International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
Article Received: *25 July 2023* ***Revised:*** *12 September 2023* ***Accepted:*** *30 September 2023*

Recent Trends in Video Surveillance System in Dense Environment: - A Review Paper

Himanshu Tyagi[1*], Prof. (Dr.) Vivek Kumar[2], Dr. Gaurav Kumar[3]

[1*]PhD. Scholar, Quantum University Roorkee, India, E-mail: himanshu.atra@gmail.com
[2]Vice Chancellor, Quantum University, Roorkee, India, E-mail: vicechancellor@quantumuniversity.edu.in
[3]Associate Professor, Alliance University, Bengaluru, India, E-mail: gauravsaini.iit@gmail.com

Abstract
Snow, fog, lightning, torrential rain, and darkness degrade outdoor surveillance footage. The detection, categorization, and event/object recognition capabilities of video surveillance systems in congested environments have attracted considerable interest. Real-time video analysis algorithms in various weather conditions have been enhanced by technology. Other examples include background extraction, the see-through algorithm, deep learning models, CNN for nocturnal incursions, the system for high-quality underwater monitoring utilising optical-wireless video surveillance, LVENet, and edge computing. In the current study, these methodologies improved monitoring efficiency and decreased human error. This study details these video surveillance techniques, platforms, and supplementary materials. After discussing prevalent building and architectural styles briefly, significant system evaluations are presented. This study contrasts current surveillance systems with various methods for real-time video processing under challenging weather conditions in order to provide readers with a thorough understanding of the system. The following research is also highlighted.

Keywords- Surveillance cameras, crowded settings, deep learning, YOLOv5, virtual neural networks, convolutional neural networks, LIVnet, and YOLOv3

Introduction

The rapid development witnessed by many regions in recent years has made daily life more challenging, including the task of ensuring the safety of its inhabitants. As such, safety measures are essential. As a result, it is essential to have security cameras in both public and private areas. In light of this, a real-time system needs to keep an eye on a number of different places and potentially hazardous conditions including snow, fog, and heavy rain. It makes sense to use live video for surveillance. The primary functions of such systems are monitoring both indoor and outdoor locations, such as workplaces, enterprises, shopping malls, and airports, and identifying anomalies and detecting movements in real time. They help people with things like traffic analysis, accident forecasting, criminal activity deterrence, homeland security, and spotting irregularities. The point is to carry them out in inclement weather that degrades the visual quality of outdoor surveillance footage, such as snow, mist, or heavy rain.

There have been major breakthroughs in this area. [1] Surveillance system analysis videos are notoriously difficult for today's computer vision technology to decipher. Numerous techniques have been implemented in this area to identify, categorise, and differentiate between objects or events that prove the viability of a video surveillance system. The tools and methods for assessing live video have improved as well [2]. These include the see-through algorithm, deep learning models, a convolutional neural network (CNN) trained to detect intrusions at night, a deep visual entanglement network (LVENet), edge computing, and optical-wireless video surveillance systems for precise observation of marine life. There are a lot more. More data exploration is required for these methods and strategies to provide adequate surveillance in congested areas. Indoors or out, public spaces present unique challenges that can only be fully understood and evaluated with improved technology. [3].

Seven sections comprise the paper. Section 1, "Introduction," discusses the study's problems, causes, and methodology. Section 2 describes this topic's research and outstanding issues. Section 3, "Video Surveillance System," introduces it. Section 4 covers adverse weather monitoring system concerns and remedies. Section 5 covers the surveillance system's issues. Section 6 covers real-time video surveillance systems in harsh weather conditions. Section 7 concludes this study. Event recognition from a group of video cameras in a hectic setting is combined with promising methodologies and models for diverse problems.

Related works

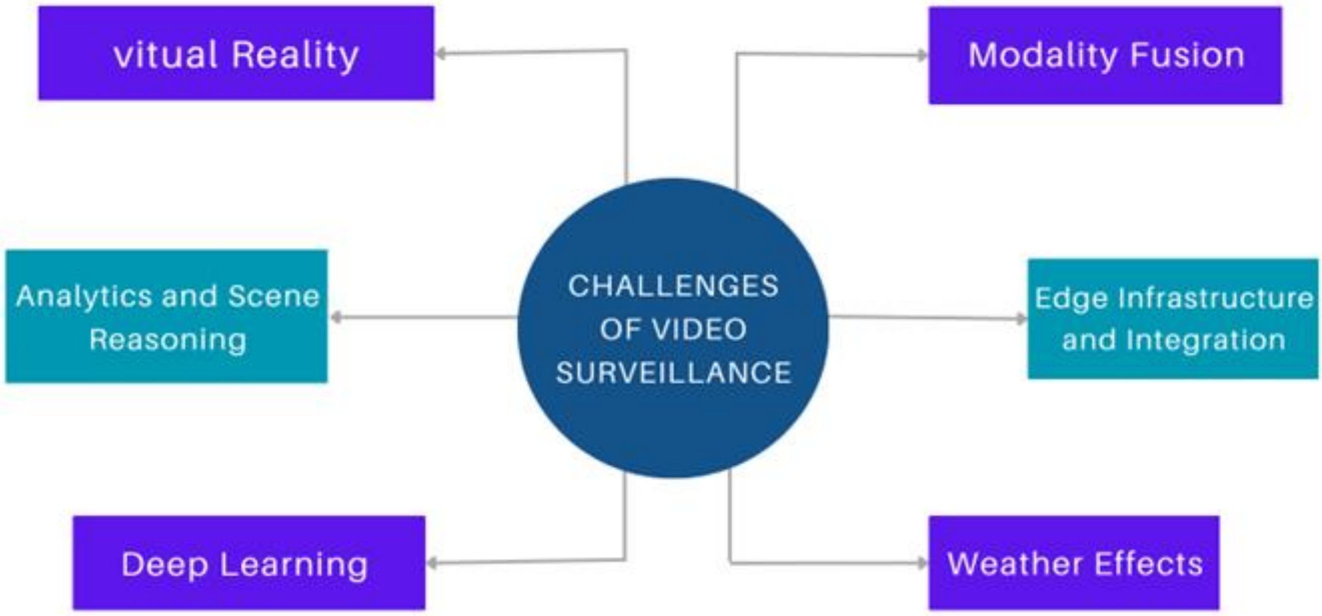
Real-time video analytics has been a major focus of both academic and industrial institutions. Automated systems analyse videos in real time without any help from humans. Moving vehicles, sudden smoke or fire explosions, stealthy people, and the worst-case circumstances in harsh weather can all be detected by video analytics programmes. Due to the ongoing evolution of video surveillance systems, automated data evaluation may one day be a possibility. Using a surveillance camera in inclement weather

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

necessitates anticipating and handling probable mishaps [7, 8].
Recent research suggests that weather can improve the accuracy of photo and video recognition. CVs have an edge over SVs in the ability to detect motion [9]. They don't rely on sensors but instead follow routines and procedures set up in advance. GNSS was developed as a solution [10, 11]. And unlike GPS, the system really shines in congested areas. To visualise data, local users employ CPE-equipped personal computers, while remote users connect to a server over the web. One can send data either wirelessly or via a connected connection [12]. Cameras can be located hundreds of kilometres away from the target region and yet get data thanks to these technologies. Wireless mesh WiMAX networks, as well as antenna alignment with the location's base, reveal the technical constraints of this strategy. Recent years have seen the development and widespread use of mobile video surveillance devices [12, 13]. The technology transfers data through wireless RTP networks. Potential snags with this novel approach include data loss or corruption. Often, the security of unformed systems is better. However, data transfer becomes difficult under unreliable network conditions, restricting its use to only a few mild environmental conditions, such as dim lighting, fog, or air pollution.

In April of 2018, we used deep learning models to build Strange Invasion: A Gradual Improvement. ResNet integrated with YOLOv2, which employed Darknet-19. YOLOv3 use more compact connections while extracting features. The new technique [15] employs Darknet-53 and 53 convolutional layers. Several studies [14, 16] have applied machine learning-based algorithms to the problem of recognising people in the dark by analysing characteristics extracted from digital infrared camera images. Similarly, the classifiers and feature descriptors can categorise human identification systems that rely on learning. Intensity distribution-based inertia features (INERTIA), histograms of oriented gradients (HOG), and scale-invariant feature transform (SIFT)-like oriented capabilities are utilised for feature extraction [17], while support vector machines (SVMs) or adversarial boosts are employed for classification. Initially, DNN was used to identify obstructions in a single image [19]. The most well-known one is CNN, of course. CNN uses machine learning based on pictures to classify images. Since CNNs can be retrained for new recognition tasks, the existing networks are still useful. The credibility of CNN [21] is well-established. Learning is enhanced by DNNs [20] due to their adaptable architecture and extra layers of neurons. Slower detection due to traffic. Directed gradient methods, such as the DPM (deformable component model) and HOG histograms [17] seem to work better with polarization-encoded images, according to this research. We may see a 20-50% increase in detection accuracy when combining deep learning with imaging systems [19].
Technologies for visual vessel identification and tracking [22] have recently emerged to provide effective maritime surveillance. The methods enhance vessel detection in everyday lighting [5]. Many important visual details, especially those of moving objects, are lost in low-light imaging. To avoid being affected by climate, a method of identifying vessels was developed. Therefore, the first stage of processing should develop a stealthy, yet effective, enhancement network [23, 24]. This approach eliminates the need for retraining in order to improve network recognition of vessels in dim light.

Fig. Problems associated with video surveillance



International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

1.

2. Video Surveillance System

Video monitoring systems serve as an additional layer of security and management, providing an extra set of eyes to protect assets and notify security staff of suspicious or potentially dangerous activities. They are a crucial component of any comprehensive safety strategy [6, 9]. These systems utilize various types of video security cameras, including color, analog, digital, monochrome, low-light level (LLL) amplified, infrared (IR), and others, to cater to different surveillance needs and environments. The architecture of a typical video surveillance system is illustrated in Figure 1. Proper lighting is essential for recording high-quality video footage regardless of the camera type, whether it is monochrome, color, or LLL ICCD. With the advancement of video surveillance technology, authorities now have virtual eyes on the ground, and the system can promptly alert them whenever suspicious or terrorist activity is detected, thereby ensuring the safety of facilities and individuals. This technology has become a vital component of comprehensive safety strategies [6, 9]. Pan or tilt components can enhance the capabilities of digital camera systems, both for indoor and outdoor surveillance. Velocity domes, which are small and movable, are commonly used in video surveillance for their flexibility in monitoring various areas. Many commercial, industrial, and governmental establishments such as offices, stores, factories, malls, ports, airports, train stations, and government buildings employ video security solutions to enhance their security measures.

To facilitate ease of use and effective deployment, video surveillance systems are often equipped with compact and user-friendly devices that can transmit data over both short and long distances. These rapid deployment devices are essential for portable personnel protection systems, offering robust transmission capabilities and convenience. Video security systems are continuously evolving, incorporating emerging technologies such as access control, intrusion alarms, fire detection, and two-way communications. These integrations enhance the overall security infrastructure and provide a comprehensive approach to safety. With the rapid advancement of technology, automatic video surveillance is becoming increasingly digital, leveraging sophisticated algorithms and intelligent systems to analyze video data and automate surveillance processes.

In conclusion, video monitoring systems are essential for ensuring safety and effective management. They offer a wide range of camera options, require proper lighting for optimal video quality, and are often integrated with other security technologies. As technology progresses, video surveillance is transitioning towards digital automation, making it more efficient and reliable.

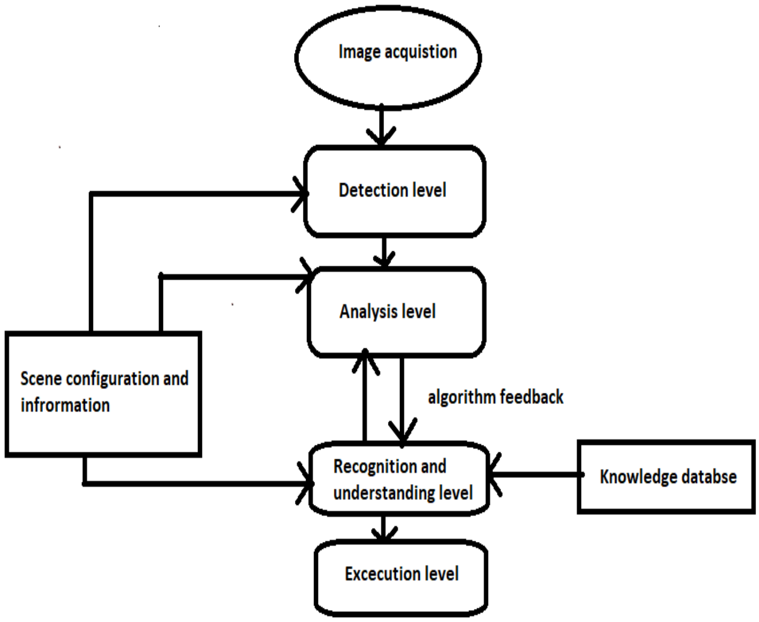


Fig. 1 System design for video monitoring

3. Video Analysis in Dense Environment

Real-time video surveillance systems in dense environments play a crucial role in ensuring public safety and security. These systems leverage advanced technologies such as computer vision, machine learning, and deep learning to analyze video feeds and detect potential threats or suspicious activities. Dense environments, such as airports, shopping malls, and urban centers, pose unique challenges to video surveillance systems due to the high volume of people and activities occurring in these areas. Designing an effective real-time video surveillance system for dense environments requires careful consideration of factors such as camera placement, lighting, and the ability to process and analyze large amounts of data in real-time. Cameras in a real-time

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

surveillance system can recognise and categorise significant events and objects, even in adverse conditions [9]. When cameras' lenses are dirty, it can compromise their ability to accurately identify objects and vehicles, detect motion, identify people and determine where vehicles are going, and much more. Video analysis in action is depicted in Fig. 2. Keeping an eye on this part of the screen is especially important when keeping tabs on a high-traffic area [3]. Complex circumstances, however, make this a challenge.

Object detection and monitoring is a common problem in computer vision jobs, especially in challenging settings [12, 36]. Every possible method of sequential image processing to address these issues has been tested, often under adverse conditions. For real-time video analysis in less-than-ideal weather-monitoring systems, Table 6 gives efficient procedures and improved accuracy.

4. Challenges

In dense environments, such as crowded urban areas or high-traffic locations, the volume of data generated by video surveillance systems can be overwhelming. Efficiently processing and analyzing this massive amount of data in real-time is a significant challenge. However, real-time video analysis is crucial for ensuring effective detection, estimation, monitoring, and recognition of events and activities in these environments. Numerous articles in recent years have explored various approaches and techniques for real-time video analysis in dense environments. These studies focus on utilizing essential data from video streams to extract meaningful information and make timely decisions. Motion analysis, for instance, plays a vital role in robotics, broadcasting, and surveillance applications, as it enables the detection and tracking of moving objects or individuals.

In the realm of video surveillance systems, there is a diverse range of methods and algorithms employed to address the challenges posed by dense environments. Researchers and practitioners have proposed innovative techniques to enhance the capabilities of surveillance systems operating in such settings. These methods encompass areas such as object detection and tracking, behavior recognition, anomaly detection, and crowd management. However, deploying video surveillance systems in dense environments requires striking a balance between security objectives and individuals' right to privacy. Ensuring that the system captures only relevant information while avoiding unnecessary invasion of privacy can be a significant challenge. Designing systems with privacy-enhancing features, such as anonymization techniques or intelligent filtering mechanisms, is essential to address these concerns.
Another crucial aspect to consider is the variability of lighting conditions in dense environments. Lighting conditions can fluctuate significantly due to factors like shadows, reflections, or artificial lighting sources. It is essential for a video surveillance system to be capable of adapting to these changing lighting conditions to capture clear and usable images. Advanced camera technologies, including low-light or wide dynamic range (WDR) cameras, can help overcome these challenges by improving image quality and visibility under varying lighting conditions.
Additionally, the system should incorporate intelligent image processing algorithms that can enhance image quality, reduce noise, and compensate for adverse lighting effects. Techniques such as image denoising, contrast enhancement, or adaptive exposure control can be employed to improve the overall image clarity and facilitate better analysis and interpretation of video data.

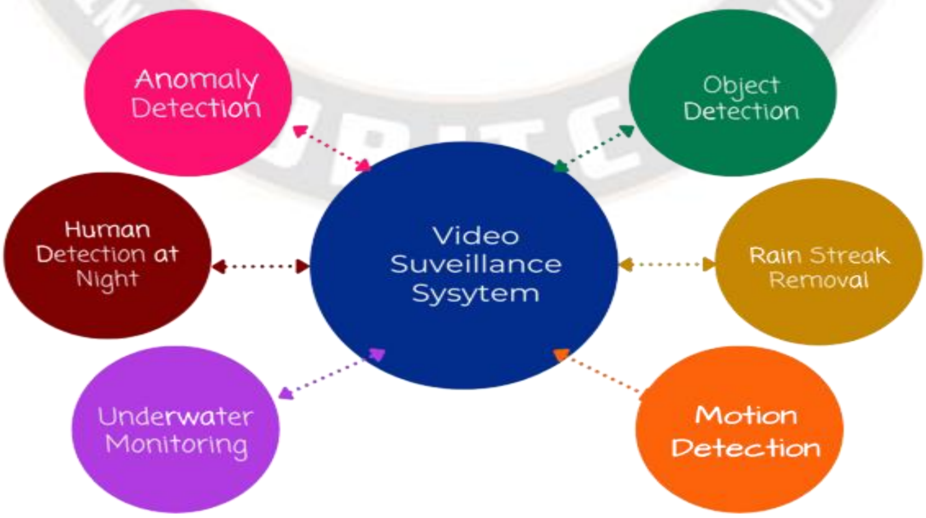


Fig.2 In-depth video examination of crowded settings

3.1 Object detection

Smart cities need people who can spot things and see them in normal traffic and weather. Useful traffic data can be retrieved for examination. The number of vehicles, their speeds, and their location can all be used for this [2]. This data can also be used to spot things like cars, people, traffic lights, ditches, and grass, trees, and bushes along the roadside [28]. Manual and semi-automated surveys are used to gather information on highways. Visible Excessive street surveillance is made possible by walking along or driving a slow vehicle on streets and highways. Inspections will be impacted by inspectors' ability to assign subjective values. Better human intervention takes time since road networks are large and varied.

Many difficult application models can be solved by deep learning with the help of traditional statistical techniques [11, 29]. DNNs like CNN can recognise, identify, and categorise images. The fundamental advantage of CNN [12, 21, 28] is that it automatically checks critical processes after training. It was computationally intensive to process photographs on devices with limited resources. Conditions like as precipitation, fog, haze, etc. might obscure the view [31]. Drivers frequently confuse vehicles and other roadside items in these scenarios. In this case, correct evaluations are achieved through the application of prediction-based training models and procedures. Using YOLOv5 [2], we analyse and classify security camera data from both rainy and dry conditions. The problems cited can be solved using this strategy. Figure 3 depicts the process of using YOLOv5 for object detection. Popular object detector YOLOv5 is quick, easy to train, and increases processing speed. The authors' strategies for determining the nature of an object are summarised in Table 5.1.

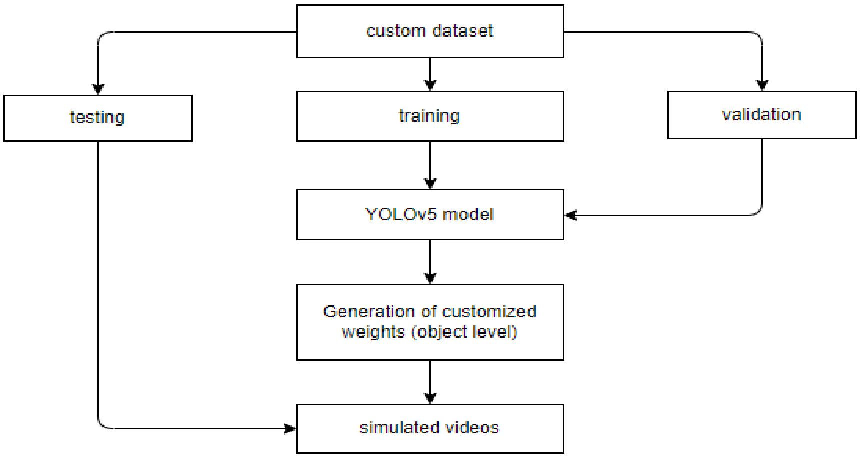


Fig. 3 The YOLOv5 Model for Object Detection Workflow

Table 3.1 Comparison of various object detection techniques

Authors & Years	Methods Used	Merits	Demerits
Teena Sharma, Paul Fortier, Benoit Debaque, Nicolas Duclos, Abdellah Chehri, and Bruno Kinder. [2] 2022.	Deep learning Methods (YOLOv5)	Roboflows' open dataset improves vehicle recognition in dry and wet conditions.	Under current weather conditions, it cannot detect road assets in autonomous vehicles.
(31), Vibhanshu Singh Sindhu 2021	YOLOv4	Its average precision beats the Yolov2's.	The second and third steps of vehicle collision detection, tracking, and accident detection need work.
Mohamed Abdel-Aty, Stephen Ison, Mohammed Quddusa, Jinghui Yuan, and Nicolette Formosa [28] 2020	R-CNN Regional–Convolution Neural Network	The DNN model used ssms, traffic variables, and a separation between traffic conflicts and safe road dynamics.	Traffic accidents decrease.
Senior Member, IEEE [10] Kai Yuan, Jian Yao, Chao Fan, Hua Zhang, Yuan Liu, and Xianling Lu 2020	ResNet, Deep learning	First, offer a specialized deep network to detect TWV's erratic behavior to intelligently manage traffic.	Selective Search should be faster or replaced with a better option.
Matteo Tiezzi, Marco Maggini, Stefano Melacci, and [11] Angelo Frosini 2019	Deep Learning, Recurrent Neural Networks, and Convolutional Neural Networks	Focused on four traffic occurrence types in real-world video footage.	Real-world operational online test.
Sami Gazzah, Najoua Essoukri Ben Amara, Ala Mhalla, and Thierry Chateau [12] 2019	Deep learning, MF R-CNN, and transfer learning	From a target video series and a generic sensor, this framework automatically creates a customized traffic-object detector.	Not relevant to upgrades.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

3.2 Human Activity Detection

Motion detection is essential in real-time video processing and other computer vision applications [32]. It extracts moving objects from video streams at time t. Motion-detecting systems highlight the scene's moving parts. Optical flow analysis, background subtraction, and temporal difference are the three most essential motion detection methods [33]. Most motion detectors use background removal [34, 35]. They typically follow these three phases. First, adjust the camera to sculpt the background. The second stage calculates the absolute difference between the current frame of the series and the background image to distinguish between background and moving object pixels. In the background initialization stage, offline methods are used to process all the data at once. Figure 4 illustrates background subtraction. Online algorithms necessitate a slow process of data extraction, much like routine upkeep. Algorithms developed by the authors to detect human activity in different climates are compared in Table 5.2. Video framing and color space changes may be pre-processed. Post-processing can fix background extraction issues. Adaptive background models prolong scene fading. Deep learning techniques improve wearable sensors that track human activity [27].

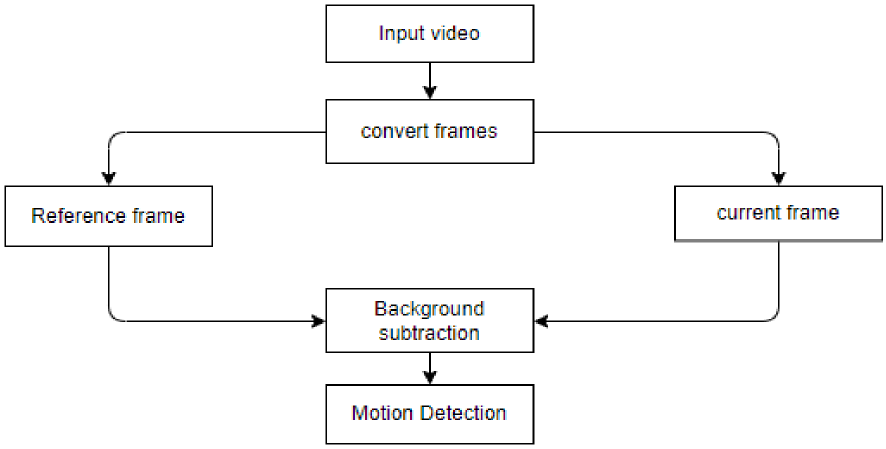


Fig. 4. Flowchart followed.

Table 3.2 Comparison of various Motion/Human Activity detection techniques

Authors and Year	Methods used	Merits	Demerits
Yale Hartmann, Hui Liu, Tanja Schultz, and Steffen Lahrberg [18] 2022	Feature Extraction	Predict human activities successfully.	Models are less efficient.
Shiva Nand Singh, Vijay Bhaskar Semwal, Nidhi Dua [36] 2021	A deep neural network model uses gated recurrent units and convolutional neural networks.	Since it uses convolutional kernels of different sizes, the model can capture local correlations at different lengths.	Deep learning methods are identical.
Jong Weon Lee, Sitara Afzal, and Imran Ullah Khan [37] 2022	Hybrid deep learning-based models	The suggested hybrid model recognizes one-person activity well but may not recognize many people.	Creating a large HAR dataset of daily activities, including physical activity.
Teodiano Bastos, Binh Nguyen, Yves Coelho, and Sridhar Krishnan [33] 2021	Machine learning methods (ML)	Wearable technology is popular for self-care, so this study explores standard power reduction methods to speed up HAR integration into wearable devices.	Not efficient for devices with wires
Hakil Kim [35], Cheng-Bin Jin [36], and Shengzhe Li 2018	Multi CNN	The suggested action detection model localizes and recognizes several people's actions with reasonable accuracy at low computing cost.	A skin-color Mih or optical flow are being researched as deep CNN architectures and more strong temporal feature methods.

3.3 Underwater Monitoring

There are three essential measures to take in order to comprehend the IoT under water [39, 40, 41]. The first step is the real-time, dynamic, careful, and intelligent utilisation of the underwater habitats. There is a wealth of in-situ oceanographic data thanks to the deployment of underwater sensor systems that measure things like conductivity, temperature, intensity, biological content, and current. [39, 10]. Subsea data transfer in real time represents the next stage of IoT deployment. Underwater aural transmission allows for

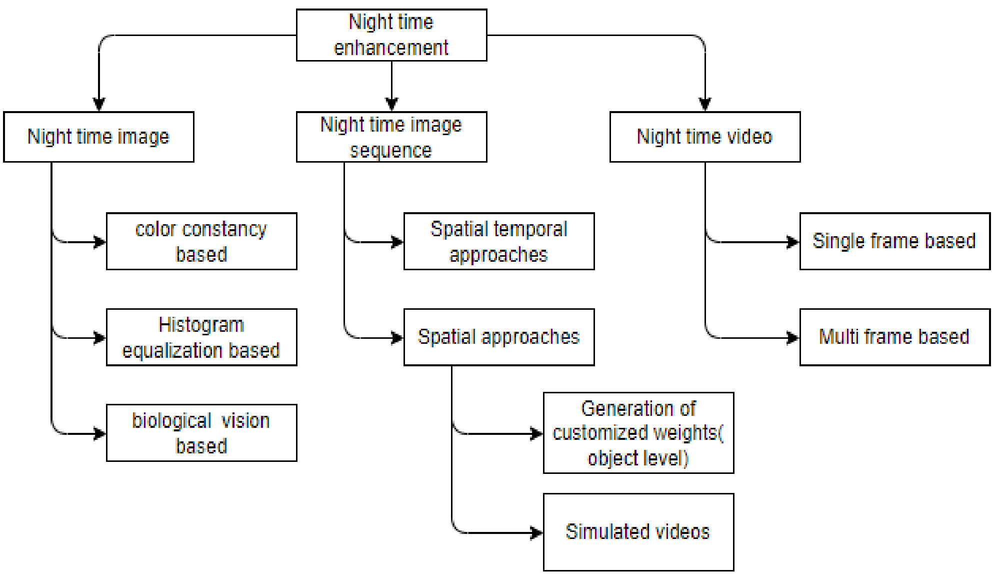
3D ocean monitoring using wireless sensor networks. It is helpful for underwater wired networks. Transmission range is in the tens of kilometres. Smart processing of vast amounts of underwater data is essential for understanding the Internet of Things. Historically [22, 23], maritime data collection was typically performed on yearly or monthly cycles, yielding scant information due to a lack of sophisticated technical approaches and a low price tag. Reduced time spent gathering data is a direct result of technological and detecting method advancements. The authors' techniques for underwater monitoring are outlined in Table 5.3.

Table 3.3 Comparison of various techniques for underwater surveillance

Authors and Year	Methods used	Merits	Demerits
Weiwei Kong, Yujian Guo, Mohammed Sait, Omar Alkhazragi, Tien Khee Ng, and Boon S. Ooi are a few authors. [39]2022	Optical-Wireless method	Aqua-seer was tested in open space and an outdoor diving pool with 46-m and 5-m video surveillance.	Aqua-seer enhancements will connect to AUV clusters for real-time, dynamic, and visual underwater monitoring.
Weidong Zhang, Fan Wang, and Yibo Ai [23] 2021	feature extraction, feature expression, and assessment criteria	The camera's optical axis is not perpendicular to the swimmer's swimming direction, therefore it prevents the outer ellipse's long and short axes from malfunctioning.	Pool monitoring only
Farahnaz Mohanna and Mohammad Kazem Moghimi [41] 2022	Convolutional neural network ResNet	accurate and simple computing architecture.	Qualitatively analyze a large shallow-deep water area.
Weiqiao Yuan, Xinqiang Chen, Ryan Wen Liu, and Yuzu Lu [24] 2021	CNN	Compared to several sample approaches, the System could accurately and real-time distinguish diverse moving ships.	Despite its drawbacks, it should be considered because it can accurately and real-time detect moving ships in challenging imaging conditions.

3.4 Nighttime Enhancement

There is still inefficiency in detecting thermal images [14]. Only a small number of cutting-edge techniques, mostly based on thermal images taken at night, have been used to positively identify individuals. People in thermal photos captured in a variety of settings and at varying distances from the camera were identified using YOLO [15, 16]. The progression of night vision is summarized in Fig. 5. Nighttime enhancements cover "nighttime picture," "image sequence," and "video." While thermal imaging has great potential for nighttime surveillance, current human/face detection and monitoring algorithms have trouble producing accurate results from thermal images. Humans use the item in a wide range of situations, such while walking, jogging, in all kinds of weather, etc. [6, 8]. The scene's brightness, coherence, polarization, and color all have an impact on the absurdity of nighttime thermal photography [9]. Tab. 5.5 demonstrates the authors' efforts to enhance the evening environment. Some temperature data was used to train a Tiny-Yolov3 network. Potentially, the method could provide rapid and accurate detection..



***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Fig. 5 Night-time enhancement classification

Table 3.4 Nighttime video surveillance comparison

Authors and year	**Methods used**	**Merits**	**Demerits**
Vaishnavi, Maithri, B. Priya, and Dharshini, 2022	Image-enhancing methods	Advanced driver assistance technologies	A back-end mechanism for security camera and other video evidence is needed.
Samah A. F. Manssor, Sun Shaoyuan, Shima Ali, and Mohammed Abdalmajed [14] 2021	YOLO algorithm	48.8% accuracy, higher than others	Detection takes 6ms.
Ajmal Shahbaz, Member, IEEE, and Kang-Hyun Jo, Senior Member, IEEE [9] 2021	CNN, dual-camera sensors	surpassed the top foreground detection algorithms	To integrate the algorithm with video surveillance system capabilities like recognizing abandoned things and illegally parked autos.
Girish KUMAR Darisi, Challaram Grandhi and M. Venkata Subbarao [6] 2022	background subtraction	It enhances sloppy visuals like atmospherically drab, hazy, and motion images.	Remote-sensing picture avoidance.

3.5 Anomaly Detection

Anomalies may be isolated, common, or contextual. Figure 6 summarizes anomalies. Contextual anomalies are data samples exhibiting unexpected behavior. Anomalies are dataset-wide data events. Cloud and edge devices must be considered in automated surveillance and anomaly detection [43, 19]. Centralized computers analyze huge monitoring data from large-scale systems. Cloud computing needs bandwidth because of network delay. Delay-sensitive video surveillance anomaly detection algorithms are needed. Cloud and edge computing improve intelligent real-time video monitoring. Data computing simplifies latency-sensitive application development and reduces system costs and network data traffic. Edge computing benefits real-time applications like anomaly detection. Edge and terminal anomalies are seldom detected by these sensors. The combination of cloud and edge computing provides significant benefits for intelligent real-time video monitoring. Edge computing brings computation and data storage closer to the data source, reducing the latency associated with transmitting data to the cloud for processing. This proximity enables faster response times and enhances real-time applications such as anomaly detection in video surveillance.

By leveraging edge computing, latency-sensitive application development becomes simpler, as the data processing and analysis can be performed locally on edge devices. This reduces system costs and minimizes network data traffic by avoiding the need to transmit all data to the centralized cloud infrastructure. It is important to note that edge computing is particularly advantageous for detecting anomalies at the edge and terminal devices. These anomalies are often challenging to identify using centralized surveillance systems alone. By incorporating edge devices and sensors, surveillance systems can capture and analyze data at the source, enabling faster anomaly detection and response, especially in scenarios where real-time action is critical.

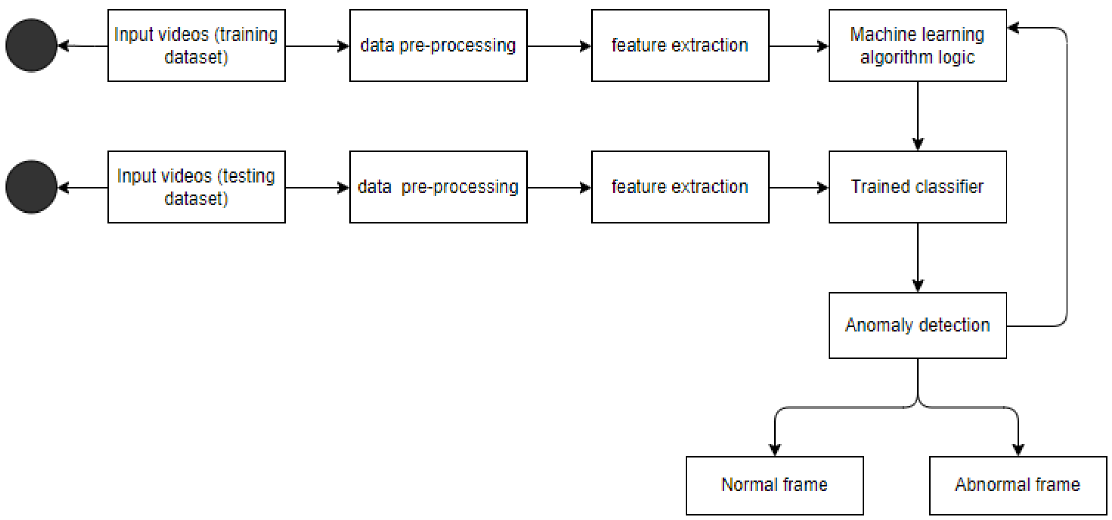


Fig. 6 Anomaly detection systems represented in a schematic format.

Table 4 Evaluation of the relative efficacy of various approaches to resolving other video surveillance system problems.

Challenges	Methods	Evaluation
Object Detection	Deep learning Methods (YOLOv5)	The experiment results reveal that the yolov5 algorithm detects automobiles on maps at 71.3% and trucks at 57.3% (0.5).
	YOLOv4	53% exact F1 is 34% 25% recall IOU average is 37.78%, and map(0.50) is 27.29%. Precision is 39%.
	Regional–Convolution Neural Network (R-CNN)	The DNN network predicts 71% and 78% of traffic conflicts at 5% and 10% false alarm rates. The best DNN model has 94% accuracy.
Human Activity Detection	ML algorithms	SVM outperforms all others with 0.9803 percent accuracy. Precision=0.97 Accuracy=0.98 F1: 0.95 0.96 recall
	Multi-input CNN-GRU	Precision = 96.20 F1-score = 96.19
	DTR-HAR model	Precision = 92%, recall = 92%, and F1 score = 92%.
Underwater Monitoring	optical wireless methods	High-resolution =1920 1080 px, error-free implementation was done over 1.5 m of open space, pure water channels with 1.53 and 42.40 ml/s bubble-induced turbulence, pure seawater with 0.043 m-1 attenuation, and coastal ocean water with 0.298 m-1.
	CNN	91.4% success rate
	LIVNet, YOLOv4, CNN	The map yields 57.96%.
Night time enhancement	Yolo Algorithm	The approach is 90% more accurate than TF-yolov3 (88%) for night pedestrian recognition.
	Deep learning, CNN	0.948 precision, 0.741 recall, 0.832 F1-score.
	dual-camera sensors, CNN	performs better than the baselines in every way, especially training length (12 minutes) and testing speed (32 fps).
Anomaly Detection	DNN	a 90%+ degree of accuracy
	Multi-branch model	The two-branch multi-branch model detects meteorological abnormalities with 78.9% accuracy.

Conclusion and Future Trends

This review paper discusses real-time video analysis for crowded video surveillance systems and its difficulties and solutions. We discussed contemporary surveillance technologies, their development, and their application. Weather-related surveillance difficulties follow. It also checks video surveillance system accuracy. We compared several methods using architectural drawings. The study concludes with real-time video in busy areas. Security-related video surveillance tasks are researched. Classification, moving object identification, and monitoring are incorporated. Algorithms and approaches have solved many issues. Numerous improvements are underway. False alarms and environmental changes are video surveillance systems' main issues. Video surveillance systems have false alerts and ecological disturbances. Video surveillance systems don't include automatic alarms since false alarms could disrupt the market and cause system failure. Unexpected weather might cause system failure. To keep up with edge computing, YOLOv5, fog computing, WSN, etc., researchers [1] are solving new problems.

References

1. Tsakanikas, V., & Dagiuklas, T. (2018). Video surveillance systems-current status and future trends. *Computers & Electrical Engineering*, *70*, 736–753.
2. Sharma, T., Debaque, B., Duclos, N., Chehri, A., Kinder, B., & Fortier, P. (2022). Deep Learning-Based Object Detection and Scene Perception under Bad Weather Conditions. *Electronics*, *11*(4), 563.
3. Sreenu, G., & Saleem Durai, M. A. (2019). Intelligent Video Surveillance: A review through Deep Learning techniques for crowd analysis. *Journal of Big Data*, *6*(1).
4. Vujović, I., Jurčević, M., & Kuzmanić, I. (2014). Traffic video surveillance in different weather conditions. *Transactions on Maritime Science*, *3*(1), 32–41.
5. Liu, H., Xu, X., Chen, X., Li, C., & Wang, M. (2022). Real-Time Ship Tracking under Challenges of Scale Variation and Different Visibility Weather Conditions. *Journal of Marine Science and Engineering*, *10*(3), 444.
6. Girish Kumar, D., Challa Ram, G., & Venkata Subbarao, M. (2022). Real-time image enhancement using DCT techniques for video surveillance. *Lecture Notes in Electrical Engineering*, 453–461.
7. Li, M., Cao, X., Zhao, Q., Zhang, L., & Meng, D. (2021). Online rain/snow removal from surveillance videos. *IEEE Transactions on Image Processing*, *30*, 2029-2044.
8. Kumari, S., Choudhary, M., Mishra, R., Chaulya, S. K., Prasad, G. M., Mandal, S. K., & Banerjee, G. (2022). Artificial intelligent-based intelligent System for safe mining during foggy weather. *Concurrency and Computation: Practice and Experience*, *34*(4), e6631.
9. Shahbaz, A., & Jo, K.-H. (2021). Dual camera-based supervised foreground detection for low-end video surveillance systems. *IEEE Sensors Journal*, *21*(7), 9359–9366.
10. Qian, P., Yuan, K., Yao, J., Fan, C., Zhang, H., Liu, Y., & Lu, X. (2021). Residual-network-leveraged vehicle-thrown-waste identification in real-time traffic surveillance videos. *IEEE Transactions on Intelligent Transportation Systems*, *22*(3), 1817–1826.
11. Tiezzi, M., Melacci, S., Maggini, M., & Frosini, A. (2018). Video surveillance of highway traffic events by Deep Learning Architectures. *Artificial Neural Networks and Machine Learning – ICANN 2018*, 584–593.

12. Mhalla, A., Chateau, T., Gazzah, S., & Amara, N. E. (2019). An embedded computer-vision system for multi-object detection in traffic surveillance. *IEEE Transactions on Intelligent Transportation Systems*, *20*(11), 4006–4018.
13. Osipov, A., Pleshakova, E., Gataullin, S., Korchagin, S., Ivanov, M., Finogeev, A., & Yadav, V. (2022). Deep Learning Method for Recognition and Classification of Images from Video Recorders in Difficult Weather Conditions. *Sustainability*, *14*(4), 2420.
14. Manssor, S. A., Sun, S., Abdalmajed, M., & Ali, S. (2022). Real-time human detection in thermal infrared imaging at night using enhanced Tiny-yolov3 network. *Journal of Real-Time Image Processing*, *19*(2), 261-274.
15. Park, J., Chen, J., Cho, Y. K., Kang, D. Y., & Son, B. J. (2019). CNN-based person detection using infrared images for nighttime Intrusion Warning Systems. *Sensors*, *20*(1), 34.
16. T, S., & Thampi, S. M. (2019). Nighttime visual refinement techniques for surveillance video: a review. *Multimedia Tools and Applications*, *78*(22), 32137–32158.
17. Jasmine, J., & Annadurai, S. (2019). Real-time video image enhancement approach using particle swarm optimization technique with adaptive cumulative distribution function based histogram equalization. *Measurement*, *145*, 833-840.
18. Hartmann, Y., Liu, H., Lahrberg, S., & Schultz, T. (2022). Interpretable high-level features for human activity recognition. *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies*.
19. Franklin, R. J., Mohana, & Dabbagol, V. (2020). Anomaly detection in videos for video surveillance applications using Neural Networks. *2020 Fourth International Conference on Inventive Systems and Control (ICISC)*.
20. Jin, C.-B., Do, T. D., Liu, M., & Kim, H. (2018). Real-time action detection in video surveillance using a sub-action descriptor with multi-convolutional neural networks. *Journal of Institute of Control, Robotics, and Systems*, *24*(3), 298–308.
21. Srinivasan, R., Wang, L., & Bulleid, J. L. (2020). Machine learning-based climate time series anomaly detection using convolutional neural networks. *Weather and Climate*, *40*(1), 16-31.
22. Guo, Y., Lu, Y., & Liu, R. W. (2022). Lightweight deep network-enabled real-time low-visibility enhancement promotes vessel detection in maritime video surveillance. *The Journal of Navigation*, *75*(1), 230-250.
23. Wang, F., Ai, Y., & Zhang, W. (2021). Detection of dangerous early state in indoor swimming pool deep water based on surveillance video. *Signal, Image and Video Processing*, *16*(1), 29–37.
24. Liu, R. W., Yuan, W., Chen, X., & Lu, Y. (2021). An enhanced CNN-enabled learning method for promoting ship detection in Maritime Surveillance System. *Ocean Engineering*, *235*, 109435.
25. Kumar, Rahul, Raman Balasubramanian, and Brajesh Kumar Kaushik. 2021. "Efficient Method And Architecture For Real-Time Video Defogging." *IEEE Transactions On Intelligent Transportation Systems* 22 (10): 6536-6546. doi:10.1109/tits.2020.2993906.
26. Pang, Y., Xie, J., & Li, X. (2019). Visual haze removal by a unified generative Adversarial Network. *IEEE Transactions on Circuits and Systems for Video Technology*, *29*(11), 3211–3221.
27. Zhang, S., Li, Y., Zhang, S., Shahabi, F., Xia, S., Deng, Y., & Alshurafa, N. (2022). Deep learning in human activity recognition with wearable sensors: A review on advances. *Sensors*, *22*(4), 1476.
28. Formosa, N., Quddus, M., Ison, S., Abdel-Aty, M., & Yuan, J. (2020). Predicting real-time traffic conflicts using Deep Learning. *Accident Analysis & Prevention*, *136*, 105429.
29. Mr. Murthy, C. B., Hashmi, M. F., Bokde, N. D., and Geem, Z. W. (2020). Investigations of object detection in images/videos using various deep learning techniques and embedded platforms—a comprehensive review. *Applied Sciences*, *10*(9), 3280.
30. Kristo, M., Ivasic-Kos, M., & Pobar, M. (2020). Thermal object detection in difficult weather conditions using Yolo. *IEEE Access*, *8*, 125459–125476.
31. Sindhu, V. S. (2021, May). Vehicle Identification from Traffic Video Surveillance Using YOLOv4. In *2021, the 5th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1768-1775). IEEE.
32. Mittal, P. (2022, January). Machine learning (ml) based human activity recognition model using intelligent sensors in IoT environment. In *2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence)* (pp. 330-334). IEEE.
33. Nguyen, B., Coelho, Y., Bastos, T., & Krishnan, S. (2021). Trends in human activity recognition focus on machine learning and power requirements. *Machine Learning with Applications*, *5*, 100072.
34. Nguyen, B., Coelho, Y., Bastos, T., & Krishnan, S. (2021). Trends in human activity recognition focus on machine learning and power requirements. *Machine Learning with Applications*, *5*, 100072.
35. Kim, C., Lee, J., Han, T., & Kim, Y.-M. (2018). A hybrid framework combining background subtraction and deep neural networks for rapid person detection. *Journal of Big Data*, *5*(1).
36. Dua, N., Singh, S. N., and Semwal, V. B. (2021). Multi-input CNN-GRU-based human activity recognition using wearable sensors. *Computing*, *103*(7), 1461-1478.
37. Khan, I. U., Afzal, S., & Lee, J. W. (2022). Human activity recognition via hybrid deep learning-based model. *Sensors*, *22*(1), 323.
38. Basly, H., Ouarda, W., Sayadi, F. E., Ouni, B., & Alimi, A. M. (2021). DTR-Har: Deep temporal residual

representation for human activity recognition. *The Visual Computer*, *38*(3), 993–1013.

39. Kong, M., Guo, Y., Alkhazragi, O., Sait, M., Kang, C. H., Ng, T. K., & Ooi, B. S. (2022). Real-Time Optical-Wireless Video Surveillance System for High Visual-Fidelity Underwater Monitoring. *IEEE Photonics Journal*, *14*(2), 1-9.
40. Shi, Z., Guan, C., Li, Q., Liang, J., Cao, L., Zheng, H., Gu, Z., & Zheng, B. (2022). Detecting marine organisms via joint attention-relation learning for maritime video surveillance. *IEEE Journal of Oceanic Engineering*, 1–16.
41. Moghimi, M. K., & Mohanna, F. (2022). Reliable object recognition using deep transfer learning for marine transportation systems with underwater surveillance. *IEEE Transactions on Intelligent Transportation Systems*, 1–10.
42. Hettiarachchi, P., Nawaratne, R., Alahakoon, D., De Silva, D., & Chilamkurti, N. (2021). Rain streak removal for single images using conditional generative adversarial networks. *Applied Sciences*, *11*(5), 2214.
43. Patrikar, D. R., & Parate, M. R. (2022). Anomaly detection using edge computing in the video surveillance system. *International Journal of Multimedia Information Retrieval*, 1-26.