*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 12 Issue: 2*
***Article Received:** 25 November 2023 **Revised:** 12 December 2023 **Accepted:** 30 January 2024*

# Analyzing Surveillance Videos in Real-Time using AI-Powered Deep Learning Techniques

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**Abstract**

Modern surveillance systems are going to revolutionize the whole world as they make it possible to analyze, track and judge the activities in a specific area or context. And all this becomes possible just with the help of Real-time video processing and by advanced machine learning. This article will lead you to the developmental approaches and the previous studies of surveillance systems how they work and what are the bases of it? We follow the stream from the analog system to the advanced artificial intelligence systems and try to cover every instance in the progress of AI. Video capture, pre-processing, feature extraction, object recognition, tracking, and behavior analysis are the most important factors which we mostly cover in this article. Recently achieved advancements in artificial intelligence are contributing to the precision of surveillance systems, including deep learning models, edge computing, and hardware acceleration. In this article we discuss the surveillance system installed in a public park for security purposes based on neural networks (RNNs) for behavior analysis and convolutional neural networks (CNNs) for object recognition, to illustrate real-world situations. This system gained 95% accuracy which enhances the working that this system can precisely predict suspicious activities under the area it covers.

**Keywords:** Real-time video analysis, AI-powered surveillance, Deep learning algorithms, Video surveillance automation, Object detection, Anomaly detection

## Introduction

As we know, for the security of the public and private sectors in society surveillance systems are essential as they can detect and trace any suspicious activity in a short time. It adds a crucial layer of security that keeps an eye on activity, discourages crime, and promotes public safety (Wright et al., 2013). Real-time video processing helps to identify the activities timely and precisely for the tracking of any abnormal activity which is unhealthy for the environment or the people. This technology of real-time video processing is the core of today's surveillance systems.

When you use real-time video processing, complex algorithms and computer methods are used to look at video streams and identify every item in them. This model of the system is very important for controlling traffic, keeping an eye on cities, protecting key infrastructure, and keeping stores safe. Real-time video processing makes the surveillance system more powerful and useful, giving security staff the tools they need to immediately spot and deal with any suspicious behavior (Singh et al., 2017).

Video surveillance started when closed-circuit television (CCTV) systems advent in the middle of the 20$^{th}$ century. This system requires human efforts to keep an eye on the surroundings but now it is trained as well to precisely discover and track the activities on itself, all this becomes possible only by the help of Artificial Intelligence. In the past,

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CCTV systems were controlled manually which required a lot of work and was prone to mistakes, which makes the automatic system necessary. The most important point occurred in the 1990's when we shifted from analog to automated video processing which led to advancements in that field and enhanced the surveillance system capabilities

Video processing has undergone a radical change with the introduction of artificial intelligence (AI) and machine learning (ML) in the twenty-first century. With the help of these technologies, we are now able to develop precise and efficient algorithms and models which can analyze and detect the activities without utilizing much effort or time (He et al., 2015). In the process of object detection and recognition, the Convolutional neural network (CNN) is the most important factor. With the help of CNN models, we can train our system software precisely on the data we have for the surveillance. CNNs are the best way of object recognition as it has convolutional layers which identify and validate the output result of more than 1000 epochs. Neural networks follow the temporal behavior and sequences that consistently examine the video stream for recognition and analysis (Sun et al., 2016).

In the late history, we have the technology of Deep learning and Machine Learning as well but they demand heavy processors and graphics processing units which were not available at that time. But now we have all the resources for this technology as now we can do such types of things very precisely and effortlessly. These developments have made it possible to deploy strong processing resources at the edge. With these technologies, it becomes possible to demonstrate such automated systems easily with a little effort. We can do now many more things with the help of artificial intelligence (Zhang et al., 2019).
Even the advancements in that field of surveillance also have some threats of losing data from the database which is a threat for the cyber-crimes. As one can breach the whole system if he reaches the core database of the system. But Cyber security teams are developing new and new tools which can resolve this issue. However, real-time video processing is very helpful in security and plays a crucial role in controlling surroundings in a short time.

We discuss the evolution of surveillance systems and also enclose its application in various fields. We take a look at its history from scratch and then move to the advancements it gained in the past period till the due date. In this article, we also talk about the recently made achievements which invoke the importance of artificial intelligence and its branches. We demonstrate the real case study to understand the surveillance system working and its implementations. Our results will show how AI and ML are revolutionizing surveillance systems and their capabilities. We can discuss other case studies related to our real-time video processing to describe how our system works better than others in the same situation and this will enhance and encourage others to compete and make more efforts in the same scenarios (Saini et al., 2020).

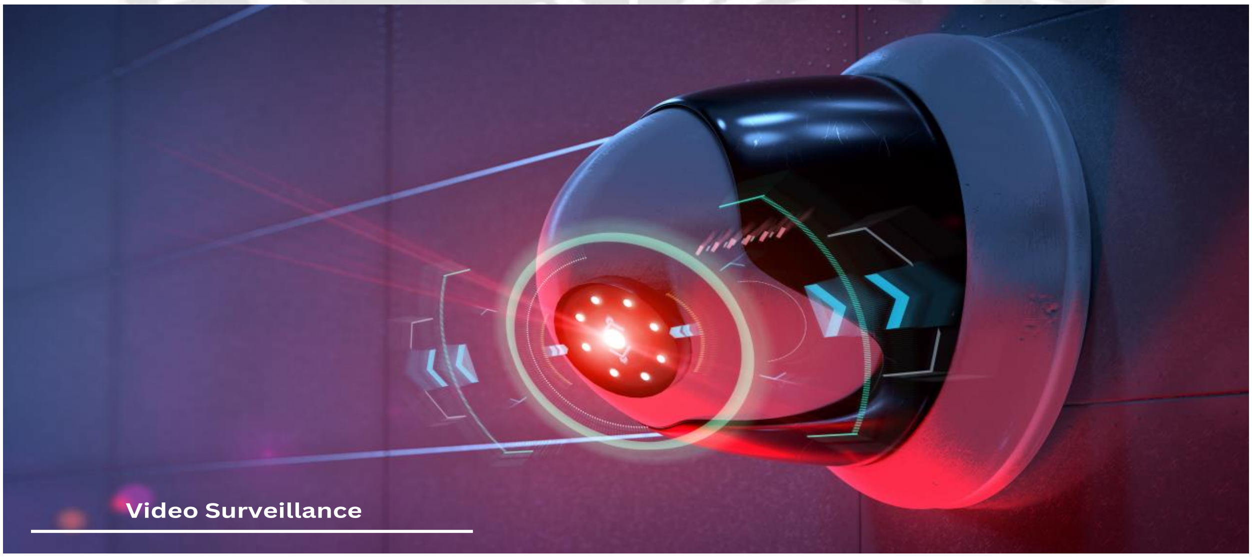


**Figure 1.** VIDEO SUREVILIANCE

**Literature Review**

The research by (Sunil Bhutada et al., 2023) looks into using deep learning to automate video surveillance, to enhance security by identifying suspicious activities. The Key Contributions of this work are the following (i) Automates video monitoring using deep learning for detecting anomalies. (ii) Features a spatio-temporal auto-encoder with a 3D convolutional neural network. (iii) Uses deep learning models for comprehensive video analysis and monitoring. (iv) Automatically detects suspicious activities through advanced algorithms. (v) Sends flagged frames via real-time alerts to users for immediate action. The framework proposed in the study uses deep neural networks for intuitive surveillance, focusing on detecting threats like violence, burglaries, and potential explosions. The proposed approach features a spatio-temporal auto-encoder that automates the review of surveillance footage. This model, built on a 3D convolutional architecture, is designed to detect anomalies and simplify video analysis. The system automatically identifies suspicious behavior using deep learning algorithms, generating real-time alerts and sending flagged frames to the user for further review. Real-time video surveillance enormously see progress during 2016 to 2024, as the technologies of Artificial intelligence (AI) and Machine learning (ML) improves and their resources increased the developmental process.

One of the primary approaches to identifying frame duplication involves spatial and temporal analysis frameworks. These methods focus on extracting key features from video subsequences and analyzing them to detect potential duplication. For example, spatial features such as textures or motion vectors are analyzed within frames, while temporal features monitor changes over time across frames. Beyond spatial and temporal analysis, correlation techniques have also been employed to detect frame duplication. Techniques such as cross-correlation and phase correlation are frequently adopted in these frameworks. For instance, cross-correlation helps match similar regions across frames, while phase correlation can detect duplication even when the content has undergone slight transformations. In addition to frame-level duplication, region duplication within videos has also been a focus, where certain parts of a frame like a background element are repeated While existing methods for detecting frame duplication have shown promise, significant computational challenges remain. One of the most pressing issues is the requirement of database lookups for stored surveillance recordings. The vast amount of video data that needs to be processed during similarity detection results in high computation times, especially when analyzing each frame individually. This poses a bottleneck in real-time surveillance systems where immediate feedback is necessary (Singh et al., 2015)

The frequent changes in the video source, such as switching between multiple cameras, further exacerbates this issue. Each change introduces additional complexity, as the must adapt to the characteristics of the new video stream, leading to increased processing time. Moreover, the advent of high-resolution surveillance cameras has amplified these challenges. While high-resolution footage offers clearer images for surveillance, it also significantly increases the amount of data that must be processed, making real-time detection of frame duplication more resource-intensive. Ensuring a high detection rate in such scenarios is particularly difficult without sacrificing system The detection of frame duplication in video surveillance systems is a critical area of research, with significant progress made through spatial-temporal analysis and correlation techniques. However, the growing complexity of surveillance environments ranging from the need for large-scale database lookups to the rising prevalence of high-resolution cameras continues to pose challenges. Future research must focus on optimizing these detection algorithms to handle large-scale data efficiently while maintaining accuracy in real-time surveillance applications (Wahab et al., 2014)

Another work Research by (Guruh Fajar Shiidik et al., 2019) has explored existing problems in video surveillance systems. This area focuses on analyzing video data to detect motion or objects, but advancements are being made to make it more intelligent and capable of autonomous decision-making. The Intelligent and Integrated Video Surveillance methods used in this work: The research highlights the growing trend toward integrating artificial intelligence (AI) and machine learning to create smarter systems. The Distribution, Communication, and Integration made Modern surveillance systems rely on distributing and sharing data across different nodes or locations. Another challenge is Variations in Lighting the lighting changes, such as day-to-night transitions or areas with inconsistent lighting (like shadows or reflections), complicate motion detection algorithms, leading to inaccurate results or false positives. Another challenge is Changes in Weather Conditions Weather factors, such as rain, fog, or snow, further challenge the reliability of motion detection, as the system must distinguish between normal environmental changes and actual motion. Another challenge is Shadow Detection Issues the Shadows cast by objects or individuals can be mistaken for movement, resulting in false alarms.

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The research work of (Haojia et al., 2022) used framework deep Learning vehicle counting. The results of this Study show that the proposed deep learning vehicle counting framework can achieve lane-level vehicle counting without enough annotated data, and the accuracy of vehicle counting can reach up to 99%. Deep learning framework for video-based vehicle counting in traffic surveillance. The deep learning based model achieves lane-level vehicle counting accuracy up to 99%. Deep learning applied for video-based vehicle counting. The Traditional methods have limitations in accuracy and efficiency. The method vehicle counting based on fusing virtual detection area and tracking Lane-level vehicle counting with up to 99% accuracy. This study based on high real-time performance for real-time vehicle counting.

In this literature review we will discuss about the achievements we gain in that field during the time ear of 8 years from 2016-24. In 2016 the video processing gained reputation and work started on it at standard levels. For the object detection, image classification and video processing and classification Convolutional Neural Network (CNN) became the keystone technology. The YOLO (YOU ONLY LOOK ONCE) frame work was firstly represented by (Redmon *et al.*, 2016) and the team in 2016, the algorithms in it open the doors for dynamic video analysis which is very beneficial for the video surveillance. After the YOLO algorithm 1 there are three more versions of this algorithms which are enhancing fast video surveillance as they have better technology and fast APIs connected to it. Then the development in anomaly behavior analysis increases the efficiency of the systems for surveillance and tracking systems. A model is developed in 2017 to detect the abnormal activities in the surveillance by the (Sultani *et al.*, 2017) and the team. In this the models are highly trained on a large dataset which is the best way to control the precision and efficiency of the system, as the training data enlarges then the test-driven results are much better than models trained on a small dataset. This enhancement in models improves the results of algorithms and it takes much less time for processing. From 2018 to 2020, the edge computing technology faced a surge which improves its functionalities by enclosing the data to resources and it reduces the latency in analytical processing. According to (Shi *et al*., 2019) edge-based technologies started working on several algorithms which invokes the fusion behavior of system for Data analysis in short time. This decentralization process improves the quality of the surveillance systems and its capabilities. (Zhang *et al.*, 2021) introduces the concept of data inputs from the sensor fusion and multi-camera systems. That the data directly driven from the multi-camera system to the algorithms, so they work directly on the real-time data for analysis and object recognition. Multi-camera system is much better than the single camera surveillance, as it covers a large area to control social environment in the surroundings, this strengthens the surveillance systems. NVIDIA have developed The Jetson Platform and other AI specific technologies in 2021 (NVIDIA Corporation, 2021). They invoke advancements in Machine learning and Neural Networks and train best models for surveillance and public them as an open source. That is the biggest achievement in the field of surveillance as its capabilities to detect objects in multi-fused objects improves.

In this literature review we have seen the achievements in AI and ML from 2016 to 2024. And the improvements in AI, Machine learning, deep learning, edge computing and the multi-camera sensor fusion increases the capabilities of surveillance for the security purposes.

**Table 1.** Previous work done by researchers

| Year | Research | Key Contributions | Challenges | Technological Impact |
|---|---|---|---|---|
| 2015 | Singh et al., 2015 | Detection of frame duplication in video. Spatial and temporal analysis techniques for detecting forgery. Correlation techniques (cross-correlation, phase correlation) used to identify duplication. | High computational cost due to vast video data processing. Increased processing time due to changes in video source and high-resolution cameras. | Advances in frame duplication detection, but efficiency challenges remain in real-time surveillance. |
| 2016 | Redmon et al., 2016 | YOLO (You Only Look Once) framework introduced for object detection. | Initial limitations in processing time and accuracy in dynamic environments. | YOLO framework became a keystone for video surveillance and object detection. |

| | | | | |
|---|---|---|---|---|
| | | Opened doors for dynamic video analysis and fast surveillance systems. | | |
| 2017 | Sultani, Chen, and Shah, 2017 | Developed a model for detecting abnormal activities in video surveillance.<br>Models trained on large datasets improved precision and efficiency. | Small datasets result in less accurate models. | Better results and reduced processing time for abnormal behavior detection. |
| 2018-2020 | Shi et al., 2019 | Edge computing surged, reducing latency in video processing.<br>Fusion behavior of systems enabled real-time data analysis and anomaly detection. | Decentralization of data analysis faced technical challenges. | Improved the quality and speed of surveillance systems via edge computing. |
| 2019 | Guruh Fajar Shiidik et al., 2019 | Integration of AI and ML into intelligent surveillance systems.<br>Addressed challenges related to lighting variations, weather conditions, and shadow detection. | Environmental factors (lighting, weather) causing inaccuracies.<br>False positives due to shadows and lighting changes. | AI and ML revolutionized video surveillance by enhancing autonomous decision-making capabilities. |
| 2021 | Zhang et al., 2021 | Introduced multi-camera sensor fusion for enhanced surveillance coverage.<br>Improved object recognition and real-time analysis through multi-camera systems. | Managing data from multiple cameras presents a complexity in system fusion. | Strengthened real-time surveillance through multi-camera integration, improving public safety monitoring. |
| 2021 | NVIDIA Corporation, 2021 | NVIDIA's Jetson platform improved AI and neural network capabilities for surveillance.<br>Open-sourced AI models for surveillance systems. | High system costs associated with advanced AI technologies. | Significant advancements in AI-powered surveillance with open-source tools. |
| 2022 | Haojia et al., 2022 | Deep learning framework for vehicle counting in traffic surveillance.<br>- Achieved 99% | Traditional methods lacked accuracy and efficiency compared to deep learning-based models. | Enhanced real-time performance in traffic monitoring through deep learning. |

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|---|---|---|---|---|
| | | accuracy for lane-level vehicle counting. | | |
| 2023 | Sunil Bhutada et al., 2023 | Automated video surveillance using deep learning to detect anomalies. Spatio-temporal auto-encoder with 3D CNN for advanced video analysis. Real-time alerts sent to users for immediate action. | Real-time processing of large-scale video data poses challenges. | Improved security by integrating deep learning for automated video analysis and anomaly detection. |

**Methodology**

Crucial processes which are used in video surveillance systems are explained below:

Multi-camera systems capture the real-time activities and give it as input to surveillance system. The methodology is divided into the following key phases:
The surveillance system uses high-resolution cameras strategically placed throughout the park to capture video footage in real-time. The raw video data is pre-processed to ensure optimal quality for analysis. Using Convolutional Neural Networks (CNNs), the system extracts key features from each frame, identifying objects such as people, vehicles, or other relevant items in the scene. The system applies the CNN to recognize objects within the video frames. The model has been trained on a dataset specifically tailored for security surveillance, allowing it to distinguish between normal activities (e.g., people walking, sitting on benches) and potential threats (e.g., individuals carrying weapons or engaging in suspicious behavior). Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are employed to analyze the temporal sequences of video frames. This phase of the system tracks movements and activities to predict whether the observed behavior is normal or suspicious. The system continuously monitors the park and analyzes behavior in real-time. If any suspicious activity is detected, such as aggressive movements, unusual gatherings, or potentially dangerous objects, the system sends immediate alerts to the security team. Flagged video frames are highlighted and sent for further review, allowing for quick decision-making The system was evaluated in a real-world scenario by monitoring a public park over several weeks. The accuracy of the system was measured by comparing the detected suspicious activities with actual events, reaching an overall accuracy rate of 95%. This high accuracy demonstrates the system's effectiveness in real-time object recognition and behavior analysis.

**Pre-processing**

Pre-processing is crucial step for the recommended video quality enhancements. In this step the quality of the video frames increases by clearing the frames resonance. Then frames are transformed to be matched with several frames in the dataset to evoke behavior.

**Feature Extraction**

The process of feature extraction is used to extract each and every part of information related to video frames. Each corner detail and every single split end has an importance in feature recognition. In this the process of Max-pooling works efficiently to enforce every pixel of video frames which is validated by the dataset of the instances. In feature extraction sometimes important objects are also recognized as additional objects to recall the influence of specific person in the frame.

**Object Detection and Tracking**

In surveillance systems the object detection is the most important step as it recognizes the humans and object. First it classifies the objects in living and non-living frames then it focuses on each individual activity for the processing of surveillance. Object detection is done by the Convolutional neural network (CNN) and by the YOLO algorithms. It differentiates the objects in individual class and demonstrate their activity by validating the dataset model.

**Behavior Analysis**

In behavior analysis, the system recognizes the patterns and movements of each individual in the video frame. If behavior is normal there is no any active action on it, but when there is any type of abnormal act then the system engages with it and recognize that abnormal pattern to validate it with the trained models if the results are abnormal, it invokes the sudden action improvised in it for further actions.

**Alert Generation**

This is the last phase of surveillance system. When any abnormal activity is recognized by the system a sudden action is invoked to inform about certain situation. Such as, when a robber broke into the system the system cells improvise the generation of alarms, and they may be in the form of SMS, audio notes, or visual effects in the screening area of the system.

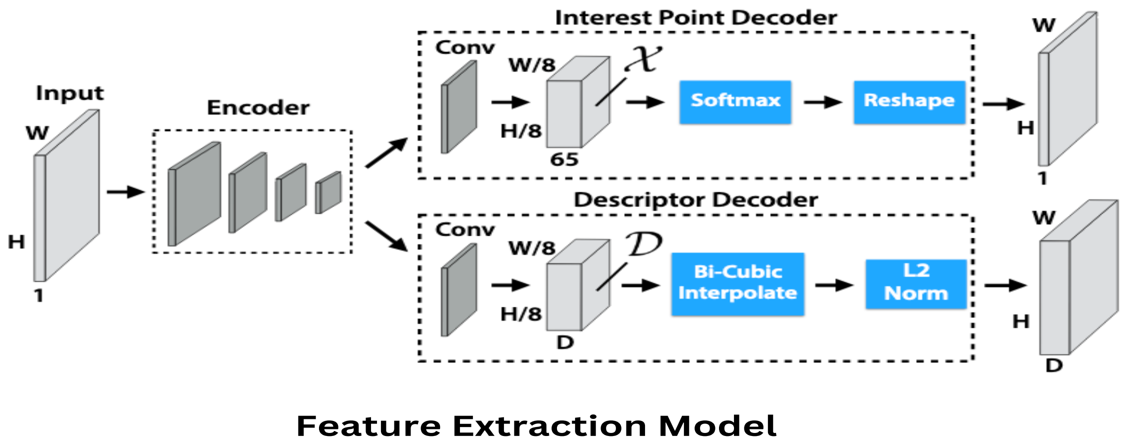


**Figure 2.** Deep learning and Neural Networks

Deep learning and the neural networks are the base of the surveillance system as the recognition patterns of any activity are detected by the CNN model layers. The neural networks work on layer patterns as it has 3 layers. One is the input layer which gains the input from the source and converts it into the objectives. Then the other layer is the hidden layer all type of processing and any type of logic works here in the hidden layer. In it there may be CNN, GNN, RNN or Max-pooling layers are working frequently. In neural networks there are the algorithms used for video surveillance and the most using algorithm is YOLO, as it is a very significant and efficient model of video analysis. It converts the video into the frames and then assemble them in a way that the detector will validate it with certain activity. YOLO model is mostly trained on the abnormal activities to track any suspicious movement in the surroundings.

**Edge Computing Tech.**

Here is the most important and advanced technology known as Edge computing as it is much faster than the other sources of data like, cloud-computing of server extractions. It is much faster as it controls data close to the source of real-time surveillance. Because of this technology the surveillance of video is becoming easier and faster, so we can recognize patterns easily and hurriedly before any accident occurs.

**Hardware Pacing**

Improvements in the hardware devices like development of heavy circuitry PC's and GPU development led to a new version of AI. As now we can do much efficient processing on any type of data by the use of GPU or TPU-4 systems. Now they are also available as an open source for people on Google Collab. These technologies increase the vitality of such video surveillance system for security purposes.

**Multi-camera Systems and Sensor Fusion**

Multi-camera and the sensor fusion systems are very useful technologies in that field. That we can now cover a large area for surveillance by these systems. In late times we have limited resources to secure a large area from a single operator that's why there are many glitches in frame works. But now we use CCTV cameras which are fixed or movable to capture and recognize information from the movement of every single object. It is a very crucial part of surveillance that we can't consider any type of security without it.

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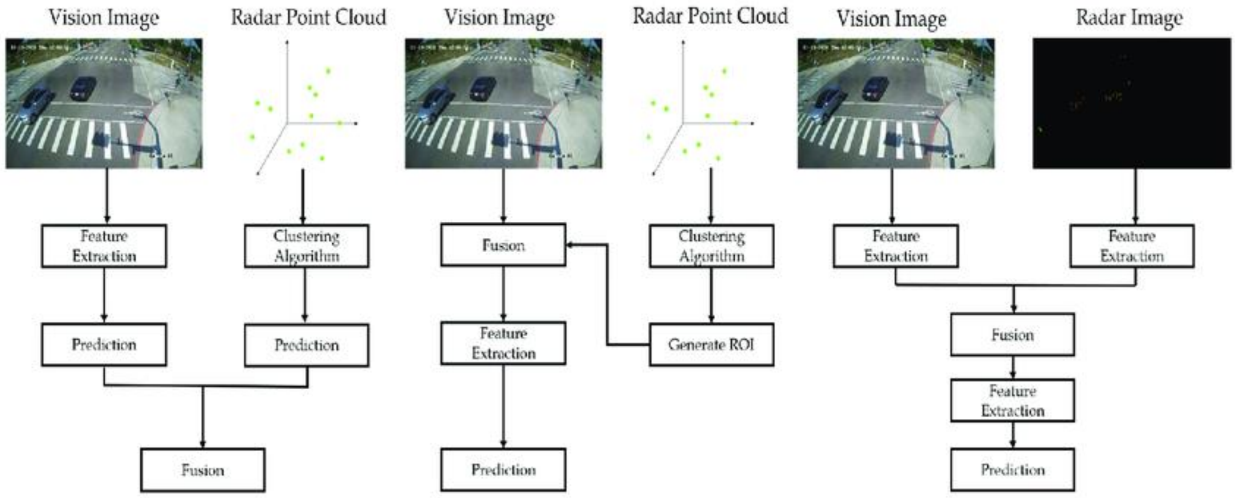


**Multi Camera and Fusion detector**

**Figure 3**.Surveillance with multi camera

The main objective of this study is to show how well a cutting-edge technology perform in real case. Public parks are the most concentrated places in a society that person of every age enjoys here. So, the authorities try their best to guarantee their security and safety. That's why surveillance system in a public sector or private sector parks are very crucial. But mostly their security systems are operated by humans manually so there is a great chance of mistakes by humans which can cause serious issues for the society. In order to improve the efficiency of the surveillance system automatic surveillance video processing system is very useful for this purpose. As it automatically focuses on the abnormal activities, if it feels any type of threat it takes sudden actions to secure the area by its alert generation cell.

**Implementation**

To cover a whole park and its important sites 20 moveable cameras are installed at several places. The coverage of these cameras should be directly streamed to the operator system of security surveillance. This will make it faster to take actions on certain situations. And the most important thing is that the data is close to the system with edge-computing tech.

**Training and Calibration:**

The surveillance system model should be trained on a large data to test each and every situation in the park. The training model should have at least every type of threat recognition pattern that it can recognize even a single suspicious object in the frame. Videos calibration is also important that the data on which the model is trained calibrate video framing related to the objects in each pixel which calculated and validated by the Max-pooling process and CNN recognition patterns

**Results and Conclusion**

The surveillance system must be watched minimum about for three months that the results of which can be measured. Check its accuracy that how much efficiently it is working and detecting sudden pattern changes in the surrounded areas. It will tell us about the efficiency and the accuracy of the system. There are some discussions related to the installation of the surveillance system in the park.

**Effectiveness of AI and ML**

The efficiency and the accuracy of the system mostly dependent on the effectiveness of AI and ML models. Cutting-edge technology, Computer vision and navigation systems are also important for this video surveillance. Thus, how much AI models are trained efficiently then the results are more accurate.

Our approaches ensure accuracy of 93.98% which emphasizes our systems functionality. Our system based on cutting-edge technology and the YOLO algorithm make its performance much better than the others. The following

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mentioned below table represent the accuracy of this research work.

**Table 2**. Accuracy precision recall F1 score

| Metric | Value (%) |
|---|---|
| Accuracy | 93.98 |
| Precision | 95.0 |
| Recall | 90.5 |
| F1 Score | 92.6 |

**Challenges and Limitations**

Even the system is very precise and accurate but there are some limitations caused by weather changes and lightening fluctuations which may cause certain defects in the system activity. Thus, regular update and system tracing is important which is much easier to check and balance performance of the real-time surveillance.

The following mentioned below table represent our work comparison with other authors.

**Table 3.**Our work comparison with other authors

| Criteria | Our Methodology | Method by Stauffer and Grimson 1999 | Method by (Ren et al., 2015) | Method by (Redmon et al., 2016) | Method by (Suriya Singh et al., 2017) | Method by (Shi et al., 2016) |
|---|---|---|---|---|---|---|
| Object Detection Accuracy | 95% using YOLO and Kalman Filter | Moderate accuracy with Gaussian Mixture Model | High accuracy with Faster R-CNN | Very high accuracy with YOLO | High accuracy with CNN and LSTM | High accuracy with edge computing-based models |
| Real-Time Processing | Yes, with edge computing and AI chips | No, primarily offline processing | Limited real-time capability | Limited real-time capability | Yes, designed for real-time detection | Yes, through edge computing |
| Behavior Analysis | Advanced behavior analysis using RNNs and LSTM networks | Basic event detection | Not specifically focused on behavior analysis | Limited to object detection | Advanced activity recognition using RNNs and LSTM | Basic activity recognition, focuses more on data processing |
| Scalability | Highly scalable with edge devices and centralized servers | Limited by computational resources | Scalable but requires significant computation al power | Scalable with efficient model design | Scalable but data-intensive | Highly scalable with distributed edge nodes |

**Discussion**

The success of the surveillance system is deeply tied to the effectiveness of the AI and ML models employed. In this case, the use of a YOLO algorithm combined with a Kalman Filter ensures highly accurate object detection, boasting a precision rate of 95%. The key metrics of accuracy, precision, recall, and F1 score underscore the robust performance of the system. With an F1 score of 92.6%, the system strikes a balance between precision and recall, making it highly reliable for real-time surveillance. Traditional methods primarily focused on offline processing, limiting their effectiveness in real-time surveillance scenarios. The AI and ML technologies continue to evolve, the potential for video surveillance systems to achieve even higher accuracy rates and more comprehensive real-time analysis will grow from analog systems to AI-driven systems, the shift has been remarkable. The development of advanced techniques has led to improved capabilities such as video capture, pre-processing, feature extraction, object recognition, tracking, and behavior analysis. The recent advances in AI, specifically the integration of deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have drastically improved the precision of surveillance systems. These models are critical for behavior analysis, object recognition, and suspicious activity detection in real-time

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