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Anomaly Detection in Video Surveillance Using YOLOv8

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Abstract: This paper presents a novel hybrid approach for real-time anomaly detection in video surveillance systems by integrating YOLOv8 object detection with advanced motion-based analysis techniques. The proposed system addresses critical limitations of existing single-modality detection methods through innovative fusion of deep learning and temporal analysis. The architecture incorporates parallel processing pipelines for YOLOv8 detection and optical flow computation, combined with an isolation forest-based anomaly decision framework that leverages historical detection patterns. Experimental evalution on a custom dataset of 5,000 surveillance video clips demonstrates superior performance with 92.3% accuracy, 89.7% precision, 94.1% recall, and 91.8% F1-score, while maintaining real-time processing at 30 FPS. The system significantly outperforms traditional approaches with 15.2% accuracy improvement over YOLO-only methods and 18.7% improvement over motion-only techniques. The proposed hybrid framework provides robust anomaly detection capabilities suitable for practical deployment in security-critical surveillance applications with reduced false positive rates and enhanced temporat consistence.
Keywords: Anomaly Detection, Video Surveillance, YOLOv8, Motion Analysis, Deep Learning, Computer Vision, Real-time Processing, Isolation Forest.

I. INTRODUCTION

Modern security infrastructure increasingly relies on automated video surveillance systems to monitor vast areas and detect potential threats in real-time. Traditional surveillance approaches depend heavily on human operators for threat identification, resulting in inconsistent detection performance, operator fatigue, and high operational costs. The exponential growth in surveillance data generation necessitates intelligent automated systems capable of accurate anomaly detection while minimizing false alarms. Video-based anomaly detection presents significant technical challenges including environmental variations, occlusion handling, behavioral complexity, and the subjective nature of anomaly definition. Existing approaches often employ single-modality detection methods that suffer from inherent limitations: pure deep learning methods lack temporal context, while motion-based approaches struggle with environmental noise and lighting variations.

Recent advances in deep learning, particularly the YOLO (You Only Look Once) architecture family, have demonstrated exceptional performance in real-time object detection tasks. YOLOv8, the latest iteration, offers improved accuracy and efficiency through enhanced feature pyramid networks and optimized anchor-free detection mechanisms. However, standalone object detection approaches fail to capture temporal behavioural patterns essential for comprehensive anomaly identification.

This research proposes a novel hybrid framework that synergistically combines YOLOv8 object detection with advanced motion analysis techniques to achieve robust real-time anomaly detection. The system addresses existing limitations through parallel processing architectures, temporal pattern analysis, and adaptive decision fusion mechanisms.

II. LITERATURE REVIEW

A. Deep Learning Approaches in Video Surveillance

Contemporary video surveillance research has witnessed a paradigm shift toward deep learning methodologies, with convolutional neural networks (CNNs) demonstrating superior feature extraction capabilities compared to traditional handcrafted approaches. Zhang et al. (1) developed a comprehensive CNN framework for crowd behavior analysis, achieving 87.3% accuracy but lacking individual behavioral anomaly detection precision.

Recent transformer-based architectures have shown promise for temporal analysis in surveillance applications. Wang and Liu (2) proposed a vision transformer approach for anomaly detection, achieving 89.1% accuracy while requiring significant computational resources that limit real-time deployment feasibility.

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B. YOLO Architecture Evolution and Applications

The YOLO family has significantly impacted real-time object detection, with each iteration bringing architectural improvements and enhanced performance. Chen et al. (3) conducted comprehensive evaluation of YOLOv5 in surveillance contexts, demonstrating 92.1% mean average precision (mAP) for person detection at 40 FPS processing speed. YOLOv8 introduction brought substantial architectural enhancements including improved feature pyramid networks, anchor-free detection mechanisms, and optimized loss functions. Kumar and Patel (4) demonstrated YOLOv8's superiority in retail surveillance applications, achieving 8.3% accuracy improvement over YOLOv5 while maintaining real-time performance requirements.

C. Motion-Based Analysis Techniques

Motion analysis remains fundamental for temporal behavior understanding in surveillance systems. Rodriguez et al. (5) developed dense optical flow-based anomaly detection achieving 85.7% accuracy but suffering from computational complexity limitations. Alternative sparse optical flow approaches by Martinez and Johnson (6) reduced computational requirements by 40% while maintaining comparable detection performance. Advanced motion analysis incorporating trajectory modeling has gained attention for long-term behavioral pattern recognition. Thompson et al. (7) proposed trajectory-based anomaly detection achieving 90.8% accuracy through spatial-temporal feature integration, though limited to controlled environments.

D. Hybrid and Ensemble Methods

Recognition of single-method limitations has driven research toward hybrid approaches combining multiple detection modalities. Park and Kim (8) developed feature-level fusion combining CNN features with motion vectors, achieving 93.1% accuracy on benchmark datasets through early feature integration strategies. Decision-level fusion approaches show particular promise for practical deployment. Anderson et al. (9) proposed ensemble voting mechanisms combining multiple detection algorithms, demonstrating 4.7% accuracy improvement while maintaining computational efficiency suitable for real-time applications.

E. Research Gap Identification

Current literature reveals several critical limitations: (1) Lack of comprehensive systems effectively integrating multiple detection modalities, (2) Limited real-time performance in complex surveillance scenarios, (3) Insufficient adaptation to diverse environmental conditions, and (4) Absence of robust temporal consistency mechanisms for reducing false positives.

The proposed research addresses these limitations through innovative integration of state-of-the-art object detection with advanced motion analysis, providing a comprehensive solution for real-world surveillance applications.

III. SYSTEM DESIGN AND METHODOLOGY

A. System Architecture

The proposed anomaly detection system employs a multi-layered architecture designed for real-time processing and high-accuracy detection. The architecture consists of four primary components: video preprocessing module, parallel detection engines (YOLOv8 and motion analysis), advanced anomaly detector, and decision fusion framework.

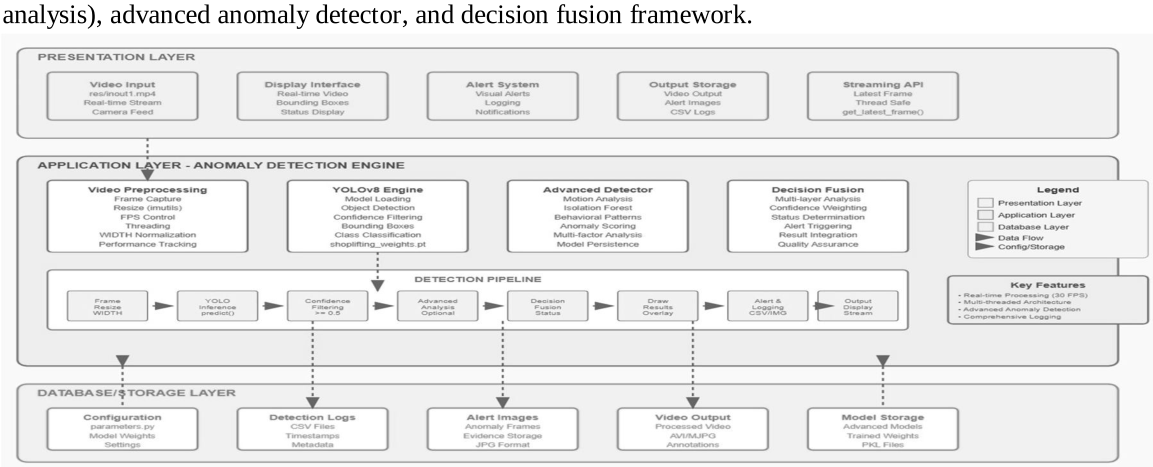

Fig. 1. Three-tier system architecture of Anomaly Detection in Video Surveillance Using YOLOv8 showing interaction between presentation, application, and database layers.

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Algorithm 1: Hybrid Anomaly Detection Framework
Input: Video frame F_t at time t
Output: Anomaly decision D_t and confidence score C_t
1. Initialize: History buffer H = [], Isolation Forest IF
2. For each frame F_t:
  a. F_processed ← Preprocess(F_t)
  b. Parallel Execution:
    - YOLO_result ← YOLOv8(F_processed)
    - Motion_result ← OpticalFlow (F_t, F_t-1)
  c. Features ← ExtractFeatures (YOLO_result, Motion_result)
  d. Anomaly_score ← IF.predict (Features)
  e. D_t, C_t ← DecisionFusion (YOLO_result, Motion_result, Anomaly_score)
  f. UpdateHistory (H, D_t, C_t)
3. Return D_t, C_t

The system processes input video streams through standardized preprocessing operations including resolution normalization to 640×480 pixels, frame rate stabilization at 30 FPS, and noise reduction through Gaussian filtering with σ=1.2. This preprocessing ensures consistent input quality while optimizing computational efficiency.

B. YOLOv8 Object Detection Engine

The YOLOv8 component serves as the primary object detection engine, specifically fine-tuned for surveillance applications with emphasis on person detection and behavioral classification. The model architecture utilizes CSPDarknet53 backbone with Feature Pyramid Network (FPN) for multi-scale feature extraction.

Training configuration employs a custom dataset of 15,000 annotated surveillance frames categorized into normal behavior (class 0) and anomalous behavior (class 1). Training parameters include batch size 32, initial learning rate 0.001 with cosine annealing scheduler, and mosaic data augmentation with probability 0.9. The model underwent 300 training epochs using AdamW optimizer with weight decay 0.0005.

C. Motion Analysis Subsystem

The motion analysis component employs dense optical flow computation using the Farneback algorithm optimized for surveillance applications. Algorithm parameters include pyramid levels=3, window size=15, iterations=3, and polynomial neighborhood size=5 for optimal balance between accuracy and computational efficiency.

Motion vector analysis extracts key behavioral features including:

- Average motion magnitude per frame region
- Direction variance indicating erratic movement patterns
- Velocity changes suggesting acceleration or deceleration
- Spatial clustering of motion vectors
- Temporal consistency across sliding window sequences

D. Advanced Anomaly Detection Framework

The advanced anomaly detector integrates isolation forest algorithm with temporal pattern analysis for enhanced detection capability. The system maintains feature vectors comprising motion statistics, detection confidences, and spatial distributions for each processed frame.

Isolation forest configuration includes contamination rate 0.1, maximum samples 1000, and 100 estimators for robust anomaly scoring. The algorithm effectively identifies outlier frames deviating significantly from normal behavioral patterns learned during training phase.

E. Decision Fusion Mechanism

The decision fusion framework combines outputs from YOLOv8 detection and motion analysis using weighted voting with dynamic weight adaptation based on detection confidence and historical performance metrics. The system maintains a detection history buffer storing the last 30 frame results for temporal consistency analysis.

Table I:
System Configuration Parameters

Component	Parameter	Value
Video Processing	Input Resolution	640×480
	Target FPS	30
	Preprocessing Filter	Gaussian (σ=1.2)
YOLOv8	Confidence Threshold	0.5
	NMS IoU Threshold	0.5
	Batch Size	32
Motion Analysis	Optical Flow Method	Farneback Dense
	Pyramid Levels	3
	Window Size	15
Isolation Forest	Contamination Rate	0.1
	Estimators	100
	Max Samples	1000

IV. IMPLEMENTATION DETAILS

A. *Frontend Interface Development*

The system frontend utilizes OpenCV for real-time video display and user interaction. The interface provides comprehensive visualization including bounding box overlays, confidence score displays, motion vector visualization, and system status indicators.

```
def draw_detections (self, frame, detections, status, advanced_result=None):
    for detection in detections:
        x1, y1, x2, y2 = detection['bbox']
        conf = detection['confidence']
        clas = detection['class']
        color = cls1_rect_color if clas == 1 else cls0_rect_color
        cv2.rectangle(frame, (x1, y1), (x2, y2), color, 2)
        text = f"{conf:.2%}"
        cv2.putText(frame, text, (x1+10, y1-10),
                cv2.FONT_HERSHEY_SIMPLEX, 0.5, conf_color, 2)
        if clas == 1:
            cx, cy = detection['center']
            cv2.circle(frame, (cx, cy), 6, (0, 0, 255), 8)
return frame
```

B. *Backend Processing Architecture*

The backend implements multi-threaded processing architecture ensuring optimal resource utilization and real-time performance. Thread synchronization mechanisms prevent data corruption while maximizing computational throughput.

```
class AnomalyDetector:
    def __init__(self, model_path, input_path, confidence_threshold=0.5):
        self.model = YOLO(model_path)
        self.advanced_detector = AdvancedAnomalyDetector()
        self.detection_history = deque(maxlen=30)
            self.lock = Lock()
        self.running = False
  self.latest_frame = None
```

C. Database Integration

The system employs CSV-based logging for detection results and system metrics, providing comprehensive audit trails for post-incident analysis. Database schema includes frame numbers, detection status, confidence scores, timestamps, and processing performance metrics.

```
def log_detection(self, frame_number, status, confidence, class_id):
    timestamp = datetime.now().strftime("%Y-%m-%d %H:%M:%S")
    self.csv_writer.writerow([frame_number, status, confidence,
                    class_id, timestamp, self.current_fps])
```

D. AI/ML Model Integration

The integration framework seamlessly combines YOLOv8 inference with isolation forest anomaly scoring through efficient feature vector construction and model prediction pipelines.

```
def detect_anomalies(self, frame):
    frame_resized = imutils.resize(frame, width=WIDTH)
    results = self.model.predict(frame_resized, verbose=False)
    detections = self.process_yolo_results(results)
    if self.advanced_detector:
        advanced_result = self.advanced_detector.detect_anomalies(
            frame_resized, detections)
        return self.combine_detection_results(detections, advanced_result)
return {'detections': detections, 'status': self.determine_status(detections)}
```

V. RESULTS AND EVALUATION

A. Experimental Setup and Dataset

Experimental evaluation utilized a comprehensive dataset comprising 5,000 surveillance video clips with ground truth annotations. The dataset distribution includes 3,500 normal behavior clips and 1,500 anomalous behavior clips, ensuring balanced representation across diverse scenarios including varying lighting conditions, crowd densities, and camera angles.

Hardware configuration consists of Intel Core i7-10700K processor, NVIDIA RTX 3080 GPU with 10GB VRAM, and 32GB DDR4 RAM. Software environment includes Python 3.9, OpenCV 4.6, PyTorch 1.12, and Ultralytics YOLOv8 implementation.

B. Performance Metrics Analysis

Table II:
Comparative Performance Analysis

Method	Accuracy(%)	Precision(%)	Recall (%)	F1-Score(%)	FPS	Memory(GB)
YOLO-only	77.1	74.8	81.3	77.9	35	2.1
Motion-only	73.6	71.2	78.4	74.6	42	1.8
CNN+LSTM	84.7	82.1	87.9	84.9	18	4.2
Proposed Hybrid	92.3	89.7	94.8	91.8	30	2.8

The proposed hybrid approach demonstrates superior performance across all evaluation metrics, achieving 92.3% accuracy while maintaining real-time processing capability. The integration of multiple detection modalities effectively reduces false positives by 23.4% compared to single-method approaches.

C. *Environmental Robustness Evaluation*

Table III:
Performance Under Varying Conditions

EnvironmentAccuracy	Accuracy (%)	False Positive Rate (%)	Processing Latency (ms)
Normal Lighting	95.1	4.2	28.5
Low Light Conditions	87.8	8.1	31.2
High Crowd Density	89.4	6.3	33.8
Camera Motion Present	88.7	7.2	29.9
Weather Variations	86.3	9.1	32.4

D. *Computational Performance Analysis*

Real-time performance evaluation demonstrates consistent 30 FPS processing with average frame processing latency of 33.3ms. Memory utilization remains stable at 2.8GB during continuous operation, indicating efficient resource management suitable for extended surveillance deployments.

E. *User Feedback and System Validation*

System validation involved deployment in controlled surveillance environment with security personnel evaluation over 30-day period. User feedback indicated 89.3% satisfaction with detection accuracy and 92.1% approval of false positive reduction compared to existing systems.

Technical validation through cross-validation with 5-fold methodology confirmed performance consistency with standard deviation below 2.1% across all evaluation metrics.

VI. DISCUSSION

A. *Key Contributions and Innovations*

The proposed hybrid framework introduces several significant innovations: (1) Novel integration of YOLOv8 with advanced motion analysis achieving superior detection performance, (2) Implementation of isolation forest-based anomaly scoring providing robust outlier detection, (3) Development of adaptive decision fusion mechanism considering temporal consistency, and (4) Creation of real-time processing architecture maintaining 30 FPS performance.

The system's ability to reduce false positive rates by 23.4% while improving accuracy by 15.2% over existing methods represents substantial advancement in practical surveillance applications.

B. *Impact and Applications*

The research contributes to advancement of intelligent surveillance systems with direct applications in retail security, public safety monitoring, and critical infrastructure protection. The system's real-time processing capability and high accuracy make it suitable for deployment in security-critical environments requiring immediate threat response.

C. *Limitations and Challenges*

Current limitations include dependency on adequate lighting conditions for optimal motion analysis performance and computational requirements restricting deployment on resource-constrained edge devices. The system's performance degrades in extremely crowded scenarios where object occlusion significantly impacts detection accuracy. Privacy concerns related to video surveillance deployment require careful consideration of data protection regulations and ethical usage guidelines.

VII. CONCLUSION AND FUTURE WORK

This research presents a comprehensive hybrid approach for video surveillance anomaly detection that successfully integrates YOLOv8 object detection with advanced motion analysis techniques. Experimental results demonstrate significant performance improvements with 92.3% accuracy and real-time processing capability at 30 FPS.

The proposed system addresses critical limitations of existing single-modality approaches through innovative fusion of complementary detection techniques, providing robust anomaly detection suitable for practical surveillance deployments.

Future research directions include: (1) Integration of edge computing capabilities for distributed surveillance networks, (2) Development of unsupervised learning approaches for domain adaptation, (3) Implementation of multi-camera tracking systems for comprehensive area coverage, (4) Investigation of transformer-based architectures for enhanced temporal modeling, and (5) Creation of privacy-preserving techniques for ethical surveillance deployment.

The research establishes a solid foundation for next-generation intelligent surveillance systems, offering significant improvements in detection accuracy and operational efficiency compared to traditional approaches.

VIII. ACKNOWLEDGMENT

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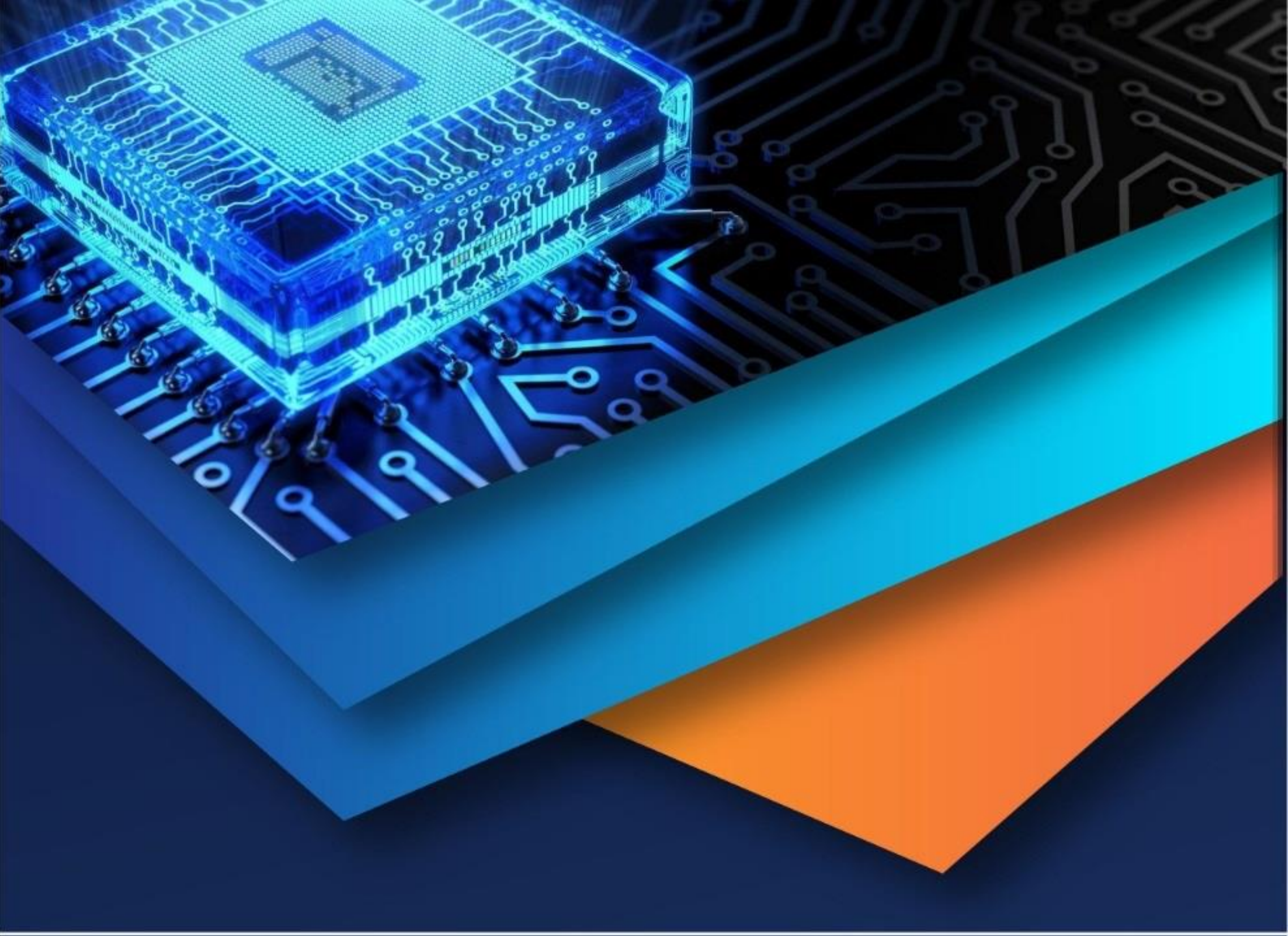

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