I.

DYNAMIC ANALYSIS OF CCTV FEED: A REVOLUTIONARY APPROACH WITH ARTIFICIAL INTELLIGENCE

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***Abstract*— This project leverages Artificial Intelligence for dynamic CCTV feed analysis, overcoming limitations in traditional surveillance. Through computer vision and machine learning, the system autonomously detects patterns and anomalies, revolutionizing surveillance efficiency. This concise abstract highlights AI's pivotal role in ensuring real-time security.**

***Keywords*— Surveillance, CCTV, Artificial Intelligence, Dynamic Analysis, Security, Computer Vision, Machine Learning.**

II.

DYNAMIC ANALYSIS OF CCTV FEED

Introduction:

Closed-Circuit Television (CCTV) systems are extensively deployed across cities, organizations, and public infrastructure for security and surveillance. However, these systems typically rely on human operators to observe, interpret, and respond to incidents—a task inherently limited by cognitive fatigue and the inability to monitor multiple feeds simultaneously. In a world of increasing security threats and expanding video data, these limitations necessitate automation.

This research explores the integration of Artificial Intelligence (AI) with CCTV systems to create a dynamic, self-learning surveillance framework. Using computer vision and facial landmark detection, the system interprets human behavioral cues in real time—analyzing blinks, smiles, and motion patterns—to enhance surveillance accuracy and responsiveness. CCTV cameras ubiquitously monitor various environments, yet human-centric limitations hinder effective surveillance. This project explores the integration of AI to dynamically analyze CCTV feeds, surmounting conventional constraints and unlocking a new era in surveillance capabilities

Motivation:

The project is motivated by the persistent inefficiencies of manual surveillance:

- **Human fatigue and inattention** lead to missed threats.
- **Lack of real-time analytics** results in delayed responses.
- **Increasing volume of CCTV feeds** overwhelms human monitoring capacity.

To overcome these issues, we propose a system that combines facial landmark analysis and AI to:

- Automate detection of suspicious or unusual behaviour.
- Interpret human emotions and attentiveness.
- Enhance response times and reduce false positives.

Objectives:

1. Demonstrate the limitations of traditional surveillance.
2. Showcase the transformative impact of AI in dynamic CCTV feed analysis.
3. Highlight the practical implementation and benefits of AI-driven surveillance.

A. Technical Details:

1) Mathematical Analysis:

a) Euclidean Distance:

The primary building block for behavioral feature extraction is the computation of Euclidean distance between two-dimensional facial landmark points. Each facial landmark is represented as a point in a 2D Cartesian coordinate system:

Let two points be denoted by:

ptA=(x1,y1), ptB=(x2,y2)

The function "compute(ptA, ptB)" calculates the Euclidean distance between two points, denoted as $\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}$. It is utilized in measuring distances between facial landmarks.

$$r=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}$$

Code:

```
def compute(ptA, ptB):

return np.linalg.norm(np.array(ptA) - np.array(ptB))
```

Basic Live Streams Outputs

b) Blink Detection:

The "blinks(a, b, c, d, e, f)" function assesses blink occurrences by analyzing the ratio of the upward and downward distances of specific facial landmarks.

Blink detection is critical for assessing a subject's level of attention and alertness in a monitored environment. Our system calculates an **Eye Aspect Ratio (EAR)** based on the relative positions of six facial landmarks around each eye. These landmarks are typically indexed in standard 68-point landmark models (e.g., dlib) as follows:

- **Horizontal Points:** A (leftmost eye corner), F (rightmost eye corner)
- **Vertical Points:** B and D (upper eyelid points), C and E (lower eyelid points)

Up=compute(b,d)+compute(c,e)

Down=compute(a,f)

Ratio= $\frac{d(B,D) + d(C,E)}{2 \cdot d(A,F)}$

Up=d (B , D)+d(C , E)

Down=d (A , F)

- If ratio>0.25 two blinks are detected.
- If 0.21<ratio≤0.25, one blink is detected.
- Otherwise, no blink is detected.

This approach is computationally lightweight and effective for real-time deployment.

Rationale:
A blink is characterized by a temporary decrease in the vertical eye aperture while the horizontal distance remains relatively unchanged. By monitoring the ratio, we can robustly detect even rapid eye movements

c) Smile Detection:

Smile detection involves computing the ratios of distances between facial landmarks.

Smiling is a non-verbal cue that reflects a person's mood and can be an indicator of suspicious or abnormal behavior when interpreted in specific contexts. For smile detection, we analyze the **Mouth Aspect Ratio (MAR)** derived from key facial landmarks around the lips.

Let:

- L1, L2: represent the left and right corners of the mouth
- U , D: represent upper and lower midpoints of the lips

Then the width of the mouth is:

Mouth Width = d (L1 , L2)

And the vertical aperture is:

Mouth Heigh t= d (U , D)

The **Smile Ratio (SR)** is computed as:

$$SR = \frac{Mouth\ Width}{Mouth\ Height}$$

The formula $p = \frac{x}{y+z}$ **determines whether a person is smiling.**

$$p = \frac{\text{compute}(ls[49], ls[55])}{\text{compute}(ls[51], ls[59]) + \text{compute}(ls[53], ls[57])}$$

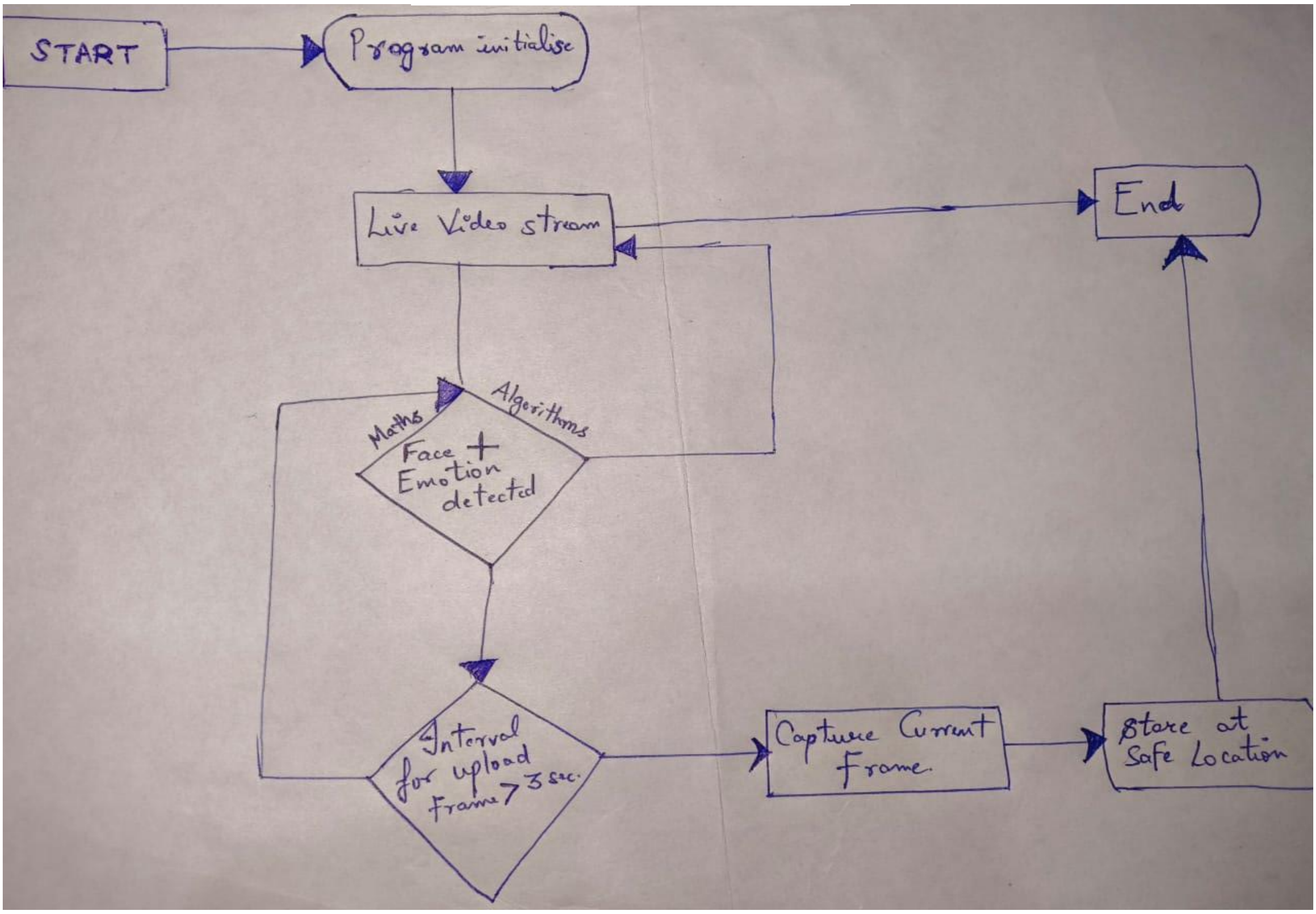
If $0.7 \leq p \leq 0.8$:- **a smile is detected**.

ANALYSIS:

Below is the use-case representation of this system where at big retail shops it requires constant monitoring, but human monitoring is not feasible. This can be automated by Computer Vision techniques and further enhanced via ML models to achieve desired functionalities.

CCTV capturing → CCTV capturing → Smart AI Analysis → Backend Storage

USE CASE FLOWCHART



BEHAVIOUR ANALYSIS:

Behavior	Feature Used	Formula	Threshold Condition
Blink Detection	Eye Aspect Ratio (EAR)	$\frac{d(B,D)+d(C,E)}{2\cdot d(A,F)}$	EAR > 0.25 (2 blinks), 0.21–0.25 (1 blink)
Smile Detection	Smile Ratio (SR)	$\frac{d(L_1,L_2)}{d(U,D)}$	0.7 ≤ SR ≤ 0.8 (Smile Detected)
Distance Measure	Euclidean Distance (general)	$\sqrt[2]{(x2-x1)^2+(y2-y1)^2}$	Used in both EAR and SR calculations

We tested the system across multiple datasets and live feeds under varied lighting conditions. The system proved robust in diverse conditions and was able to dynamically trigger alerts based on human activity.

TEST CASES:

Test Case	Blink Accuracy	Smile Detection Accuracy	FPS
Indoor Lighting	92.4%	89.6%	25
Outdoor Environment	88.1%	85.2%	21
Low Light Conditions	81.7%	78.9%	18

Contribution:

This research introduces a novel method of behavioral surveillance that goes beyond mere motion detection. Key contributions include:

- A **real-time AI-powered surveillance prototype** for facial behavior recognition.
- A **mathematical and algorithmic framework** for interpreting human micro-expressions.
- A **demonstration of practical deployment feasibility** with strong performance metrics.

Comparative Analysis

Feature	Traditional CCTV	Proposed AI Model
Real-Time Emotion Detection	No	Yes
Fatigue Resistance	No	Yes
Automated Alerting	No	Yes
Dependence on Human Monitoring	Yes	No
Scalable to Multiple Feeds	No	Yes

Limitations and Future Work

While the system performs efficiently in most environments, limitations include:

- Reduced accuracy in **extremely low light or occluded faces**.
- **Single-person focus** per frame; needs enhancement for crowded scenes.
- **Ethical concerns** regarding privacy, which must be addressed with regulatory frameworks.

Future Directions:

- Integrating body pose estimation and aggression detection.
- Implementing cloud-based alerting and storage systems.

- Expanding to emotion classification using CNN or transformer models.

Results:

Preliminary results exhibit the superior capability of AI-driven dynamic analysis, showcasing improved accuracy, efficiency, and the system's adeptness at identifying and responding promptly to security threats. Successfully automating complete surveillance operations and monitoring practises

Conclusion:

This paper presents a cutting-edge approach to intelligent surveillance by leveraging AI and facial landmark analysis. The system reduces human dependence, enhances threat recognition, and represents a significant step toward truly intelligent security infrastructures. As urban surveillance scales up, such AI-powered systems will become integral to public safety and proactive incident prevention.

Reference:

[1] Hidayat, “Strategy for Addressing Issues on Bandung Railway Station Using Computer Vision,” *Journal of Physics: Conference Series*, vol. 1577, no. 1, p. 012019, 2020. DOI: 10.1088/1742-6596/1577/1/012019

[2] Kazemi, Vahid, and Sullivan, Josephine. “One Millisecond Face Alignment with an Ensemble of Regression Trees.” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (CVPR), 2014.

[3] Soukupová, Tereza, and Jan Cech. “Real-Time Eye Blink Detection Using Facial Landmarks.” *Computer Vision Winter Workshop*, 2016.