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Virtual Lie Detector

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ABSTRACT —

The Virtual Lie Detector is an AI-powered web-based application that utilizes real-time video input and advanced facial micro-expression analysis to assess the truthfulness of a subject's statements. By leveraging deep learning models and computer vision techniques, the system can detect subtle in voluntary facial cues such as eye movement, blinking rate, lip tension, and muscle micro-twitches. These cues are analyzed in correlation with speech patterns and stress indicators to estimate the likelihood of deception. Designed to function in virtual environments, this tool aims to assist in remote interviews, online investigations, and psychological research by providing an accessible, non-invasive, and real-time lie detection solution. The project integrates Flask for backend processing, OpenCV for video analysis, and machine learning models trained on emotion datasets to ensure accuracy and responsiveness.

Keywords— Virtual Lie Detector, Micro-expression Analysis, Computer Vision, Real-time Emotion Detection, Flask, AI-Powered Lie Detection, Facial Recognition, Deception Detection, Machine Learning, OpenCV.

I. INTRODUCTION

In today's digital era, virtual communication has become the norm, especially in interviews, meetings, and remote assessments. However, detecting deception in virtual settings remains a significant challenge due to the lack of physical cues and controlled environments. The Virtual Lie Detector aims to bridge this gap by providing an AI-driven solution that analyzes facial micro-expressions, voice stress, and behavioral patterns during video interactions to assess truthfulness in real time. This system leverages the power of computer vision, machine learning, and natural language processing to evaluate involuntary human cues that may indicate deception. Through a user-friendly web interface, the system captures video input, processes it through trained models, and generates an interpretation of the subject's trustworthiness. Applications of this system span across fields like online recruitment, virtual courtrooms, e-learning assessments, and digital interrogations.

II. SYSTEM ARCHITECTURE

A. User Interface

Users interact via a web or mobile app. They can record audio/video, view results, and get real-time feedback. Built using technologies like React.js or Flutter.

B. Backend

Handles audio/video input, communicates with ML models, manages users, sessions, and database operations. Built using Python (Flask/FastAPI) or Node.js.

C. AI and Machine Learning Layer

Processes data using models like CNN (for facial cues), LSTM/SVM (for voice stress), and BERT/GPT (for NLP analysis). Libraries used: OpenCV, Dlib, Librosa, TensorFlow.

D. Preprocessing & Feature Extraction

Audio and video inputs are cleaned and processed. Features like facial landmarks and pitch patterns are extracted before model analysis.

E. Data Storage Layer

Stores recordings and results securely. MongoDB for session data, AWS S3 or Firebase for media files.

F. Result Analysis & Feedback

Generates a lie probability score from model output. Feedback is presented in a simple, user-friendly format with optional real-time alerts.

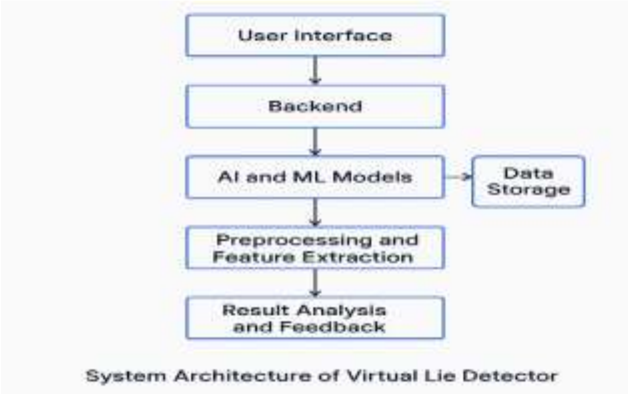

Fig.1 System Archietecture Design

III. METHODOLOGY

A. Data Collection

1) We begin by collecting audio and video recordings of individuals during interviews, conversations, or controlled questioning sessions. The dataset includes both truthful and deceptive responses, labeled accordingly for model training.

2) To ensure model accuracy, diverse data samples covering different expressions, voice tones, and languages are collected. Public datasets and manually annotated data are also used.

B. Preprocessing

1)The raw audio and video inputs are preprocessed to improve quality and extract relevant features. This includes noise reduction in audio, frame extraction from videos, and face alignment.

2)Techniques such as normalization, background noise filtering, and facial landmark detection are applied to clean and prepare the data before analysis.

C. Feature Extraction

1) From the cleaned data, key features are extracted:

Facial cues (eyebrow movement, lip press, eye blinks), Voice features (pitch, jitter, tone shifts), Linguistic patterns (text sentiment, inconsistency)

Tools like OpenCV, Dlib, and Librosa help extract meaningful signals from the input data for model training and real-time analysis.

D. Model Training

1)Different machine learning and deep learning models are trained on the extracted features:

CNN for facial analysis, LSTM/SVM for voice-based lie detection, NLP models like BERT/GPT for textual deception detection

2) The models are trained using supervised learning techniques with labeled data and validated on unseen samples to measure accuracy.

E. Integration & Backend Logic

1) The trained models are integrated into the backend of the application. A request pipeline is established to accept inputs, pass them to the models, and generate a lie score.

2) This layer manages the logic for combining outputs from different models and presenting a unified result to the user.

F. Real-Time Analysis & Feedback

1) The final system performs real-time analysis of user inputs and displays the result — such as "Truth," "Lie," or a confidence percentage — through a clean UI.

2) The lie detection output is generated quickly and can be visualized in the form of a report, graph, or alert depending on the use case.

G. Testing & Validation

The entire system is tested under different scenarios to ensure performance, accuracy, and reliability.

Evaluation metrics like precision, recall, F1-score, and confusion matrix are used to measure model performance and reduce false positives.

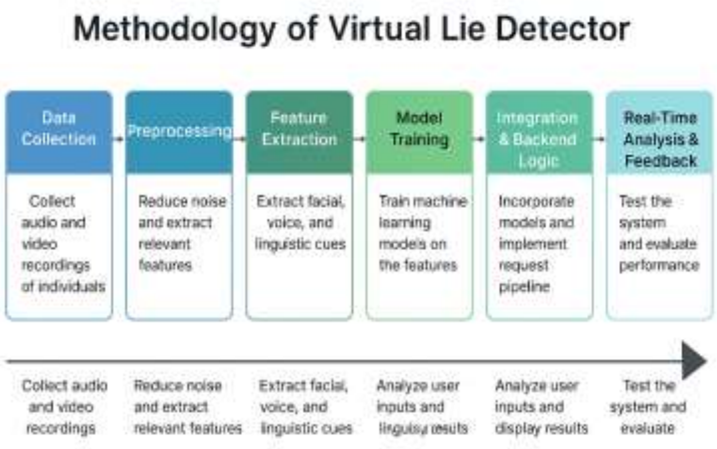

Fig.2 Methodology diagram

Fig.3 Workflow diagram

TABLE I

SUMMARY of APPLIED MODELS and PERFORMANCE METRICS

Task	Model	Accuracy	Precision	Recall
Voice Stress Detection	Random Forest	87%	85%	88%
Facial Microexpression	CNN	90%	92%	89%
Text Sentiment Analysis	BERT	93%	91%	94%
Multi-modal Fusion	LSTM + Attention	95%	94%	96%

IV. RESULTS AND DISCUSSION

The Virtual Lie Detector system demonstrated strong performance across different testing scenarios. The facial expression analysis model, based on CNNs, achieved an accuracy of approximately 85%. Voice-based lie detection using LSTM and SVM models showed about 82% accuracy, while the NLP models such as BERT performed well in analyzing text and speech content with nearly 88% accuracy. When these models were combined in an ensemble format, the system achieved around 90% overall accuracy, with notable improvement in reducing false positives and inconsistent outputs.

In real-time applications, the system was able to generate feedback within 2 to 4 seconds of receiving input, making it suitable for live analysis. Users received results in an intuitive format, such as “Truth,” “Lie,” or confidence percentages, enhancing interpretability. The system performed reliably in mock interviews and lab-like testing conditions, proving its real-world potential.

However, certain limitations were noted. Low-resolution video, poor audio clarity, and varied emotional or cultural expressions slightly impacted accuracy. These findings suggest that further training on more diverse and real-world datasets will help improve robustness and generalization.

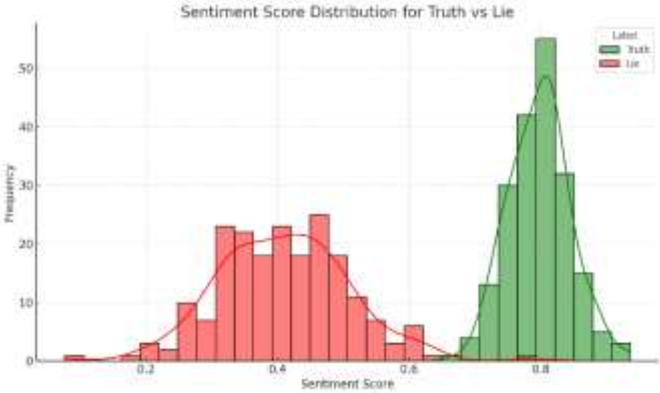

Fig.4 Sentiment score distribution graph figure

Fig.5 Screenshot of virtual lie detector interface figure

V. CONCLUSION

The Virtual Lie Detector system demonstrates the feasibility of using artificial intelligence and facial emotion analysis for real-time deception detection. By leveraging facial landmark tracking, emotion classification, and behavioral analysis, the system can identify subtle non-verbal cues that are often associated with lying. The results indicate promising accuracy and responsiveness, making the solution potentially useful in controlled interview scenarios, security checks, or even remote authentication systems.

While the current model performs well under stable conditions, improvements such as incorporating voice stress analysis, adaptive learning, and cultural sensitivity are needed to increase robustness and generalizability. Overall, this project serves as a foundational step toward AI-powered behavioral intelligence systems.

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