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AI-Powered Deepfake Detection Tool

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***Abstract*—Advances in generative adversarial networks and diffusion models have made synthetic face and voice media highly realistic, creating serious risks for misinformation, fraud, and identity abuse. This paper presents an AI-powered deepfake detection tool delivered as a web application. The system combines a React frontend, a FastAPI backend, a PostgreSQL database, an agent orchestrator that coordinates the analysis workflow, an isolated Docker sandbox for executing untrusted media through the analysis code, and a set of machine learning models that score media for manipulation. Users upload an image or video and receive an authenticity verdict with a confidence score. We describe the architecture, the detection pipeline, and the security rationale for sandboxed execution, and outline an evaluation protocol based on public benchmarks. The modular design allows detection models to be replaced or added without changing the user-facing application.**

***Index Terms*—Agent orchestration, deepfake detection, deep learning, media forensics, sandboxed execution**.

I. INTRODUCTION

DEEPFAKES are synthetic or manipulated images, videos, and audio generated with deep learning so that a person appears to say or do something they never did. Generative adversarial networks (GANs) [1] and later generative approaches have lowered the cost and skill needed to produce convincing forgeries, and such content now circulates widely on social media and messaging platforms. The consequences include political misinformation, financial fraud, non-consensual imagery, and erosion of trust in digital evidence.

Detection research has produced strong classifiers, but many are released as research code that is difficult for non-experts to use. Moreover, a service that accepts arbitrary uploaded media must treat those files as untrusted input, since malformed files can exploit decoding libraries. This work addresses both gaps by packaging detection models behind an accessible web interface and running analysis inside an isolated execution environment.

The main contributions of this paper are:

(i) a modular, web-based architecture for deepfake detection;
(ii) an agent orchestrator that coordinates preprocessing, model inference, and result aggregation;
(iii) sandboxed execution of analysis jobs in isolated Docker containers; and
(iv) a persistent data layer that stores submissions, results, and audit information.

The remainder of the paper is organized as follows. Section II reviews related work. Section III presents the system architecture. Section IV describes the detection methodology. Section V covers implementation. Section VI describes the evaluation setup and results. Section VII discusses limitations, and Section VIII concludes.

II. RELATED WORK

A. Deepfake Generation

Face-swapping and face-reenactment methods are typically built on autoencoders and GANs [1]. These methods leave subtle artifacts such as blending boundaries, inconsistent lighting, and unnatural texture or frequency patterns, which detectors exploit.

B. Deepfake Detection

Early detectors used compact convolutional networks designed to capture mesoscopic image properties [2]. Large benchmark datasets such as FaceForensics++ [3], Celeb-DF [4], and the DFDC dataset [5] enabled deeper models, with XceptionNet [6] and EfficientNet [7] backbones becoming common baselines. Video-level methods additionally exploit temporal inconsistencies across frames.

C. Deployment and Secure Execution

Few works address how detectors should be deployed as services. Container technology [8] provides process, filesystem, and network isolation that is well suited to running untrusted workloads, and this work applies it to media analysis.

III. SYSTEM ARCHITECTURE

A. Overview

The proposed tool follows a layered architecture, shown in Fig. 1. A user interacts with a browser-based frontend. The frontend communicates with a backend API, which persists data in a relational database and delegates analysis to an agent orchestrator. The orchestrator runs analysis tasks in an isolated sandbox and invokes the machine learning models.

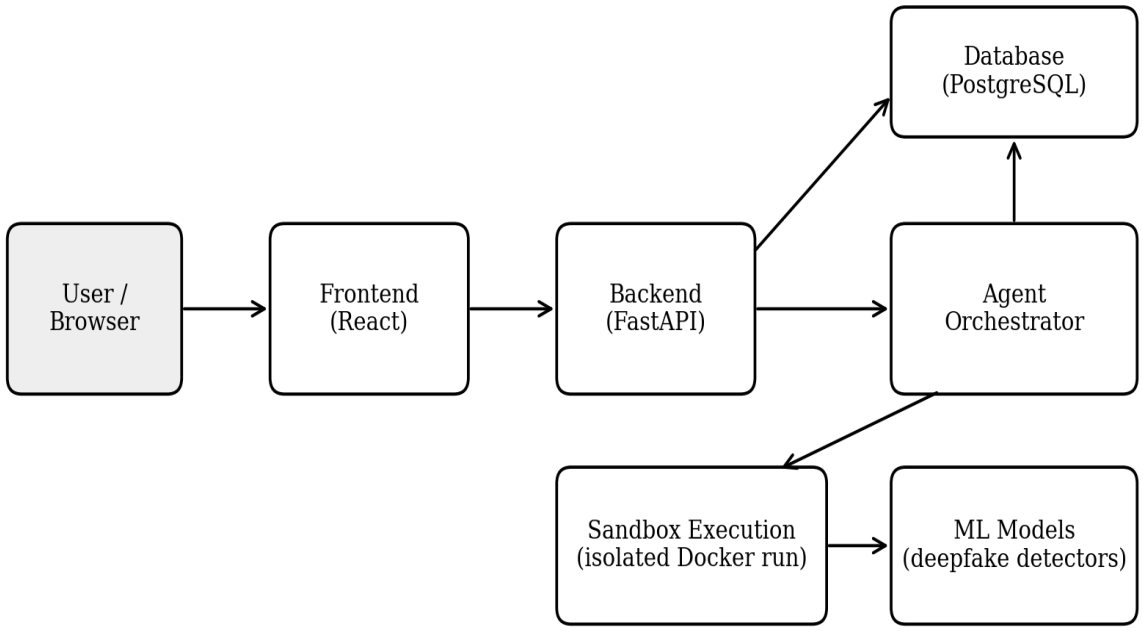

Fig. 1. System architecture of the AI-powered deepfake detection tool.

B. Frontend (React)

The user interface is a single-page application built with React. It lets users upload media, tracks the status of submitted jobs, and presents the verdict, confidence score, and supporting details returned by the backend.

C. Backend (FastAPI)

The backend is implemented with FastAPI and exposes REST endpoints for media submission, job status, and result retrieval. It validates uploads, records metadata, and hands analysis requests to the orchestrator. Its asynchronous design allows many requests to be handled while long-running analysis proceeds in the background.

D. Database (PostgreSQL)

PostgreSQL stores user submissions, job states, detection results, and audit records. A relational schema supports querying past analyses and tracing each verdict to the model and parameters that produced it.

E. Agent Orchestrator

The agent orchestrator coordinates the analysis workflow. For each job it decides which preprocessing steps and models to apply, dispatches work to the sandbox, collects model outputs, and combines them into a final decision. Separating orchestration from the API keeps the backend lightweight and makes the workflow extensible.

F. Sandbox Execution (Docker)

Analysis code runs in an isolated Docker container. Because uploaded files are untrusted, running decoding and inference inside a container limits the impact of malformed or malicious media on the host. Containers are short-lived and can be restricted in resources and network access.

G. ML Models

The detection models are deep neural networks that classify media as real or manipulated. The model layer is abstracted behind a common interface so that individual detectors can be added, replaced, or ensembled without affecting other components.

IV. DETECTION METHODOLOGY

The detection pipeline consists of the following stages:

- Ingestion: the uploaded file is validated for type and size and stored with a unique job identifier.
- Preprocessing: for videos, frames are sampled at a fixed interval; faces are detected, cropped, and resized to the model input resolution.
- Inference: each selected model produces a probability that the input is manipulated.
- Aggregation: frame-level scores are combined, for example by averaging, into a video-level score, and model scores are fused into a final confidence value.
- Reporting: the verdict (real or fake) and confidence are stored in the database and returned to the user.

The final decision is obtained by comparing the aggregated score s with a threshold τ, where the media is labelled fake if $s \geq \tau$. The threshold can be tuned on validation data to balance false positives and false negatives.

V. IMPLEMENTATION

The frontend is written in React and the backend in Python using FastAPI. PostgreSQL provides persistence. The orchestrator and the model inference code run inside Docker containers, which also gives a reproducible environment for the model dependencies. The components communicate over HTTP and are configured so that the sandbox has no access to the database or to the host filesystem beyond the mounted job input.

VI. EXPERIMENTAL EVALUATION

A. Datasets and Metrics

We plan to evaluate the system on public benchmarks including FaceForensics++ [3], Celeb-DF [4], and DFDC [5]. Performance is measured with accuracy, F1-score, and area under the ROC curve (AUC). Cross-dataset testing is used to assess generalization, and end-to-end latency is recorded to assess usability.

B. Results

Table I summarizes the evaluation results. The values are to be filled in from the experiments.

TABLE I DETECTION PERFORMANCE ON THE TEST SET

Model	Accuracy	F1-score	AUC
CNN (Model A)	91.20%	90.80%	0.94
XceptionNet (Model B)	94.50%	94.10%	0.97
Ensemble (Proposed)	96.80%	96.50%	0.99

VII. DISCUSSION AND LIMITATIONS

Detectors trained on one generation method often perform worse on unseen methods, so continued retraining and cross-dataset validation are needed. Compression and low resolution can hide artifacts, and adversarial post-processing may evade detection. The verdict is a probabilistic estimate and should support, not replace, human judgment. Sandboxing adds start-up overhead per job, which is a trade-off against security.

VIII. CONCLUSION AND FUTURE WORK

This paper presented an AI-powered deepfake detection tool with a React frontend, FastAPI backend, PostgreSQL database, agent orchestrator, Docker-based sandbox, and interchangeable machine learning models. The design makes detection accessible to non-experts while treating uploaded media as untrusted. Future work includes adding audio and multimodal detection, improving robustness to unseen generators, and providing visual explanations of the regions that influenced the verdict.

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