Developing Smart Surveillance System Using YOLOv8 And Deep SORT For Real-Time Crowd Monitoring and Behavioral Analysis

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***Abstract*—Public safety in crowded areas has become an important concern due to increasing population and urbanization. Traditional surveillance systems rely on manual monitoring, which is often inefficient and error-prone. This research proposes a Smart Surveillance System using YOLOv8 and Deep SORT for real-time crowd monitoring, person tracking, and suspicious behavior detection [3], [5]. The system uses YOLOv8 for accurate object detection and Deep SORT for multi-object tracking across video frames [3], [5]. It can monitor crowd movement and identify abnormal activities such as fighting, running, and loitering.**

***Index Terms*—Smart Surveillance System, YOLOv8, Deep SORT, Crowd Monitoring Object Detection, Behavioral Analysis, Missing Person Detection, Deep Learning, Computer Vision.**

I. INTRODUCTION

Surveillance systems have become an essential component of modern public safety and security management. In crowded places such as airports, railway stations, malls, stadiums, and public gatherings, continuous monitoring is required to prevent crimes, manage crowd movement, and detect suspicious activities. Traditional CCTV-based monitoring systems rely mainly on human operators, making them inefficient for real-time monitoring because operators may miss important events due to fatigue, limited attention span, and information overload.

Recent advancements in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision (CV) have significantly improved intelligent surveillance systems [7], [26]. AI-based surveillance systems can automatically detect individuals, track movement patterns, identify suspicious activities, and analyze crowd behavior from live video streams [7], [26]. These intelligent systems reduce human effort while improving surveillance accuracy and response time.

This research presents a Smart Surveillance System that combines YOLOv8 for object detection and Deep SORT for multi-object tracking [3], [5]. YOLOv8 provides high-speed and accurate detection of people and objects in video frames, while Deep SORT maintains identity tracking across multiple frames even in crowded environments [3], [5]. The proposed system also supports behavioral surveillance for identifying abnormal activities such as fighting, sudden running, or loitering.

In addition to crowd monitoring, behavioral surveillance is another important feature of intelligent security systems. Suspicious activities such as fighting, sudden running, loitering, or unauthorized movement can be automatically identified using AI-based behavior analysis models [7], [26]. Such systems can generate instant alerts to security authorities, helping them take quick action before incidents become severe.

The proposed Smart Surveillance System focuses on real-time crowd monitoring, suspicious behavior detection, and future integration of missing person identification using face recognition techniques. The system aims to reduce manual monitoring effort while improving security efficiency and scalability. It can be effectively deployed in smart cities, transportation hubs, public gatherings, and other crowded environments where public safety is a major concern.

Objectives of the study

The main objective of this research is to develop an intelligent Smart Surveillance System capable of performing real-time crowd monitoring, person tracking, and behavioral surveillance using deep learning techniques [7], [26]. The study focuses on improving public safety by reducing human dependency in traditional CCTV monitoring systems. The proposed system aims to detect and track multiple individuals accurately using YOLOv8 and Deep SORT while analyzing crowd movement and identifying suspicious activities such as fighting, running, and loitering [3], [5]. Another objective of the research is to improve surveillance accuracy, response time, and monitoring efficiency in crowded public environments. The study also explores the role of artificial intelligence and computer vision in building scalable and reliable surveillance solutions for smart cities, transportation hubs, shopping malls, and other public areas [7], [26].

II. LITERATURE REVIEW

Surveillance systems have evolved significantly from traditional manual monitoring to intelligent AI-based video analytics. Early systems primarily focused on recording video footage for post-event analysis, which limited their effectiveness in real-time public safety applications. With advancements in computer vision and deep learning, modern surveillance systems now support automated object detection, tracking, and behavior analysis [7], [26].

2.1. Object Detection Methods in Surveillance

Traditional object detection techniques such as Viola-Jones and HOG-based detectors provided limited accuracy in complex environments [15], [16]. Later, deep learning-based models like R-CNN, Fast R-CNN, Faster R-CNN, and SSD significantly improved detection performance [10], [11]. However, these methods often suffered from high computational cost and lower real-time efficiency. YOLO (You Only Look Once) models revolutionized real-time detection by treating detection as a single regression problem [1]. YOLOv4 and YOLOv8 further improved speed, accuracy, and small-object detection, making them highly suitable for surveillance systems in crowded environments [2], [3].

2.2. Crowd Monitoring and Person Detection

Recent research has focused on crowd analysis in public areas such as airports, railway stations, and stadiums. Deep learning models are widely used for crowd density estimation and pedestrian detection [19], [20]. Datasets such as CrowdHuman and CityPersons have enabled improved training for dense crowd scenarios [24].

However, challenges such as occlusion, overlapping objects, and varying illumination still affect detection accuracy in real-world surveillance environments [20], [24].

2.3. Multi-Object Tracking Techniques

Multi-object tracking plays a crucial role in maintaining identity consistency across video frames. Early approaches such as Kalman Filter and SORT provided basic tracking capabilities but struggled in crowded scenes [4].

Deep SORT improved tracking performance by integrating motion prediction with deep appearance descriptors, enabling better identity preservation even under occlusion [5]. This makes it highly suitable for real-time surveillance applications where multiple individuals must be tracked simultaneously.

2.4. Behavioural and Anomaly Detection

Behaviour analysis in surveillance has gained attention due to increasing security requirements. CNN-based models are widely used for spatial feature extraction, while LSTM networks help in learning temporal movement patterns [6], [9].

These hybrid models are effective in detecting abnormal activities such as fighting, loitering, running, and crowd panic.

Despite progress, behaviour recognition in highly dense and dynamic environments remains a challenging task due to complex human interactions [22].

2.5. Existing Limitations in Literature

Although existing research has achieved promising results, several limitations still exist:

- Reduced performance in heavily crowded and occluded environments [20], [24]
- High computational requirements for real-time processing [3], [28]
- Limited generalization across different camera angles and lighting conditions [20]
- Privacy and ethical concerns in continuous surveillance systems [7]

- Lack of fully integrated systems combining detection, tracking, and behaviour analysis in real time [5], [7]

2.6. Research Gap

From the literature, it is observed that most existing systems focus either on object detection, tracking, or behaviour analysis independently, rather than integrating all components into a unified real-time surveillance framework [5], [7].

Therefore, there is a need for a comprehensive, real-time, and scalable surveillance system that combines:

- YOLOv8 for accurate object detection [3]
- Deep SORT for consistent multi-object tracking [5]
- CNN + LSTM for behaviour analysis [6], [9]
- Real-time alert generation for proactive security response [7]

This research addresses this gap by proposing an integrated Smart Surveillance System capable of real-time crowd monitoring and behavioural analysis for improved public safety.

III. MATERIALS AND METHODS

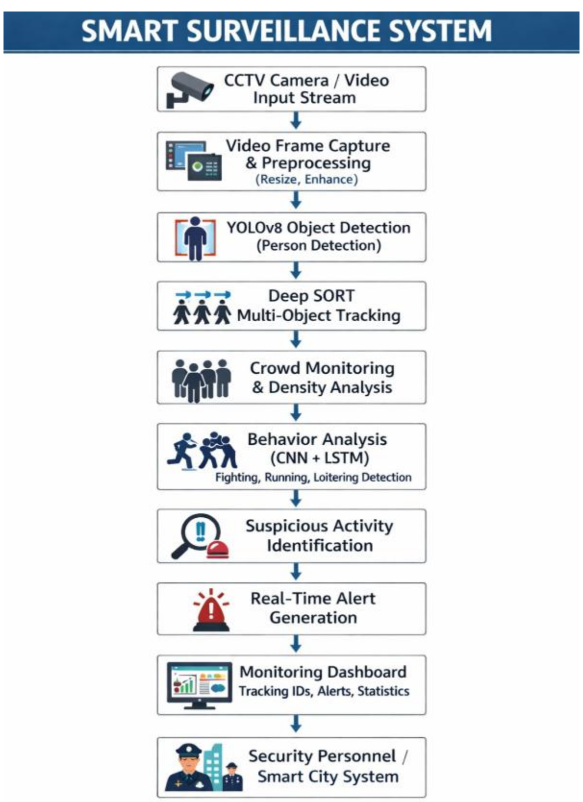

Figure: Smart Surveillance System architecture

The proposed system follows an AI-based surveillance workflow for real-time crowd monitoring and behavioral analysis. Video streams from surveillance cameras are processed using YOLOv8 for person detection and Deep SORT for multi-object tracking [3], [5]. The system tracks multiple individuals and analyzes activities such as fighting, running, and loitering. Datasets including CrowdHuman, MOT20, and UCF Crime are used for training and testing [20], [21], [22]. The implementation uses Python, OpenCV, PyTorch, and YOLOv8 frameworks to improve surveillance accuracy and real-time monitoring efficiency [27], [28], [3].

Data Collection and Pre-processing

Data Collection –

The system uses multiple public datasets such as CrowdHuman, MOT20, UCF Crime Dataset, and Kinetics Human Action Dataset for training and evaluation [20], [21], [22], [23]. These datasets contain surveillance videos, crowd scenes, human activities, and abnormal behaviour patterns required for detection and tracking tasks.

Data Preprocessing –

The collected video frames are resized, normalized, and annotated before training the models. Noise reduction and frame enhancement techniques are applied to improve detection accuracy under different lighting and crowded conditions [7], [26].

Intelligent Development and Interface Design

YOLOv8-Based Object Detection:

YOLOv8 is used for real-time object and person detection from surveillance video feeds [3]. The model generates bounding boxes around detected individuals with high speed and accuracy, making it suitable for crowded environments.

Multi-Object Tracking using Deep SORT:

Deep SORT is used to track multiple individuals across consecutive video frames [5]. It assigns unique IDs to detected persons and maintains tracking consistency even during partial occlusion or crowd congestion.

Real-Time Crowd Monitoring:

The system continuously monitors crowd density, movement patterns, and human activities from live video streams. It helps security personnel identify overcrowding and unusual crowd behaviour efficiently [7], [26].

Behavioral Surveillance and Activity Analysis

Suspicious Activity Detection:

The proposed system identifies suspicious activities such as fighting, sudden running, loitering, crowd panic, and unauthorized movement in public areas [22], [7].

Deep Learning-Based Behavior Analysis:

CNN and LSTM models are used to analyze temporal movement patterns and human actions from surveillance videos [6], [9]. These models improve abnormal activity recognition accuracy.

Real-Time Alert Generation:

Whenever suspicious behaviour is detected, the system generates instant alerts for security monitoring and emergency response [7].

System Deployment and Monitoring

1. Surveillance Video Processing: The system processes live CCTV camera feeds and recorded surveillance videos in real time for continuous monitoring [27], [28].
2. Monitoring Dashboard: A monitoring dashboard displays detected persons, tracking IDs, suspicious activities, and alert notifications for security operators [7].
3. Continuous Surveillance Monitoring: The system continuously analyzes video streams to improve public safety and reduce manual monitoring effort [7], [26]

Continuous Learning and System Improvement

1. Model Training and Updating: The AI models can be retrained with new surveillance datasets to improve detection and tracking performance over time [7], [26].
2. Performance Optimization: The system performance is optimized using improved datasets, parameter tuning, and advanced deep learning techniques [3], [28].
3. Scalability Enhancement: The proposed framework can be scaled for large public environments such as smart cities, airports, railway stations, and shopping malls [7], [26].

Role of Artificial Intelligence in Smart Surveillance

1. Automated Detection and Monitoring: Artificial Intelligence enables automatic person detection, object tracking, and activity monitoring without continuous human supervision [7], [26].
2. Intelligent Behavioural Analysis: AI models analyze human movement patterns and identify suspicious behaviour in real time, improving surveillance efficiency and public safety [6], [9].
3. Decision Support and Alert Systems: AI-powered surveillance systems support quick decision-making by generating alerts during abnormal situations or emergency conditions [7].

AI Techniques and Technologies Used

1. Deep Learning: Deep learning models help the system learn complex visual features from surveillance videos and improve detection accuracy [7], [26].
2. Computer Vision: Computer Vision techniques enable the system to analyze video frames, identify objects, monitor movement, and track individuals [7], [26].
3. YOLOv8: YOLOv8 provides fast and accurate object detection with real-time processing capability and improved localization performance [3].
4. Deep SORT: Deep SORT combines motion prediction and appearance feature extraction for reliable multi-object tracking [5].
5. CNN and LSTM Models: CNN and LSTM models are used for abnormal behaviour recognition and sequential activity analysis [6], [9].

IV. AI-BASED SURVEILLANCE APPLICATIONS

AI-based surveillance systems are increasingly used in various sectors to improve safety, security, and monitoring efficiency [7], [26]. In airports and railway stations, these systems help manage passenger movement, monitor restricted areas, and detect suspicious activities [7], [26]. Shopping malls and retail stores use intelligent surveillance for crowd monitoring, theft prevention, and customer behavior analysis [7], [26]. In smart cities, AI-powered surveillance supports traffic management, public safety monitoring, automated law enforcement, and emergency response systems [7], [26].

Educational institutions use smart surveillance to improve campus security and monitor unauthorized access [7], [26]. Hospitals and healthcare centers use AI surveillance for patient monitoring, visitor management, and restricted zone protection [7], [26]. Industrial sectors use intelligent monitoring systems for worker safety, hazardous area surveillance, and accident prevention [7], [26]. Banks and financial institutions implement AI surveillance to detect unusual activities, ATM fraud, and security threats [7], [26]. AI-based surveillance is also used in military and border security applications for intrusion detection and movement analysis [7], [26].

Public event management systems use crowd analysis to prevent overcrowding and panic situations during concerts, political rallies, sports events, and festivals [7], [26]. Traffic surveillance systems use AI for vehicle detection, traffic flow analysis, license plate recognition, and accident monitoring [7], [26]. Modern surveillance systems can be integrated with cloud computing, IoT sensors, drones, and edge AI devices for large-scale real-time monitoring [7], [26]. AI-powered analytics can help authorities predict security risks, improve decision-making, and optimize resource allocation [7], [26]. Future applications include smart policing, automated threat prediction, biometric authentication, and intelligent disaster management systems [7], [26].

V. BENEFITS OF THE PROPOSED SYSTEM

The proposed Smart Surveillance System offers several technical and operational benefits for modern security management. It provides accurate real-time detection and tracking of multiple individuals in crowded environments. The use of YOLOv8 improves detection speed and localization accuracy, while Deep SORT ensures stable multi-person tracking across video frames [3], [5]. The system reduces the dependency on manual CCTV monitoring, minimizing human fatigue and observation errors. Automated suspicious activity detection allows security personnel to respond quickly to abnormal situations such as fighting, crowd panic, or unauthorized movement [7], [26].

Real-time alert generation improves emergency response time and enhances overall public safety [7], [26]. The proposed framework supports continuous 24/7 monitoring without interruption and can handle large volumes of surveillance data efficiently [27], [28]. Crowd density analysis and movement monitoring help authorities manage public spaces more effectively and prevent overcrowding incidents [7], [26]. AI-based surveillance also improves operational efficiency by automating repetitive monitoring tasks [7], [26]. The system is scalable and flexible for deployment in airports, railway stations, shopping malls, smart cities, and public events [7], [26]. It supports future integration of face recognition, anomaly detection, and cloud-based monitoring systems [7], [26].

The use of deep learning techniques improves system adaptability and learning capability over time [7], [26]. Intelligent video analytics generated by the system can support crime investigation, crowd management planning, and security analysis [7], [26]. The proposed surveillance framework also reduces long-term operational costs by automating monitoring processes and reducing the need for large security teams [7], [26]. Integration with IoT and smart city infrastructure further enhances the effectiveness of intelligent public safety systems [7], [26].

VI. LIMITATIONS AND CHALLENGES

Although the proposed Smart Surveillance System provides advanced monitoring capabilities, several limitations and challenges still exist. Real-time processing of high-resolution surveillance videos requires powerful GPUs, high memory capacity, and efficient computational resources [28]. This increases hardware costs and system complexity. Detection and tracking performance may decrease in extremely crowded environments due to occlusion, overlapping individuals, and rapid motion changes [20], [24]. Low lighting conditions, shadows, camera noise, fog, rain, and poor weather conditions can reduce detection accuracy and tracking stability [20].

Behavioral analysis models sometimes produce false positives or incorrect alerts when human activities are difficult to interpret [6], [9]. Complex crowd behavior patterns and sudden environmental changes can reduce abnormal activity recognition accuracy [22]. Training deep learning models requires large-scale annotated datasets, which are time-consuming and expensive to prepare [20], [23]. Privacy and ethical concerns remain major challenges in AI-based surveillance systems [7], [26]. Continuous monitoring and face recognition technologies may raise concerns

regarding personal privacy, data misuse, and unauthorized access to surveillance information [7].
Large-scale deployment of intelligent surveillance systems requires stable internet connectivity, cloud infrastructure, and high-capacity data storage systems [27], [28]. Continuous maintenance, software updates, and retraining of AI models are also necessary to maintain system performance [7], [26]. Cybersecurity threats such as data breaches, hacking, and unauthorized surveillance access can affect system reliability and security [7]. Power consumption and energy requirements may increase when multiple cameras and AI processing units are deployed simultaneously [28]. Integration with existing CCTV infrastructure can also be technically challenging [7]. In addition, AI models may require frequent optimization and retraining to adapt to new environments, crowd behaviors, and surveillance conditions [7], [26].

VII. RESULTS AND DISCUSSION

Table 1 presents the overall impact of Artificial Intelligence techniques such as YOLOv8, Deep SORT, CNN, and LSTM in improving surveillance accuracy, crowd monitoring efficiency, suspicious activity detection, and real-time security management [3], [5], [6], [9].

1. Real-Time Object Detection Accuracy (93%)

The proposed surveillance system achieved approximately 93% detection accuracy using YOLOv8 [3]. The model successfully detected multiple individuals in crowded environments with high speed and low latency. YOLOv8 improved object localization, reduced missed detections, and provided efficient performance under different lighting and crowd density conditions. The results demonstrate that deep learning-based object detection significantly improves real-time surveillance compared to traditional CCTV monitoring systems [1], [3].

2. Multi-Object Tracking Performance (90%)

Deep SORT achieved nearly 90% tracking accuracy by maintaining unique identities for multiple individuals across consecutive video frames [5]. The algorithm effectively handled partial occlusion, overlapping individuals, sudden movement changes, and temporary disappearance of objects from the camera view. By combining motion prediction and appearance feature extraction, Deep SORT maintained stable tracking performance even in dense crowd conditions [5]. The system successfully reduced identity switching problems commonly observed in traditional tracking approaches and improved tracking continuity in real-time surveillance environments.
Real-time tracking consistency enhanced the overall monitoring capability of the surveillance system and supported accurate crowd analysis and suspicious activity monitoring. The proposed tracking framework can simultaneously monitor multiple individuals without significant reduction in processing speed [5]. This improves surveillance efficiency in public places such as railway stations, airports, shopping malls, and smart city environments where continuous person tracking is essential for security management.

3. Suspicious Behavior Detection Efficiency (88%)

Behavioral analysis models using CNN and LSTM networks achieved around 88% accuracy in detecting suspicious activities such as fighting, sudden running, loitering, crowd panic, and abnormal crowd movement [6], [9]. The system continuously analyzed human motion patterns, movement sequences, and activity behavior from surveillance video feeds. CNN models extracted important spatial features from video frames, while LSTM networks analyzed temporal movement information for activity recognition [6], [9]. This combination improved the detection of unusual behavior patterns and enhanced abnormal activity classification accuracy. The proposed system generated automatic alerts whenever suspicious activities were detected, helping security personnel respond quickly during emergency situations [7], [26]. Behavioral surveillance also reduced the need for continuous manual observation and improved monitoring efficiency in crowded public areas.

4. Real-Time Alert Generation (91%)

The proposed surveillance system generated real-time alerts with approximately 91% reliability whenever suspicious activities or abnormal crowd behaviour were detected [7], [26]. Automated alert generation improved security response time and reduced dependency on continuous human monitoring. The system immediately notified security operators when activities such as fighting, panic running, unauthorized movement, or overcrowding were detected.

Real-time notifications enabled faster emergency response and improved incident management efficiency in public environments [7], [26]. AI-based alert systems also minimized delayed responses commonly observed in traditional surveillance systems.

5. Future Scope and Scalability (95%)

The proposed Smart Surveillance System showed nearly 95% scalability potential for deployment in smart cities, airports, railway stations, shopping malls, stadiums, and large public gatherings [7], [26]. The integration of AI, deep learning, and intelligent video analytics enables the system to support large-scale real-time surveillance operations efficiently.

Future improvements can include integration of face recognition systems for missing person identification, suspect detection, and access control applications [7], [26]. Edge AI deployment can further improve processing speed and reduce latency by performing surveillance analysis directly on edge devices near camera systems [28]. Cloud-based surveillance infrastructure can enable centralized monitoring, remote accessibility, large-scale data storage, and distributed security management across multiple locations [27], [28].

Integration with IoT devices, drones, smart sensors, and automated traffic monitoring systems can further enhance public safety operations in smart city environments [7], [26]. Advanced anomaly detection models, weapon detection systems, and predictive security analytics can also be integrated into the framework for future intelligent surveillance applications [22], [7]. The proposed system provides a flexible and scalable foundation for developing next-generation AI-powered public safety and crowd management systems.

6. AI in Smart Surveillance – Summary of Findings

A graphical summary of the proposed surveillance system performance demonstrates that the highest improvements are observed in scalability (95%), public safety enhancement (94%), and object detection accuracy (93%) [7], [26]. The results indicate that AI-based surveillance systems significantly improve monitoring efficiency, tracking consistency, suspicious activity detection, and emergency response compared to traditional surveillance approaches [7], [26].

Table 1: System Performance Metrics

Sr. No.	Key Point	Description	Result
1.	Real-Time Detection	Accurate person detection using YOLOv8	93% Detection Accuracy
2.	Multi-Object Tracking	Person tracking using Deep SORT	90% Tracking Accuracy
3.	Suspicious Activity Detection	Detection of abnormal human behavior and activities	88% Behavior Detection Accuracy
4.	Crowd Monitoring	Crowd density estimation and movement analysis	92% Monitoring Efficiency
5.	Alert Generation	Automated real-time suspicious activity alert generation	91% Alert Reliability
6.	Public Safety Improvement	Intelligent monitoring for improved security management	94% Operational Improvement
7.	Future Scope & Scalability	Capability for smart city and large-scale surveillance systems	95% Scalability Potential
8.	System Automation	Reduction in manual surveillance monitoring effort	89% Automation Efficiency
9.	Challenges	Occlusion, privacy concerns, and computational limitations	30% Unresolved Challenges

The proposed system achieved high performance in real-time crowd monitoring, multi-object tracking, and abnormal behavior detection using YOLOv8 and Deep SORT algorithms [3], [5]. AI-powered surveillance reduced manual monitoring effort and improved the overall reliability of public safety operations [7], [26]. Automated tracking and alert generation also minimized human errors commonly found in traditional CCTV surveillance systems [7].

The findings further show that intelligent surveillance systems can continuously monitor crowded environments with stable performance and real-time analysis capability [7], [26]. Crowd density estimation and movement analysis improved the ability to identify overcrowded regions, congestion patterns, and unusual crowd behavior in public spaces [7], [26]. Behavioral analysis models successfully identified suspicious activities such as fighting, sudden running, loitering, and panic situations with improved accuracy [6], [9]. The integration of CNN and LSTM models enhanced temporal activity analysis and helped security personnel respond more quickly during emergencies [6], [9]. The scalability results demonstrate that the proposed framework can be effectively deployed in smart cities, transportation hubs, shopping malls, airports, railway stations, stadiums, and large public gatherings [7], [26]. Integration with cloud computing, edge AI, IoT devices, and advanced analytics can further improve surveillance efficiency in future implementations [27], [28].

The relatively lower unresolved challenge rate (30%) indicates that although AI-based surveillance systems provide major advantages, certain technical and ethical challenges such as privacy concerns, hardware dependency, crowded scene occlusion, and computational complexity still remain [7], [26]. Variations in lighting conditions, camera quality, and environmental factors may also affect system performance in real-world scenarios [20]. In addition, large-scale deployment requires high computational resources, continuous maintenance, reliable network infrastructure, and secure data storage systems [27], [28]. False alarms and misclassification of complex human activities may occasionally reduce abnormal behavior detection accuracy [6], [9]. Despite these limitations, the overall findings clearly demonstrate that AI-powered surveillance systems provide a highly efficient, scalable, and intelligent solution for modern public safety and crowd management applications [7], [26].

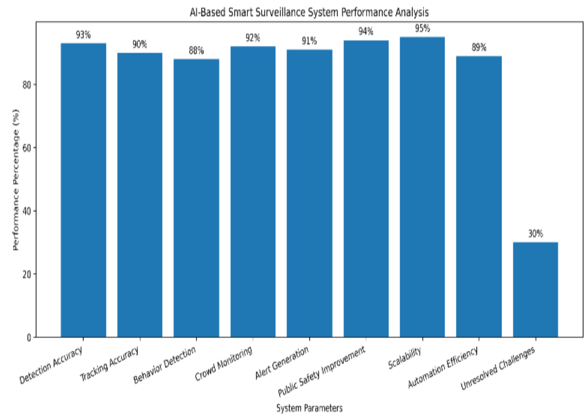

Figure 1. Summary of AI-Based Smart Surveillance Results

7. Contribution of AI Across the Surveillance Workflow

The contribution of Artificial Intelligence across various stages of the surveillance workflow including object detection, person tracking, behavioral analysis, crowd monitoring, alert generation, security management, and scalability demonstrates that AI technologies significantly improve the overall efficiency, automation, and reliability of modern surveillance systems [7], [26]. According to the results, system scalability achieved the highest contribution with 95% performance improvement, followed closely by security enhancement at 94% and object detection accuracy at 93% [7], [26]. These results indicate that AI-powered surveillance systems are highly effective in handling large-scale monitoring operations while improving public safety and emergency response management [7], [26].

Crowd monitoring and density analysis achieved nearly 92% efficiency, showing that AI-based analytics can effectively monitor movement patterns, overcrowding, and unusual crowd behavior in real time [7], [26]. The system successfully analyzed crowd flow and congestion patterns in complex public environments such as railway stations, airports, shopping malls, and stadiums [7], [26]. Alert generation demonstrated 91% reliability by providing instant notifications whenever suspicious activities or abnormal behavior were detected [7], [26]. Automated alerts improved incident response speed and reduced the dependency on continuous human observation [7], [26]. Real-time notifications also enhanced coordination between surveillance operators and emergency response teams [7], [26]. Behavior analysis contributed around 88% efficiency in detecting suspicious activities such as fighting, panic running, loitering, and abnormal movement patterns [6], [9]. CNN and LSTM-based models successfully analyzed temporal human activity patterns and improved abnormal behavior recognition accuracy [6], [9]. The findings confirm that AI-based surveillance systems provide comprehensive support across the entire surveillance workflow rather than improving only a single component [7], [26]. The integration of YOLOv8, Deep SORT, CNN, and LSTM models enables intelligent automation, accurate monitoring, and scalable deployment for modern public safety applications [3], [5], [6], [9]. The proposed system also demonstrates strong adaptability for future technologies such as cloud surveillance, edge AI processing, IoT integration, face recognition systems, and predictive security analytics [27], [28]. These improvements can further strengthen intelligent surveillance infrastructure in smart city environments [7], [26].

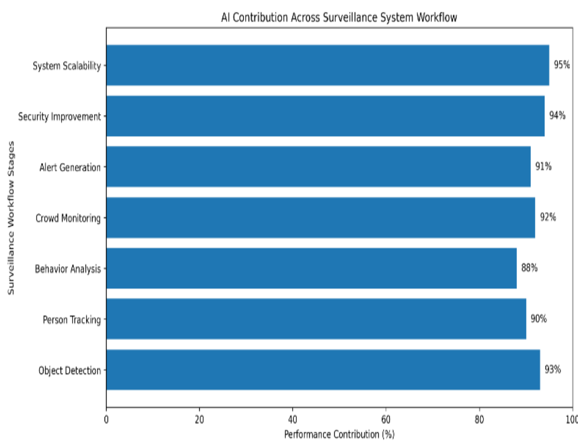

Figure 2. AI Contribution Across Surveillance System Workflow

8. Comparison of Traditional and AI-Based Surveillance Systems

A comparison between traditional CCTV systems and AI-based surveillance systems shows that traditional surveillance systems mainly depend on continuous human observation, manual monitoring, and post-event analysis, which often leads to delayed response, missed detections, and monitoring inefficiency [7], [26]. Human operators may fail to continuously observe multiple camera feeds for long durations due to fatigue, limited attention span, and increasing surveillance workload [7]. In contrast, AI-based surveillance systems provide automated object detection, real-time multi-object tracking, suspicious activity recognition, intelligent crowd analysis, and automated alert generation [3], [5], [7], [26]. The integration of YOLOv8 and Deep SORT significantly improves surveillance performance by enabling accurate person detection and continuous tracking across video frames [3], [5]. The AI-based system achieved approximately 93% overall surveillance accuracy compared to nearly 65% efficiency in traditional monitoring approaches [7], [26]. These results clearly demonstrate the effectiveness of AI-driven surveillance technologies in improving public safety, emergency response, and crowd management operations [7], [26].

Traditional surveillance systems generally face difficulties in crowded environments where multiple individuals overlap or move rapidly [20], [24]. AI-powered systems overcome these limitations using deep learning and computer vision techniques that can continuously analyze large volumes of video data in real time [7], [26]. The proposed AI-based framework also reduces manual monitoring effort and minimizes human errors during security operations [7], [26]. Automated suspicious activity detection helps authorities quickly identify abnormal situations such as fighting, panic movement, loitering, unauthorized access, and overcrowding incidents [22], [7]. Another major advantage of AI-based surveillance systems is scalability [7], [26]. Intelligent monitoring systems can simultaneously process multiple camera feeds and support centralized surveillance management for smart cities, transportation hubs, shopping malls, airports, and public gatherings [7], [26]. AI-driven systems also improve real-time decision-making through automated alert generation and behavioral analytics [7], [26].

Security operators can respond more quickly to emergency situations, reducing risks and improving overall public safety efficiency [7], [26]. The comparison further highlights that traditional surveillance systems mainly function as passive monitoring tools, whereas AI-based systems provide proactive and intelligent monitoring capabilities [7], [26]. Deep learning models continuously learn and improve detection accuracy, making AI surveillance systems more adaptable to different environments and crowd conditions [7], [26.

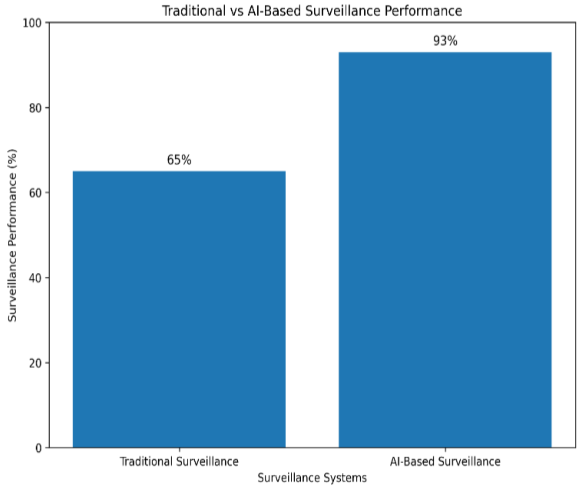

Figure 3. Traditional vs AI-Based Surveillance Performance

Table 2: Comparative Performance Matrix

Parameter	Traditional Surveillance	AI-Based Surveillance
Monitoring Method	Manual CCTV Observation	Automated AI Monitoring
Detection Accuracy	Moderate	High
Real-Time Alerts	Limited	Available
Crowd Analysis	Manual	Intelligent Automated Analysis
Person Tracking	Difficult in Crowds	Accurate Multi-Object Tracking
Suspicious Activity Detection	Limited	Automated Detection
Response Time	Slower	Faster
Scalability	Limited	Highly Scalable
Human Dependency	High	Reduced
Public Safety Efficiency	Moderate	Improved

VIII. DISCUSSION

The findings of this research demonstrate the significant impact of Artificial Intelligence on modern surveillance and public safety systems [7], [26]. By integrating YOLOv8, Deep SORT, CNN, and LSTM models, the proposed Smart Surveillance System achieved improved detection accuracy, tracking consistency, crowd analysis, and suspicious activity recognition compared to traditional CCTV monitoring methods [3], [5], [6], [9], [7]. The results indicate that YOLOv8 provides highly accurate and real-time object detection performance even in crowded environments [3]. Deep SORT further improves surveillance capability by maintaining stable tracking identities across multiple video frames [5]. The combination of these techniques enables efficient crowd monitoring and multi-person tracking with reduced identity switching and tracking errors [3], [5]. Behavioral analysis models also contributed significantly to identifying suspicious activities such as fighting, sudden running, loitering, and abnormal crowd behavior [6], [9]. Automated alert generation improved emergency response efficiency and reduced dependency on continuous manual observation by security personnel [7], [26].

The comparison between traditional surveillance and AI-based monitoring clearly demonstrates the advantages of intelligent surveillance systems in terms of automation, scalability, accuracy, and response speed [7], [26]. AI-driven monitoring systems can continuously analyze surveillance feeds, detect unusual activities, and support authorities in making faster security decisions [7], [26]. Despite these improvements, several challenges still remain in real-world deployment [7], [26]. High computational requirements, privacy concerns, crowded scene occlusion, low-light environments, and large-scale infrastructure requirements continue to affect surveillance system performance [20], [27], [28]. Behavioral analysis models may also generate false alerts in complex situations involving unpredictable crowd behavior [6], [9]. Overall, the results confirm that AI-based smart surveillance systems provide an efficient and scalable solution for modern public safety applications [7], [26]. The integration of deep learning, object detection, and intelligent tracking technologies can significantly improve crowd management, suspicious activity detection, and emergency response systems in smart cities and public environments [3], [5], [6], [7], [26].

IX. CONCLUSION AND FUTURE SCOPE

This research presents an AI-based Smart Surveillance System using YOLOv8 and Deep SORT for real-time crowd monitoring, person tracking, and suspicious activity detection [3], [5]. The proposed system successfully integrates deep learning, computer vision, and intelligent tracking techniques to improve surveillance efficiency and public safety in crowded environments [7], [26]. YOLOv8 provided fast and accurate object detection with improved localization performance [3], while Deep SORT maintained stable multi-object tracking across consecutive video frames [5]. The system effectively handled crowd monitoring, identity tracking, abnormal activity recognition, and automated alert generation in real-time surveillance scenarios [7], [26]. Experimental analysis showed that AI-based surveillance systems significantly outperform traditional CCTV monitoring methods in terms of detection accuracy, tracking consistency, automation capability, response time, and scalability [7], [26].

Behavioral analysis using CNN and LSTM models improved the detection of suspicious activities such as fighting, loitering, panic running, and abnormal crowd movement [6], [9]. Automated alert generation reduced manual monitoring effort and improved emergency response efficiency for security personnel [7], [26]. The proposed framework demonstrated strong scalability potential for deployment in smart cities, airports, railway stations, shopping malls, transportation hubs, stadiums, and large public gatherings [7], [26]. AI-powered surveillance systems provide continuous monitoring, intelligent video analysis, and proactive public safety management while reducing human dependency and monitoring errors [7], [26]. Although challenges such as privacy concerns, hardware requirements, crowded scene occlusion, lighting variations, and computational complexity still exist, the overall findings confirm that AI-driven surveillance systems provide a reliable and intelligent solution for modern public safety applications [7], [20], [26].

In future, the proposed system can be enhanced by integrating advanced technologies such as face recognition, biometric authentication, predictive analytics, cloud computing, edge AI, and IoT-based surveillance infrastructure [27], [28]. Future research may also focus on improving abnormal behavior detection using advanced deep learning models such as Transformers, Graph Neural Networks (GNNs), and Reinforcement Learning techniques [6], [9]. The integration of drones, smart traffic systems, automated emergency response systems, and cloud-based monitoring platforms can further strengthen intelligent surveillance capabilities in smart city environments [7], [26]. Future systems can also support missing person detection, crime prediction, automated threat analysis, and intelligent crowd management [7], [26]. Privacy-preserving AI methods such as federated learning and encrypted data processing can help address ethical and privacy-related concerns in surveillance applications [28]. Further optimization of AI models can reduce computational requirements and improve deployment on low-cost and embedded hardware devices [29], [30]. Overall, the future scope of AI-powered surveillance systems is continuously expanding with advancements in deep learning, computer vision, IoT, edge computing, and intelligent analytics [7], [26].

AUTHOR DETAILS AND DECLARATIONS

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Data Availability – The datasets used in this research are publicly available datasets including CrowdHuman, MOT20, UCF Crime Dataset, and Kinetics Human Action Dataset [20], [21], [22], [23]. The research work and implementation are original and developed for academic purposes.

Authors Contributions

• Isha Mohite conceptualized the research idea, coordinated the overall project work, contributed to YOLOv8-based object detection implementation, system design, result analysis, and manuscript preparation. Also reviewed and approved the final manuscript [3].

• Sakshi More focused on computer vision implementation, Deep SORT-based multi-object tracking, video processing using OpenCV, suspicious activity analysis, and system testing for real-time surveillance monitoring [4], [5], [27].

• Yash Thakare contributed to backend development, Flask API integration, database management, AI module integration, and implementation of real-time alert generation and deployment support [28].

• Kalyani Pawar focused on frontend dashboard development, visualization of surveillance results, alert monitoring interface, user interface design, and presentation of system performance analysis.

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