Real-Time Dashcam Anomaly Detection Using Edge AI

Abstract

Road traffic accidents and unexpected driving events remain a major global safety concern. Real-time dashcam-based anomaly detection systems aim to identify unusual, dangerous, or abnormal driving situations such as sudden pedestrian crossings, collisions, abrupt braking, and erratic maneuvers. This project presents a comprehensive edge-AI-based real-time dashcam anomaly detection framework that integrates computer vision, optical flow analysis, and deep-learning-based object detection using TensorFlow Lite. The system is designed for low-latency, on-device inference and is suitable for deployment on embedded platforms such as NVIDIA Jetson Orin Nano. By combining spatial feature extraction and temporal motion analysis, the proposed approach minimizes false positives while maintaining high responsiveness, making it suitable for intelligent transportation and advanced driver-assistance systems (ADAS).

1. Introduction

1.1 Overview

Modern transportation systems demand intelligent safety mechanisms capable of operating in real time. Dashcams are increasingly common, yet most systems lack the ability to interpret video content automatically. Anomaly detection in driving scenes enables early identification of hazardous situations, potentially preventing accidents and saving lives.

Human reaction times are limited, especially during sudden or unexpected road events. Cloud-based video analytics suffer from latency, bandwidth dependency, and privacy concerns. Edge AI addresses these issues by enabling local processing directly on the vehicle.

1.2 Project Goals

The goals of this project are:

- Real-time detection of anomalous driving events
- Low-latency, edge-based video processing
- Combination of spatial object detection and temporal motion analysis
- Scalable architecture for embedded deployment

2. Literature Review

2.1 Classical Computer Vision Approaches

Early anomaly detection relied on background subtraction, frame differencing, and handcrafted features. These approaches are computationally simple but fragile under varying lighting and traffic conditions.

2.2 Deep Learning-Based Video Analysis

CNNs such as ResNet and MobileNet excel at spatial feature extraction. Temporal modeling using LSTM and GRU networks captures motion patterns over time, enabling more robust anomaly detection.

2.3 Transformer-Based Models

Recent work such as MOVAD employs Video Swin Transformers to model long-range dependencies. While accurate, these methods are computationally expensive and unsuitable for low-power edge devices without aggressive optimization.

2.4 Edge AI and Model Optimization

Edge platforms like NVIDIA Jetson Orin Nano support GPU acceleration. Techniques such as INT8 quantization and TensorRT significantly reduce inference time while maintaining accuracy.

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3. Problem Statement

Detecting anomalies in dashcam footage is challenging due to diverse traffic scenarios, lighting variations, and camera motion. A reliable system must distinguish between normal driving behavior and genuinely dangerous events while operating under real-time constraints.

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4. System Architecture

4.1 High-Level Design

The system consists of:

- Video acquisition module
- Preprocessing and motion analysis
- Optical flow computation
- CNN-based object detection

- Temporal anomaly confirmation logic
- Visualization and alert generation

4.2 Data Flow

Each video frame is processed sequentially. Motion features and detection outputs are combined over time to determine anomalies.

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5. Hardware and Software Requirements

5.1 Hardware

- Webcam or dashcam
- NVIDIA Jetson Orin Nano (recommended)
- Minimum 4 GB RAM

5.2 Software

- Python 3.10
- OpenCV
- TensorFlow Lite

- NumPy

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6. Computer Vision Fundamentals

6.1 Image Representation

Images are represented as matrices of pixel intensities. RGB images contain three channels, while grayscale images contain a single channel.

6.2 Real-Time Constraints

Maintaining a frame rate above 15 FPS is critical for responsive anomaly detection.

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7. Optical Flow Analysis

7.1 Optical Flow Concept

Optical flow measures apparent pixel motion between consecutive frames, providing insight into dynamic scene changes.

7.2 Farnebäck Algorithm

The Farnebäck method computes dense optical flow efficiently, making it suitable for real-time systems.

7.3 Role in Anomaly Detection

Sudden increases in optical flow magnitude often indicate abnormal events such as collisions or abrupt pedestrian movement.

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8. Deep Learning Object Detection

8.1 CNN-Based Detection

A lightweight CNN model exported to TensorFlow Lite is used to detect objects in each frame.

8.2 TensorFlow Lite Inference

TFLite enables optimized inference on edge devices with minimal overhead.

8.3 Spatial Filtering

Bounding boxes are filtered using area and aspect ratio constraints to reduce false positives.

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9. Temporal Modeling

9.1 Motion History Buffers

Deque-based buffers store recent motion and optical flow values, mimicking sequence learning.

9.2 Temporal Confirmation

An anomaly is confirmed only if abnormal conditions persist across multiple frames.

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10. Hybrid Anomaly Detection Logic

10.1 Decision Criteria

An anomaly is detected when:

- Optical flow exceeds a threshold
- Motion deviation is significant
- Objects are detected
- Conditions persist for several frames

10.2 Advantages

This hybrid approach balances sensitivity and robustness.

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11. Implementation Details

11.1 Project Folder Structure

```
ai_video_project/
 ├── detect.py
 ├── model.tflite
 ├── labels.txt
```

11.2 Main Detection Code (detect.py)

```
import cv2
import numpy as np
import tensorflow as tf
import time
from collections import deque

# ==============================
# CONFIG (EDGE / DASHCAM STYLE)
```

```
# ==============================
MOTION_HISTORY = 40
FLOW_THRESHOLD = 2.0        # optical flow anomaly
MOTION_THRESHOLD = 1.0      # pixel motion
CONFIRM_FRAMES = 3
MIN_BOX_AREA = 0.02
MAX_BOX_AREA = 0.6

# ==============================
# LOAD TFLITE MODEL (CNN)
# ==============================
interpreter = tf.lite.Interpreter(model_path="model.tflite")
interpreter.allocate_tensors()

input_details = interpreter.get_input_details()
output_details = interpreter.get_output_details()

MODEL_H = input_details[0]['shape'][1]
MODEL_W = input_details[0]['shape'][2]

print("Model loaded")
print("Output shape:", output_details[0]['shape'])

# ==============================
```

```
# WEBCAM (DASHCAM SIM)
# ==============================
cap = cv2.VideoCapture(0)
if not cap.isOpened():
    raise RuntimeError("Camera not accessible")

# ==============================
# TEMPORAL STATE (LSTM-LIKE)
# ==============================
prev_gray = None
motion_buffer = deque(maxlen=MOTION_HISTORY)
flow_buffer = deque(maxlen=MOTION_HISTORY)
anomaly_counter = 0

# ==============================
# MAIN LOOP
# ==============================
while True:
    start = time.time()
    ret, frame = cap.read()
    if not ret:
        break

    h, w, _ = frame.shape
```

```
gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

# -------------------------
# OPTICAL FLOW (Motion Field)
# -------------------------
if prev_gray is not None:
    flow = cv2.calcOpticalFlowFarneback(
        prev_gray, gray,
        None, 0.5, 3, 15, 3, 5, 1.2, 0
    )
    mag, ang = cv2.cartToPolar(flow[..., 0], flow[..., 1])
    flow_mean = np.mean(mag)
else:
    flow_mean = 0.0

prev_gray = gray
flow_buffer.append(flow_mean)

# -------------------------
# BASIC MOTION (PIXEL DIFF)
# -------------------------
if len(motion_buffer) > 0:
    motion = abs(flow_mean - np.mean(flow_buffer))
else:
```

```
        motion = 0.0

    motion_buffer.append(motion)

    # ------------------------
    # AI INFERENCE (CNN)
    # ------------------------
    resized = cv2.resize(frame, (MODEL_W, MODEL_H))
    input_tensor = np.expand_dims(resized,
axis=0).astype(np.uint8)

    interpreter.set_tensor(input_details[0]['index'], input_tensor)
    interpreter.invoke()
    detections =
interpreter.get_tensor(output_details[0]['index'])[0]

    boxes = []

    for det in detections:
        xmin, ymin, xmax, ymax = det

        x1 = int(xmin * w)
        y1 = int(ymin * h)
        x2 = int(xmax * w)
```

```
        y2 = int(ymax * h)

        if x2 <= x1 or y2 <= y1:
            continue

        area_ratio = ((x2 - x1) * (y2 - y1)) / (w * h)
        if area_ratio < MIN_BOX_AREA or area_ratio >
MAX_BOX_AREA:
            continue

        boxes.append((x1, y1, x2, y2))

    # ------------------------
    # ANOMALY DECISION (HYBRID)
    # ------------------------
    anomaly = False

    if (
        flow_mean > FLOW_THRESHOLD and
        motion > MOTION_THRESHOLD and
        len(boxes) > 0
    ):
        anomaly_counter += 1
    else:
```

```
    anomaly_counter = max(0, anomaly_counter - 1)

if anomaly_counter >= CONFIRM_FRAMES:
    anomaly = True

# ------------------------
# VISUALIZATION
# ------------------------
for (x1, y1, x2, y2) in boxes:
    color = (0, 0, 255) if anomaly else (0, 255, 0)
    cv2.rectangle(frame, (x1, y1), (x2, y2), color, 2)

if anomaly:
    cv2.putText(frame, "DASHCAM ANOMALY DETECTED",
                (40, 80),
                cv2.FONT_HERSHEY_SIMPLEX,
                1.2,
                (0, 0, 255),
                3)

fps = 1.0 / (time.time() - start)

cv2.putText(frame, f"FPS: {fps:.1f}", (20, 30),
            cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 255, 0), 2)
```

```
    cv2.putText(frame, f"Optical Flow: {flow_mean:.2f}", (20, 55),
                cv2.FONT_HERSHEY_SIMPLEX, 0.6, (255, 255, 0),
2)

    cv2.imshow("Real-Time Dashcam Anomaly Detection",
frame)

    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

# ==============================
# CLEANUP
# ==============================
cap.release()
cv2.destroyAllWindows()
```

The code integrates webcam capture, optical flow analysis, TensorFlow Lite inference, temporal buffering, and visualization.

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12. Performance Metrics

12.1 Accuracy

Hybrid detection significantly reduces false positives.

12.2 Latency

Edge-based inference ensures millisecond-level response times.

12.3 Frame Rate

The system maintains real-time performance on consumer hardware.

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13. Experimental Results

13.1 Normal Driving

Normal scenarios show stable motion and green bounding boxes.

13.2 Anomalous Events

Confirmed anomalies display red bounding boxes and alert messages

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14. Use Cases

- Dashcam accident detection
- ADAS systems
- Smart traffic monitoring
- Autonomous vehicle safety

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15. Edge AI Deployment

15.1 Jetson Orin Nano

The architecture is compatible with Jetson devices.

15.2 TensorRT Optimization

TensorRT can further accelerate inference.

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16. Comparison with Existing Approaches

The proposed system offers a practical balance between accuracy and computational cost.

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17. Limitations

- Limited semantic understanding
- Dependence on camera quality

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18. Future Enhancements

- Integration of trained LSTM/GRU models
- Multimodal sensor fusion
- Cloud-assisted analytics

19. Ethical and Safety Considerations

Ensuring privacy and responsible AI deployment is essential.

Hybrid Anomaly Decision Strategy

An anomaly is confirmed when:

- Optical flow exceeds threshold
- Motion deviation is significant
- Objects are detected in scene
- Conditions persist for multiple frames

20. Conclusion

This project demonstrates a complete, real-time dashcam anomaly detection system using edge AI. By combining optical flow, motion analysis, and CNN-based object detection, the system achieves reliable anomaly detection with low latency and high practicality for real-world deployment.