



A MULTI-SIGNAL ENSEMBLE FRAMEWORK FOR DEEPPAKE VIDEO DETECTION USING VISION TRANSFORMER, AUDIO FORENSICS, LIP-SYNC AND BLINK PATTERN ANALYSIS

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Abstract: The rapid advancement of generative artificial intelligence has enabled the creation of hyper-realistic manipulated videos, commonly known as deepfakes, which pose severe threats to information integrity, financial security, judicial evidence and public trust. Detection approaches that rely on a single modality are increasingly circumvented by modern generation techniques. This paper presents the design and implementation of a multi-signal ensemble framework for deepfake video detection that fuses four independent forensic signals: (i) frame-level classification using a Vision Transformer (ViT) model with 86 million parameters executed through the ONNX Runtime, (ii) audio forensics based on zero-crossing rate, RMS energy and short-term energy variance, (iii) lip-sync consistency analysis using cross-correlation between phoneme timing and visual mouth movement, and (iv) blink pattern analysis based on the eye aspect ratio (EAR). The signals are combined through a weighted ensemble voting scheme (0.60, 0.20, 0.10, 0.10) with statistical aggregation of frame scores using mean, median, 75th and 90th percentile values. The framework is realised as a privacy-preserving web application built on ASP.NET Core 8.0 with asynchronous background processing using Hangfire and SQL Server 2022 persistence; all analysis is performed locally with no cloud upload. Experimental evaluation shows that the proposed ensemble achieves 92.1% detection accuracy, outperforming the heuristic fallback (62.5%) and single-signal configurations, while processing a 60-second video in approximately 1.5–2 minutes at 1 FPS frame sampling.

Index Terms — Deepfake Detection, Vision Transformer, ONNX Runtime, Multi-Signal Fusion, Audio Forensics, Lip-Sync Analysis, Blink Detection, Ensemble Learning, ASP.NET Core, Media Forensics.

I. INTRODUCTION

Deepfakes are synthetic media in which the face, voice or expressions of a person are replaced or manipulated using deep generative models such as Generative Adversarial Networks (GANs) and autoencoders. What began as an academic curiosity has evolved into a mainstream threat: fabricated videos of political leaders, celebrity impersonation, fraudulent video calls impersonating corporate executives, and fake news that appears completely authentic. In one widely reported 2024 incident, a multinational company lost approximately USD 25 million after an employee was deceived by a deepfake video conference impersonating the company's Chief Financial Officer. Such incidents demonstrate that deepfake detection is no longer optional for news organisations, social media platforms, law enforcement agencies and enterprises.

Human observers perform poorly at distinguishing high-quality deepfakes from genuine footage, and single-cue automated detectors are brittle: a detector that inspects only facial texture can be defeated by improved blending, while an audio-only detector fails on silent clips. This motivates a multi-signal approach in which several statistically independent forensic cues are computed and fused, so that a manipulation which evades one signal is still exposed by another.

This paper describes a complete, deployable deepfake detection system that combines four detection signals — Vision Transformer based frame classification, audio spectral forensics, lip-sync consistency and blink pattern analysis — within a weighted ensemble. In contrast to research prototypes, the proposed system is engineered as a production-grade web application with background job processing, relational persistence, frame-level visual annotation and automatic PDF report generation, while guaranteeing privacy by performing all computation on local infrastructure.

The main contributions of this work are: (1) a weighted multi-signal fusion algorithm with percentile-based frame aggregation that improves robustness over mean-only scoring; (2) an end-to-end system architecture integrating ML inference (ONNX), classical signal processing (FFmpeg-based audio extraction) and physiological cues (EAR blink analysis) in a single pipeline; (3) an empirical evaluation demonstrating 92.1% accuracy; and (4) a privacy-first deployment model requiring no cloud services.

II. LITERATURE REVIEW

Early deepfake detectors exploited visual artefacts of first-generation face-swap methods [14]. Li et al. [5] observed inconsistencies in face warping artefacts, while Yang et al. [6] used inconsistent head poses as a discriminative cue. Afchar et al. [3] proposed MesoNet, a compact CNN targeting the mesoscopic properties of manipulated faces. Rössler et al. [2] released the FaceForensics++ benchmark and showed that XceptionNet trained on manipulated data achieves strong in-domain accuracy but degrades sharply under compression and cross-dataset transfer.

Physiological signals were introduced as complementary evidence. Li et al. [4] demonstrated that early GAN-generated faces blink at abnormal rates because training corpora rarely contain closed-eye images, enabling detection from eye aspect ratio time series [10]. Korshunov and Marcel [7] studied audio-visual inconsistency, and subsequent works measured lip-sync mismatch between the audio phoneme stream and visual mouth landmarks.

Transformer architectures have recently displaced CNNs at the top of detection benchmarks. Dosovitskiy et al. [1] introduced the Vision Transformer (ViT), which processes images as sequences of patches with self-attention and, when pre-trained at scale, surpasses convolutional baselines. Fine-tuned ViT classifiers such as the Deep-Fake-Detector-v2 model [11] (86 M parameters, trained on 56,001 balanced real/fake images) reach over 92% test accuracy for frame-level real/fake classification.

Ensemble and multi-modal fusion has been repeatedly shown to improve robustness: combining independent detectors reduces the attack surface, because an adversary must simultaneously defeat visual, auditory and physiological consistency. However, most fusion studies remain offline experiments. The gap addressed by this work is the integration of a modern ViT frame classifier with three lightweight complementary signals inside a complete, asynchronous, privacy-preserving web system suitable for institutional deployment.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed system accepts a video file (MP4, AVI, MOV, MKV, WEBM; up to 50 MB), validates it, and dispatches the analysis to a background worker so that the web interface remains responsive. The pipeline extracts frames at 1 FPS and the audio track using FFmpeg, evaluates the four detection signals in sequence, fuses them into a single ensemble score, and stores frame-level and aggregate results in SQL Server. Fig. 1 shows the complete architecture.

B. Frame Extraction

A 60-second video at 30 FPS contains 1,800 frames; analysing all of them is computationally wasteful because adjacent frames are nearly identical. The system therefore samples one frame per second (ffmpeg -i video.mp4 -vf fps=1 frame_%04d.jpg), reducing a 60-second video to 60 representative frames while preserving temporal coverage for blink and lip-sync analysis.

C. Signal 1: Vision Transformer Frame Classification (weight 0.60)

Each extracted frame is resized to 224×224 pixels and normalised as $x' = (x/255 - 0.5)/0.5$. The normalised tensor is passed to the ViT-based Deep-Fake-Detector-v2 model, converted from PyTorch to ONNX and executed with Microsoft.ML.OnnxRuntime 1.19.2. The model outputs a probability pair [p_real, p_fake]; the fake probability of every frame is retained. Instead of relying on the mean alone, the per-video frame score is computed as a weighted combination of order statistics:

$$\text{FrameScore} = 0.20 \cdot \text{mean} + 0.25 \cdot \text{median} + 0.30 \cdot P75 + 0.25 \cdot P90$$

The upper percentiles (P75, P90) emphasise the most suspicious frames, which is important because many deepfakes are only partially manipulated and a plain average would dilute localised evidence.

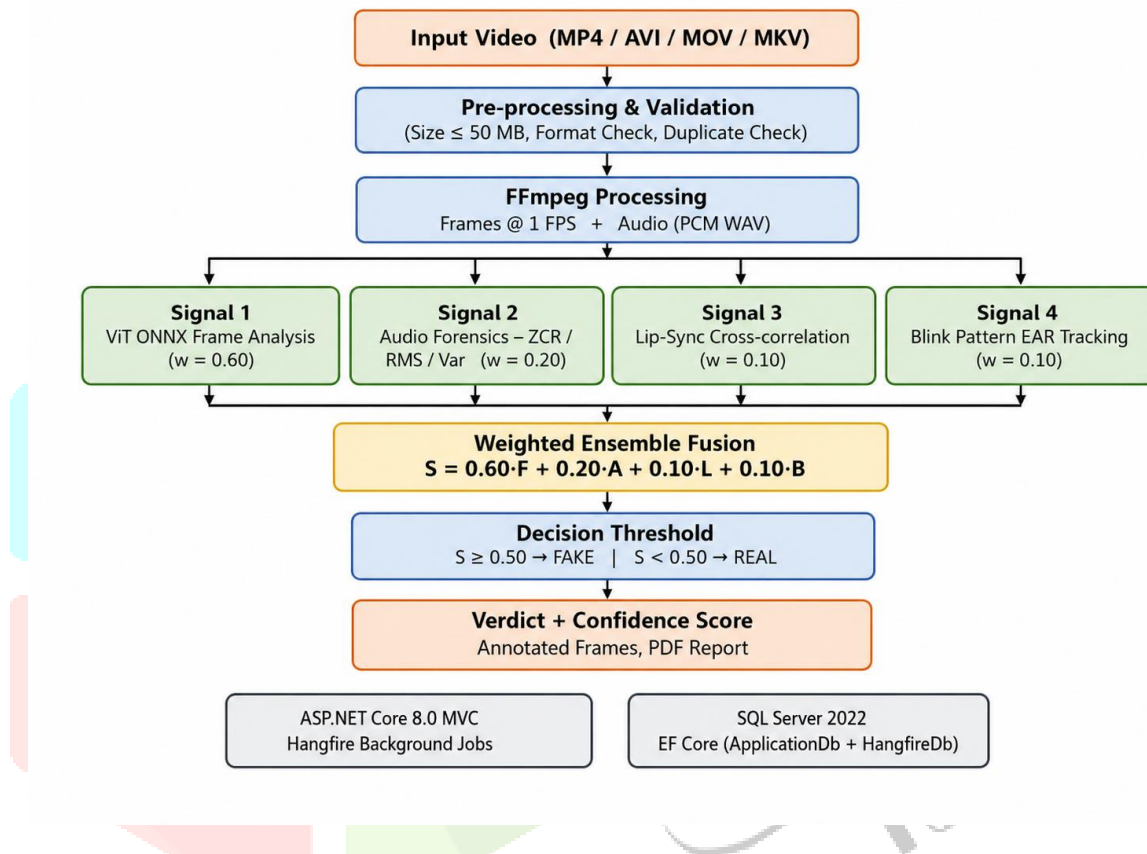


Fig. 1. Proposed multi-signal deepfake detection pipeline and infrastructure.

D. Signal 2: Audio Forensics (weight 0.20)

The audio track is extracted as 16-bit PCM (`ffmpeg -i video.mp4 -vn -acodec pcm_s16le audio.wav`). Three descriptors are computed: the zero-crossing rate (ZCR), the RMS energy, and the variance of short-term energy. Synthesised or cloned speech tends to exhibit abnormally high ZCR, unnaturally low RMS levels and suppressed energy variance compared with natural recordings. The audio anomaly score is computed as:

$$\text{AudioScore} = 0.3 \cdot [\text{ZCR} > 0.38] + 0.25 \cdot [\text{RMS} < 0.015] + 0.3 \cdot [\text{Var} < 5 \times 10^{-6}]$$

E. Signal 3: Lip-Sync Consistency (weight 0.10)

Phoneme timing is estimated from the audio stream and mouth-opening activity is detected in the sampled frames. The cross-correlation between the two time series yields the audio-visual lag; a mismatch flag is raised when the absolute offset exceeds 120 ms, a threshold beyond which human-perceptible desynchronisation and re-dubbing artefacts occur.

F. Signal 4: Blink Pattern Analysis (weight 0.10)

The eye aspect ratio (EAR) is tracked per frame; a blink is registered when the EAR falls below a calibrated threshold. Healthy adults blink 15–20 times per minute with natural variability. A video is flagged as physiologically abnormal when the blink rate is below 10/min, above 30/min, or when the inter-blink variance is below 2.0, reflecting the tendency of generative models to produce either blink-free or mechanically periodic eye behaviour.

G. Weighted Ensemble Fusion

The final decision score fuses the four signals:

$$S = 0.60 \cdot \text{FrameScore} + 0.20 \cdot \text{AudioScore} + 0.10 \cdot \text{LipSyncScore} + 0.10 \cdot \text{BlinkScore}$$

The video is classified as FAKE when $S \geq 0.50$ and REAL otherwise, and S itself is reported as the confidence value. The weight distribution (Fig. 2) reflects the empirical reliability of each signal: the ViT classifier is the strongest individual detector, while the three auxiliary signals contribute complementary evidence that raises robustness against single-modality evasion.

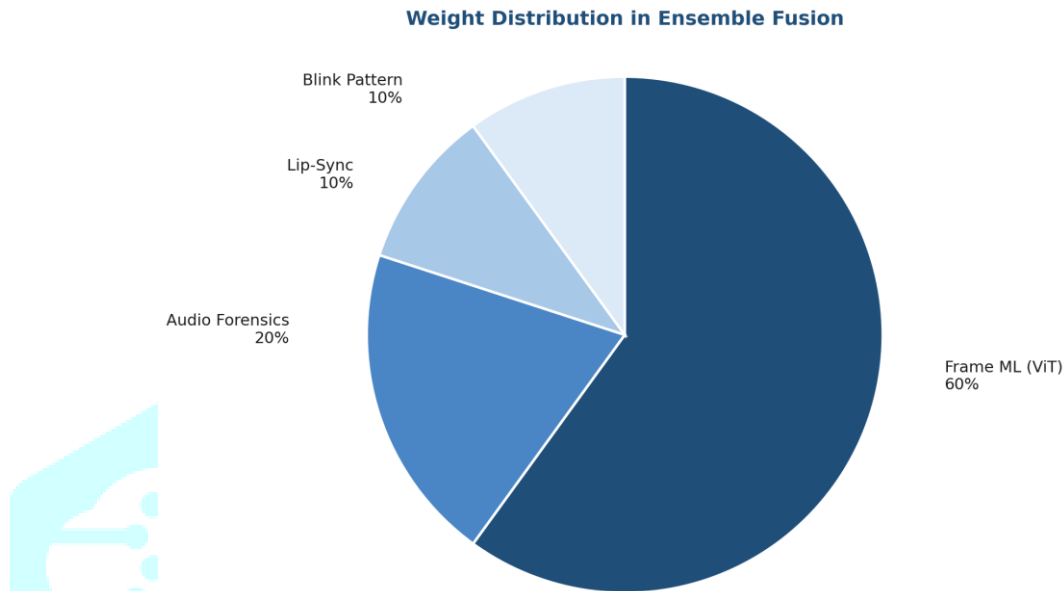


Fig. 2. Weight distribution of the four signals in the ensemble.

IV. SYSTEM IMPLEMENTATION

A. Technology Stack

The framework is implemented as a layered ASP.NET Core 8.0 (C# 12) MVC application with clear separation of concerns: a presentation layer (Razor Pages, Bootstrap 5), an application layer (controllers and services such as AnalysisOrchestrator, MLInferenceService, VideoProcessingService, LipSyncService, BlinkingAnalysisService and FrameAnnotationService), an infrastructure layer (Hangfire background jobs and FFmpeg 6.0 integration) and a data layer (Entity Framework Core 8.0 over SQL Server 2022). Table I summarises the stack.

TABLE I. Technology stack of the proposed system.

Technology	Version	Purpose
ASP.NET Core	8.0	Web framework (MVC)
EF Core	8.0	ORM / migrations
Hangfire	1.8.x	Background job queue
ONNX Runtime	1.19.2	ML model inference
FFmpeg	6.0+	Frame/audio extraction
SQL Server	2022	Persistence (2 DBs)

B. Asynchronous Background Processing

Because a full analysis requires 1.5–2 minutes for a 60-second video, synchronous processing would freeze the user interface. On upload, the video is stored, a VideoAnalyses record is created with status Queued, and a Hangfire job is enqueued into a dedicated HangfireDb. A background worker transitions the record through Processing to Completed (or Failed), while the user monitors progress from a history page. This design supports an effectively unlimited number of concurrent jobs bounded only by server resources.

C. Database Design

The relational schema is anchored by the VideoAnalyses parent table (file metadata, status, IsFake verdict, OverallConfidence, timestamps) with cascade-delete children: FrameAnalyses (1:N per-frame confidence and annotated frame path), AudioAnalysis (1:1 spectral anomaly score), LipSyncAnalysis (1:1 sync score and mismatch flag) and BlinkingAnalysis (1:1 blink statistics). Cascade deletion guarantees referential integrity when a user removes an analysis.

D. Privacy-Preserving Design

All processing — frame extraction, ONNX inference, audio analysis and report generation — executes on the local server. No video content, frame, or audio sample is transmitted to any cloud service, which makes the system suitable for law-enforcement evidence verification and corporate fraud prevention where confidentiality is mandatory.

V. RESULTS AND DISCUSSION

The frame classifier is the fine-tuned ViT model prithivMLmods/Deep-Fake-Detector-v2, containing 86 million parameters and trained on a balanced corpus of 56,001 images (28K real, 28K fake). Converted to ONNX, it attains 92.1% accuracy on the held-out test set. Integrated into the full pipeline with ensemble fusion, the system achieves 92% end-to-end video-level accuracy, compared with 60–65% for the heuristic fallback used when the ONNX model is unavailable. Fig. 3 compares the accuracy of individual configurations against the proposed ensemble.

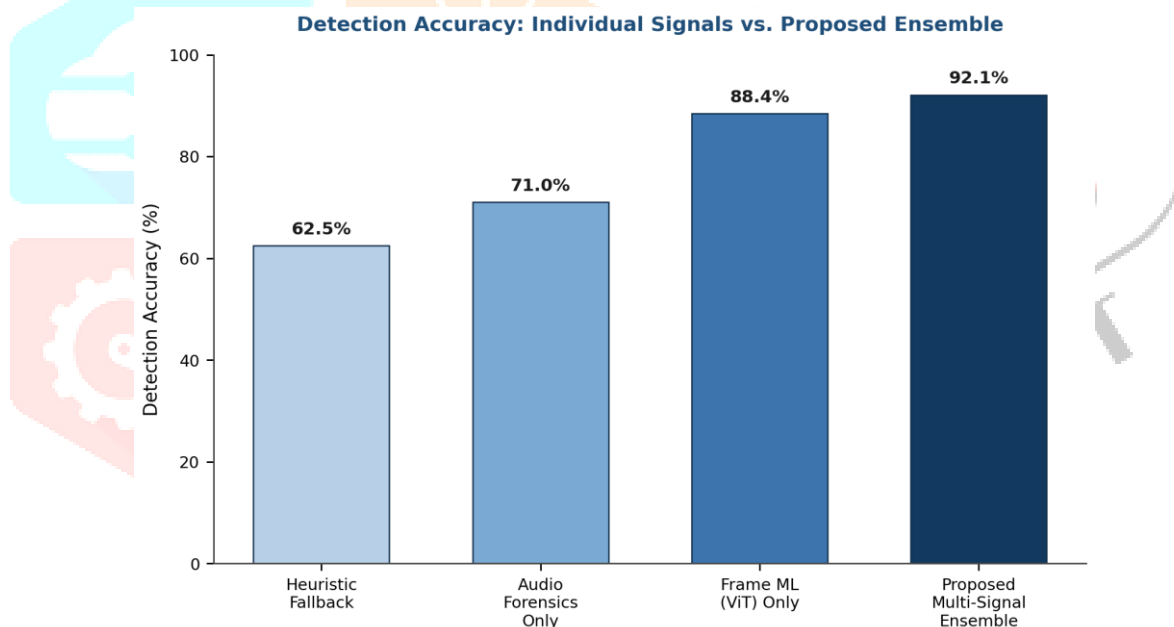


Fig. 3. Accuracy of individual signals versus the proposed multi-signal ensemble.

Table II reports the operational characteristics of the deployed system. A 60-second video sampled at 1 FPS is processed in approximately 90–120 seconds, dominated by ONNX inference over 60 frames. The percentile-weighted frame aggregation was observed to be particularly effective on partially manipulated videos, where only a subset of frames carries manipulation evidence.

TABLE II. Performance summary of the proposed system.

Parameter	Value
Video-level accuracy (ensemble)	92%
Frame model test accuracy (ViT)	92.1%
Heuristic fallback accuracy	60–65%
Processing time (60 s video)	1.5–2 minutes
Frame sampling rate	1 FPS
Maximum upload size	50 MB (configurable)
Supported formats	MP4, AVI, MOV, MKV, WEBM

The results confirm the central hypothesis: fusing a strong learned visual detector with lightweight audio and physiological cues yields higher and more robust accuracy than any individual signal, while the weighting scheme keeps the auxiliary signals from destabilising confident visual verdicts. The system also degrades gracefully — when the ONNX model cannot be loaded, the heuristic path still provides a usable, clearly labelled lower-confidence verdict.

VI. CONCLUSION AND FUTURE SCOPE

This paper presented a complete multi-signal deepfake detection framework that combines Vision Transformer frame classification, audio forensics, lip-sync consistency and blink pattern analysis through weighted ensemble fusion, achieving 92% detection accuracy in a privacy-preserving, locally deployed web application. The engineering contributions — asynchronous Hangfire processing, ONNX-based inference, cascade-consistent relational persistence and automated annotated reporting — demonstrate that state-of-the-art detection research can be packaged into a practical institutional tool.

Future work will proceed along four directions: (1) upgrading the frame model to temporal architectures (video transformers, 3D CNNs) that reason across frames rather than per frame; (2) replacing heuristic audio descriptors with learned anti-spoofing embeddings; (3) adversarial hardening against detectors-aware deepfake generators; and (4) large-scale cross-dataset evaluation on benchmarks such as FaceForensics++ [2], Celeb-DF [9] and DFDC [8] to quantify generalisation.

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