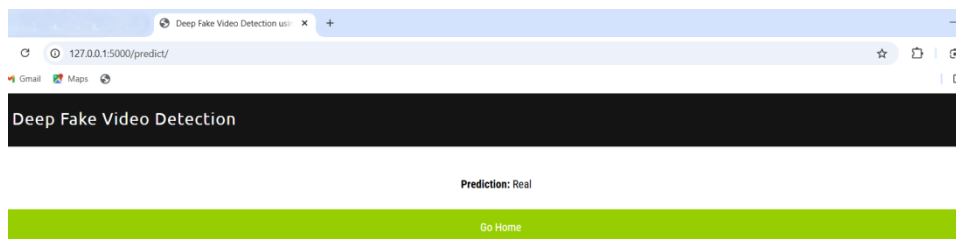


Fig 3 . output

V. CONCLUSION

Deepfake technology has rapidly advanced, making it easier to create highly realistic yet misleading content. In this project, we developed an effective deepfake detection system using a combination of ResNeXt CNN for feature extraction and LSTM for temporal pattern analysis. By training on a balanced and diverse dataset, the model demonstrates strong accuracy and generalization to real-world scenarios. The user-friendly interface further allows individuals to upload videos and receive instant classification results, making the tool both practical and accessible. This work contributes toward building more secure and trustworthy digital media environments.

Additionally, the model's ability to process video input in real-time and provide a confidence score enhances transparency and user trust. The integration of advanced deep learning techniques with an intuitive front-end interface shows the potential for wide-scale deployment. As deepfake generation methods evolve, our system provides a scalable and adaptable solution for early detection, raising awareness and supporting digital media verification.

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