Enhancing IoT-Based Intelligent Video Surveillance through Multi-Sensor Fusion and Deep Reinforcement Learning

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Abstract

Currenlty, wireless communication that is successful in the Internet of Things (IoT) must be long-lasting and self-sustaining. The integration of machine learning (ML) techniques, including deep learning (DL), has enabled IoT networks to become highly effective and self-sufficient. DL models, such as enhanced DRL (EDRL), have been developed for intelligent video surveillance (IVS) applications. Combining multiple models and optimizing fusion scores can improve fusion system design and decision-making processes. These intelligent systems for information fusion have a wide range of potential applications, including in robotics and cloud environments. Fuzzy approaches and optimization algorithms can be used to improve data fusion in multimedia applications and e-systems. The camera sensor is developing algorithms for mobile edge computing (MEC) that use action-value techniques to instruct system actions through collaborative decision-making optimization. Combining IoT and deep learning technologies to improve the overall performance of apps is a difficult task. With this strategy, designers can increase security, performance, and accuracy by more than 97.24 %, as per research observations.

Keywords: Machine Learning; Internet of Things; DRL; Intelligent Video Surveillance; Mobile Edge Computing; Fusion System Design.

1- Introduction

Monitoring has been a vital part of many routine practices to protect human beings' welfare, resources, and properties [1]. It can be seen in various sites: institutions, clinics, airlines, auto parks, gas stations, restaurants, and any potential enterprise or organization [2]. It increases the urge of security personnel to automate monitoring tasks and work more effectively [3]. Every monitoring system has one centrally located video recording source, such as a security camera [4]. Computer vision analysis may be utilized to automate numerous video detection processes and derive useful information from these recordings by notifying when unsafe situations are seen in video recordings [5]. The specific usage of video surveillance is highlighted in many kinds of research, namely identifying odd human activities in shopping malls, etc., [6]. For example, any situation, such as a shop's entrance or exit, an occurrence leading to robbery, or an unsupervised cash desk, must be examined [7]. There are a few exceptions to the rule; before sending out the listed alarms, several earlier stages identify and track dangerous individuals in videos [8].
Context subtraction procedures are used to segment the photographs in the previous methods [9]. This research aims to compare the best appropriate subtraction method for this particular context among the most recent technological advancements [10]. Tests conducted in virtual scenarios have proven the effectiveness and efficiency of the professional surveillance camera system in real-time [11]. The focus of this research is on the numerous video surveillance algorithms that are used [12]. To find the best approach, the researchers combed through a plethora of available data [13]. he process of information fusion involves integrating data from multiple sources to obtain more comprehensive and accurate information. The categorization step in information fusion is crucial, and it depends on the preceding procedures for removing contextual information [14].

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However, to achieve optimal fusion, there are several intelligent techniques and system architectures that can be used. For example, fusion optimization algorithms can be employed to improve the scores obtained from various fusion techniques. Additionally, deep learning models can be used to combine multiple models for intelligent systems, which can improve the performance of the fusion system. Fusion in decision-making and robotics can also benefit from these techniques, as well as data fusion in cloud environments and multimedia applications. Fuzzy approaches and optimization algorithms are also commonly used for data fusion applications, especially in e-systems. Overall, the most recent monitoring algorithm offers an intriguing new approach to traditional state-of-the-art methodologies, focusing on routes [15], which can be further optimized and improved using various fusion techniques.

1.1- Deep Reinforcement Learning in Video Surveillance

An independent personality system, reinforcement learning, basically learns by doing [16]. In other words, it learns to attain the best results possible by performing activities to maximize compensation [17]. In addition to helping software agents achieve their goals, deep reinforcement learning integrates artificial neural networks with a reinforcement training approach [18]. And as such integrates approximate function computation with optimization for a specific goal by connecting states and actions with their associated financial gains or losses [19]. The smart home control system uses intelligent video surveillance to record criminal activities from the user's house, company, and more [20]. Surveillance video entails looking for certain wrong behavior that could signal wrongdoing or has already occurred [21]. Besides the representative, a reinforcement learning system does have four key sub-components [22]: a strategy, a learning algorithm, a measurement method, and a model of the surroundings as an optional third component [23]. Policies specify how the learning agent should behave at a given point in time [24]. Moreover, reinforcement learning has its own unique and complicated issues [25], such as tough training/design set-up and problems connected to the balance of exploration and facing several problems similar to supervised and unsupervised approaches [26].

The significant contributions of this research are as follows;

- Reinforcement management is used to dynamically generate surveillance tasks, and optimizing the delay of all produced activities over time is essential.
- A key feature of deep learning is to evaluate the benefit of various actions without assuming a modeling approach.
- To ensure optimum usage thorough resource-based reinforcement learning structure is implemented.

The rest of the article is as follows. Section 2 deals with the literature and background of the video surveillance system. The proposed detecting and preventing abnormal activities EDRL-IVS framework is designed and discussed in section 3. The software analysis and performance evaluation are discussed in section 4. Section 5 shows the conclusion and future scope.

2-Related Works

According to the results of our latest survey, DRL applications in cyber environments can be broadly divided into two groups: those that optimize and enhance the communications and networking capabilities of IoT apps and those that fight against hacking attempts.

Monitoring systems such as video surveillance or multimedia web things are becoming increasingly significant in our daily lives. The number of network systems has grown dramatically, and as a result, these systems are more vulnerable than ever to cyber-attacks. Cyber-attacks were dynamic and complex, requiring defense mechanisms that are flexible, responsive, and scalable, given in [27]. Deep reinforcement learning (DRL) methods have been widely proposed to address these problems using machine learning (ML). Here proposed the method DRL-ML; these findings should lay the groundwork for future research into emerging DRL's ability to deal with highly complicated cyber security issues.

Moreover, processing and communication resources can be a bottleneck of the entire system if valuable surveillance information is obtained as quickly and precisely as possible stated in [28]. Here proposed mobile edge computing for video surveillance systems (MEC-VSS), and the experiments demonstrate the suggested system's advantages in the relationship between leadership, economic, and cognitive video surveillance. Low latency and excellent quality of service (QoS) are critical in future smart city applications, and fog computing plays an important role in supporting them [29]. Researchers tackle the optimization problem for quick migration decisions using deep deterministic policy gradient (DDPG) based on a deep reinforcement learning (DRL) technique. Robust and autonomous wireless networks (RSSWN) were proposed for the next generation in the daily lives of humans; the Internet of things (IoT) is changing technological adaption. Applications for IoT might be as crucial as smart cities or health-based sectors or as simple as industrial IoT [30]. One type of ML is deep learning (DL), which is computationally complex and costly. Combining deep learning approaches

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with IoT applications to run more smoothly overall is a challenge. Fog radio access network (F-RAN) was created for fifth-generation (5G) wireless communications to address the latency restrictions of Cloud-RAN due to recent developments in IoT devices and the coming new breed of IoT applications driven by artificial intelligence (AI) in [31]. Challenge of network slicing in dynamic environments, where uneven latency and processing needs necessitate allocating limited resources at the network edge (fog nodes).
The above traditional surveys compare DRL-ML, MEC-VSS, DDPG, RSSWN, and F-RAN with the proposed system EDRL-IVS. The reinforcement process in intelligent system-based video surveillance is implemented and analyzed in the below sections.

3- Enhanced Deep Learning Reinforcement-Based Intelligent Video Surveillance (Edrl-Ivs)

Increasing attention is being paid by academic and industrial researchers alike to the implementation of wireless networks to enable the Internet of Things concept. As a result of their complexity and widespread use, these systems pose numerous challenges, such as the integration of heterogeneous communication systems, dynamic adaptation to various working scenarios, and the ability to extract information from massive amounts of data collected and transmitted by sensors.

3.1-Detection Anamoly In Smart City From Surveillance Video

In addition to monitoring activities in a smart city, the suggested system will use camera footage and send alerts to the appropriate authorities when anything suspicious happens. Our suggested approach for detecting suspicious activities from video surveillance uses a deep learning network.

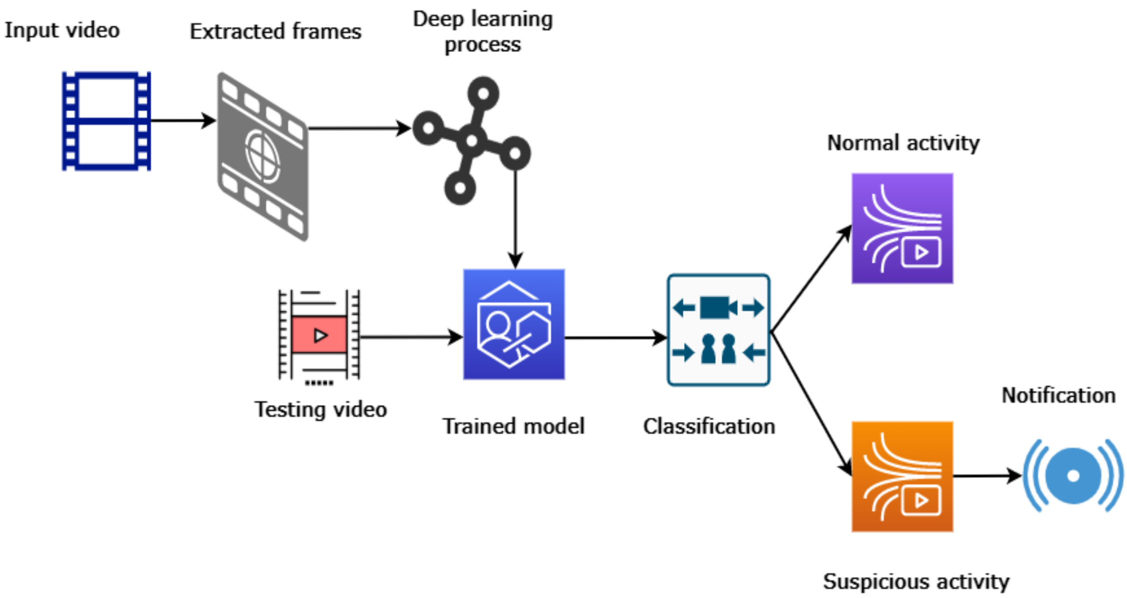

Figure 1: Detection of suspicious from video surveillance

Deep learning architectures can improve accuracy while working better with large datasets because of deep learning techniques. Extraction of features, classification, and predictions are only a few of the architecture's design processes. Figure 1 depicts the overall system architectural arrangement. A neural network and Gaussian distribution were used to construct a system for monitoring peoples behavior in a city. Face recognition system, suspicious state recognition, and abnormal detection are the three stages of the algorithm from the input video stream. The trained model determines whether or not the person is in a suspicious state from the extracted frames, and the random variable determines whether or not the student exhibits any abnormal behavior with the deep learning process.

For computer vision systems to extract sequences or motion patterns and understand the progression of video sequence characteristics, a significant amount of classification is required. The extracted frames using deep learning classification are divided into normal and suspicious activity. The feature extraction used here is based on static background hypotheses, which are frequently not applicable in real-time circumstances. The suspicious activity can be identified by setting the alarm. These can be obtained by solving resource process and it is given below,

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$$AV^*(vf) = \max_{\pi} \int Sc\, AV^{\pi}(vf) \quad (1)$$
$$BV^*(vf,b) = max_{\pi} \int Sc\, BV^{\pi}(vf,b) \quad (2)$$
$$\sqrt[2]{R(Sc_{tf+1(vf0,ovf0,\ldots\ldots,vft,ovft)}R(Sc_{tf+1/S_{tf,ovf_{tf}}})} \quad (3)$$

Markov Decision Process (MDP) is used as the key reinforcement learning process and satisfies the resource process, which defines the current state, determines the process's future, the present situation, and the representative is unwanted in the entire video streaming process. It can be summarized in equations (1), (2), and (3). Where vf denotes the value function, tf determines the time function. Here AV and BV represent best and action-value functions, respectively. ovf denotes optimal value functions$(vf0, ovf0, \ldots\ldots, vftf, ovftf)$, The representative obtains a reward R after choosing an action at a time max_{π}. $tf + 1$ scalar reward and enters a new stage Sc_{tf+1}

Most problems in the real world develop when a large group of people is involved. The strategies described above are very effective in dealing with large crowds.

3.2- INTELLIGENT VIDEO SURVEILLANCE

The technology's technical aspects are outstanding, and they can help a large number of individuals deal with the security difficulties they confront regularly. When deciding on the type of security system to implement, keep these factors in mind. Using cameras positioned on the wall to cover a specified region and researchers were able to identify a human subject.

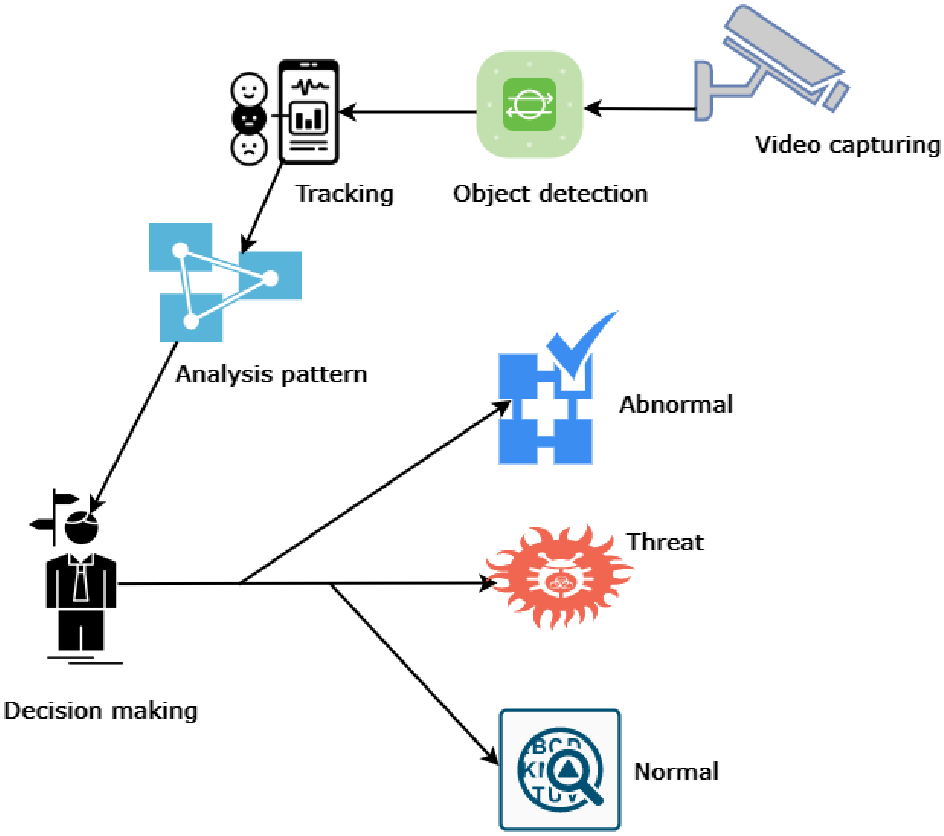

Figure 2: Overall design process of video surveillance

A basic understanding of locating moving objects is critical for engaging in photography, videography, or video game design. A more comprehensive look at this intelligent multi-camera video surveillance system is demonstrated in figure 2 above. Investigating everyday living areas requires multi-camera video surveillance for decision-making. A video reconnaissance system categorizes and tracks various objects and scenarios following analysis patterns. Current methods of video capturing rely on object detection. An administrator must watch the video a great deal of the time in an attempt to discern unusual activity, which is exceedingly tedious and identify any kind of threats. The threats can be normal or abnormal; problems are being solved with a continuous

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robotized video investigation. On-going programming advancement will be at the heart of the moving item locating outline for spectacular video observation.

$$\mathrm{fn}(\mathrm{IV}: \mathrm{X}, \mathrm{Y}, \mathrm{Z}) = \begin{cases} 0 & \mathrm{IV} < X \\ \frac{2(\mathrm{IV}-\mathrm{X})^2}{(\mathrm{Z}-\mathrm{X})^2} & \mathrm{X} \leq \mathrm{IV} \leq \mathrm{Y} \\ 1 - \frac{2(\mathrm{IV}-\mathrm{Z})^2}{(\mathrm{Z}-\mathrm{X})^2} & \mathrm{Y} \leq \mathrm{IV} \leq \mathrm{Z} \\ 1 & \mathrm{IV} > Z \end{cases} \quad (4)$$

The intelligent feature fn specifies where X, Y, and Z are customization attributes that match the required participation video data. In addition, Z is the precise intended value for that prescribed area, X indicates the set of outcomes of the object detected, and Y depicts the pattern analysis. The video stream can be given as an input value denoted as IV, and The IVS observed function is expressed in equation (4).

$$\mathrm{P} = (\mathrm{C}, \mathrm{M}|\mathrm{w}) = -\sum_{x=1}^{c} a_x c_x - \sum_{y=1}^{m} b_y m_y - \sum_{x=1}^{c}\sum_{y=1}^{m} c_x m_y W_{xy} \quad (5)$$

Where $w = (W_{xy}, a_x, b_y)$ relates to DRL, a_x relates to the observable distance, b_y relates to the hidden distance, and W_{xy} shows the $x - y$ weighting. It comprises C nodes accessible on the interface layer and M nodes buried in hidden levels. $c_x$is a state of the x element and m_y is the condition of the y element. The computing algorithm is constructed for a particular system(C, M), as illustrated in equation (5).

$$\mathrm{P}(c, m) = \frac{1}{\mathrm{PF}} e^{-E(c,m)} \quad (6)$$

$$\mathrm{PF} = \sum_{x=1}^{iv}\sum_{y=1}^{m} e^{-E(x,y)} \quad (7)$$

The estimation is denoted as E, the node position is denoted as (x, y), and the video input is denoted as iv. The abnormal threat detection is denoted as PF. The chance of every exposed and concealed layer combination is mentioned as PF is the partitioning formula with the summation using limits $x = 1$ to iv shown in equations (6) and (7). The obtained value $P(c, m)$ is inversely proportional to exposed and concealed layers.

Creating moving target architecture utilizes the field of picture preparation expertise. Configured frameworks using software rather than equipment save money in the long run. Multi-camera surveillance, a server for storing and processing the data collected, and high-speed communication networks will make up our system.

3.3-Enhanced Deep Reinforcement Learning In Video Surveillance

One of the most intriguing problems in computer vision is identifying and classifying human behavior from video. A sensory front end must be created to identify, separate, categorize and track individuals in psychological science.

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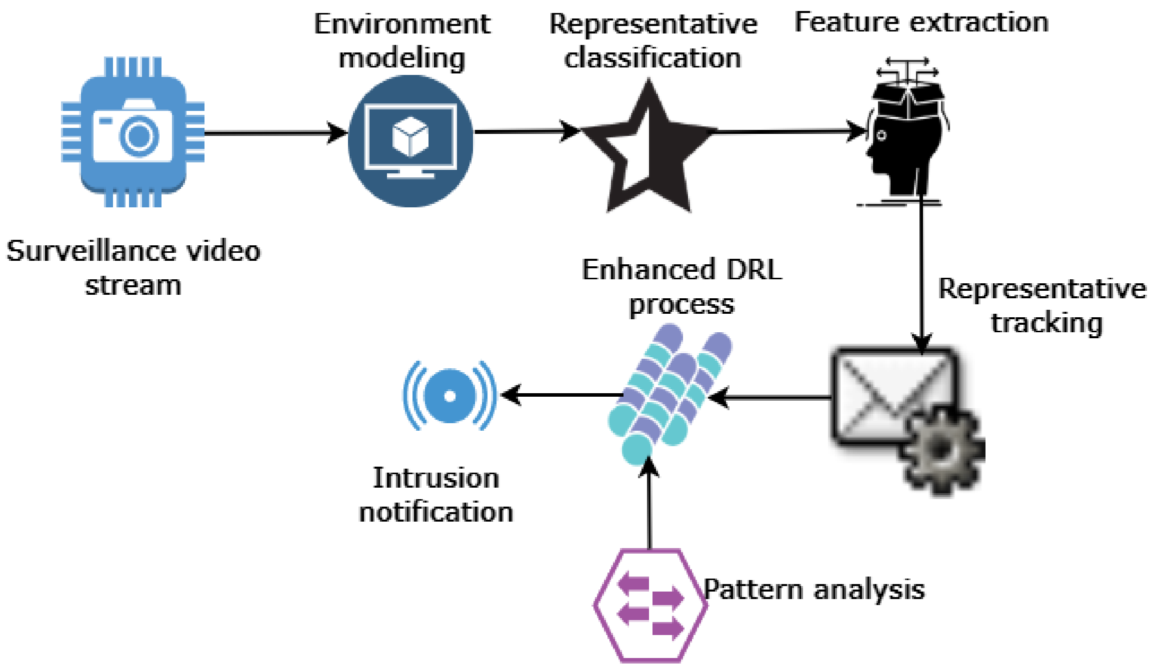

Figure 3: Enhanced DRL process

Figure 3 illustrates one of machine learning professionals' most exciting challenges: identifying and characterizing abnormal behavior in a surveillance video stream. One of the most intriguing challenges in computer vision research involves environment modeling for detecting and classifying individual representative interactions from feature extraction videos. Behavior analysis requires developing a front-end vision that represents tracking, separating, organizing, and tracking body parts in various contexts. This includes conducting a comprehensive behavior description that distinguishes between brief and basic movements and intermediate actions. Studying human behavior opens up new possibilities for describing and grouping activity, especially difficult-to-study behavioral patterns analysis. It's important to look at group tracking and event recognition in surveillance since they help uncover illicit activity. Use a method that distinguishes activity in long videos and addresses numerous actions at once to identify through intrusion notification which is expressed as

$$Ri = a\sum \frac{bj}{\pi ij} + b\sum_{m,n\varepsilon B} \tag{8}$$

$$Ri(x,y) = \frac{1}{2\pi}\int_{-\infty}^{\infty} e(-\partial|nsB|)e^{\frac{-(a+b)}{bj-m(a,b)|^3}} \tag{9}$$

The preceding equations (8) and (9) define the attitudes, behaviors, and outcomes of the DRL-based paradigm. The πij relationship between intermediate layers i and j for the pattern analysis allocated for transmission $\pi\, ij$ from one to another compensation user $n\varepsilon$. The indicators tend to be better B for both a and b. Both equations above show the $Ri(x,y)$ Where Ri is the parameter of state and the record is x and y axis in any contribution. z is the external source of environmental modeling and explicit visual instruction and∂ is the total evaluation criteria.S is the difference of an image to identify, u is the velocity for the lower state, and v is the intrusion at the higher state.∂ is the random variable defined as a constant.

Understanding computer systems is necessary to understand the multi-camera video system concept. The approach used is the foundation for the systems' functionality, making it easier for the system's end-user to use the equipment.

3.4-MOBILE EDGE COMPUTING IN IVS

Mobile edge computation is the approach by which the cloud computing concept is enlarged by mobile devices and executing data on the edge network through IVS. Such platforms allow for the creation of ad hoc mobile platforms.

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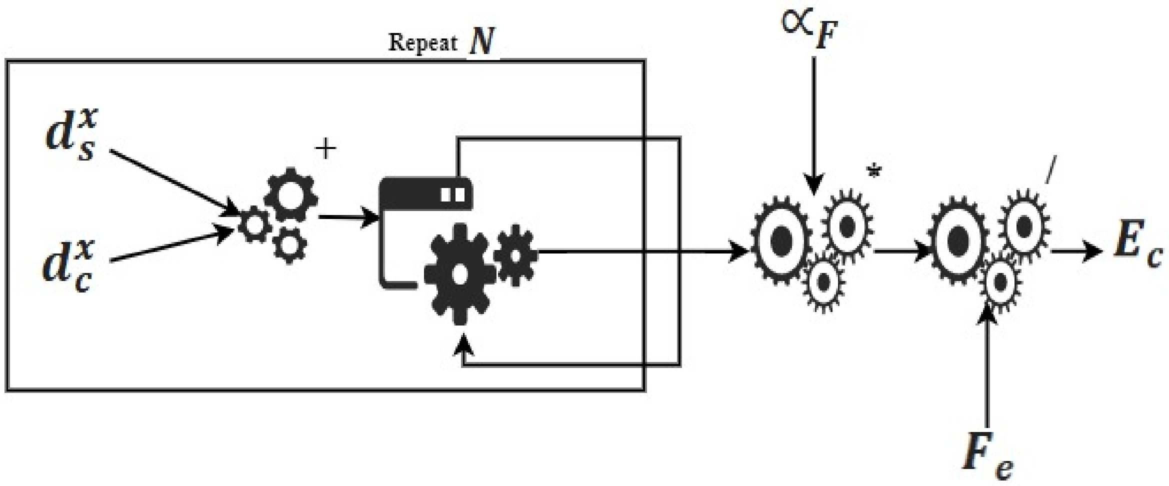

Figure 4: Representation of MEC process

$$E_c = \frac{1}{F_e}\left(\sum_{x=1}^{N} d_c^x + d_s^x\right) \times \propto_F \tag{10}$$

The scaling factor is denoted as $\propto_F$. E_c is represented pictorially in figure 4, as shown. When calculating E_c, the suggested system makes use of numerous parameters F_e, including the position of the source to the destination and the scaling factor $(d_c^x + d_s^x)$. Edge computing is a novel idea for utilizing the Internet to connect various heterogeneous devices. The architectural pattern requires an adaptive hierarchical model of IoT architecture. It facilitates an application activity by combining items like people and cloud storage with the summation of having limits $x = 1\ to\ N$ in the above-inclined equation (10). There is currently a centralized pay-as-you-go model for virtual computing data centers. Diverse needs, such as housing, computation, and communication, can be challenging to meet at the neighborhood level. It is possible to overcome these issues by constructing micro-cloud computing facilities closer to the consumer.

The smart display concept is innovative since it combines calculation with power conservation. Smart city elements must always have enough capacity and precise communication strategies to be able to adapt.

3.5- DRL Framework

A satisfaction criterion is optimized via deep reinforcement learning. Interacting with an environment through trial and error, on the other hand, yields a cumulative set of benefits over time. It is essential for the framework to reinforce the learning system to put this decision-maker, referred to as the agent, into action.

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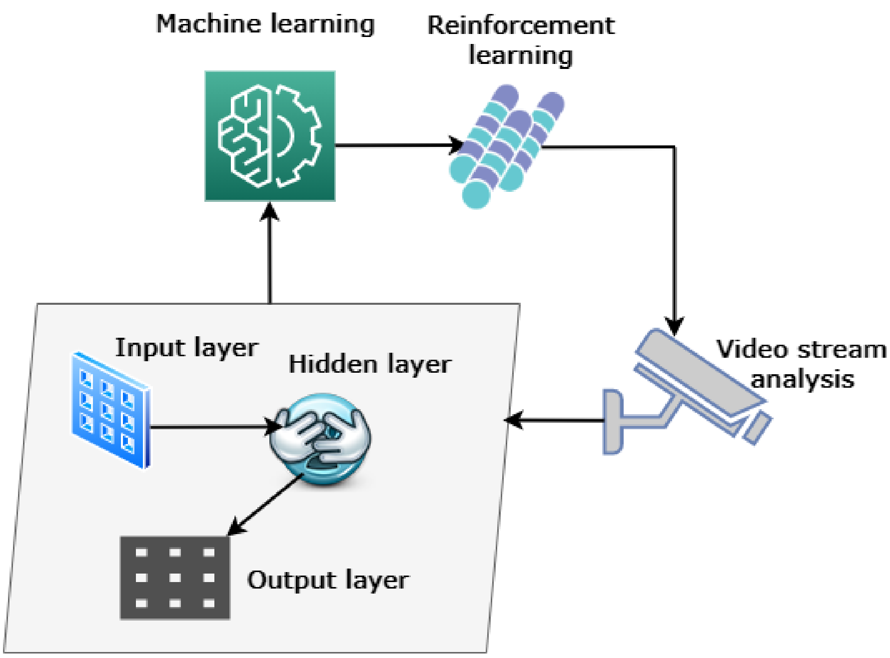

Figure 5: DRL framework

As a result of the current scenario, the representative can perform specific activities, as shown in figure 5. Next, the user will go over some of the mathematical underpinnings and reinforcement learning principles. For this problem, a machine learning algorithm instead of a table is employed to parameterize a representation of approximate value functions in DRL learning with functional form. Reinforcement learning can perform difficult tasks with minimal prior knowledge because their capacity to acquire various degrees of abstraction from data involves a three-layered process;

$$V_{add} = \sum CV_b \tag{11}$$

When transmitting volume C, collected data V_b, the additional energy V_{add} is calculated in equation (11). This involves video as the input layer, processing as a hidden layer, and processing the output layer.

$$V_b = V_s + \sum_{x=1}^{K} V_{add}(x) \tag{12}$$

Where V_b the communication device's energy consumption (C) is when a binary video bit is sent V_s. It may calculate the V_b quantity with summation $x = 1 \; to \; K$ as expressed in the above-stated equation (12).

$$V_{cn} = V_l + V_f + V_c \tag{13}$$

The total node video formatted is V_s, bit energy required to transmit is denoted V_b. The incremental energy V_l per distance is denoted V_{add}. When transferring data via the network, the information used by the servers during data streamingV_{cn} is downloading. The time spent by a storage device for accessing and storing in the edge of the surveillance process and the patterns used by the smart city devices rely on three variables. The overall formatted video required E_{cn} is then calculated as expressed in equation (13).

$$V_l = \sum_{x=1}^{M} (V_{re}^{x} + V_{wr}^{x}) \tag{14}$$

Here is the edge location V_l, storing device V_{wr}^{x} and the energy utilization V_{re}^{x} are denoted as V_l, V_f and V_c. Assume that unformatted video streaming is utilized to receive the edge of the wireless communication, then V_l is the overall power spent by the servers when sending and receiving data at the sender and receiver is, therefore, computed in equation (14).

Smart grid, manufacturing, smart procedures, and environmental monitoring are a few areas where DRL approaches have been used. The IVS network may store, process, and distribute this data to the IoT node.

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3.6-Optimization Of Offloading Decision

Offloading is a critical strategy for increasing the effectiveness of low-power devices by making better use of their resources. Smart devices use offloading to send part of their processing to a more powerful one. This state transition requires sufficient samples of value estimates and corresponding values to accumulate knowledge and use experience memory to make the training phase move more smoothly to see the following states.

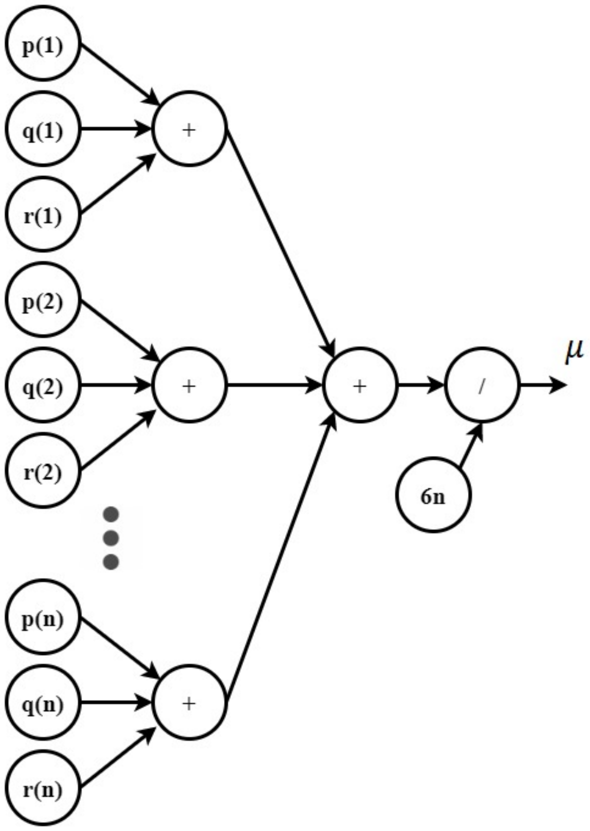

Figure 6: Pictorial representation of μ

$$\mu = \frac{1}{6n} \iint_{x=1}^{n} p(x) + q(x) + r(x) \tag{15}$$

To determine whether or not the Internet of things uses deep reinforcement learning is symbolized by the symbol and expressed as an equation (15). p(x), q(x) and r(x) all indicate that the estimated duration depends on the number of simulated items x elevation n, and circumference μ. The experiment has 6n objects, representing the wide range of possibilities being explored with the integration of limits $x = 1\ to\ n$. Developers can shift computationally heavy work to another processor or external platform using a hardware accelerator, clustering, road network, or cloud are given in figure 6.

Deep learning is a computationally hard and expensive machine learning type presented as an improved DRL for intelligent video surveillance. Action-value techniques design mobile edge computing algorithms for camera sensors to train the system's actions. EDRL-IVS, which improves reinforcement learning performance, is compared to other ways for improving security and communication performance.

4. Results and Discussions

When the DRL approach is suitable to tackle complex events, dynamic behaviors, and limitations, it is rapidly being employed in many power systems, such as security, economic dispatch, system optimization, etc., as research continues. Comparison of security analysis in Table 1.

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Table 1: Comparison of security analysis

NUMBER OF NODES	SECURITY ANALYSIS RATIO (%)	
	F-RAN	EDRL-IVS
10	39	97
20	37	96
30	35	94
40	31	92
50	29	89
60	26	87
70	24	85
80	23	83

Table 1 depicts the proposed EDRL-IVS system's security ratio analysis. The simulation is run with a step size of 10 nodes and several nodes ranging from 10 to 80. The proposed EDRL-IVS system's simulation results, such as a service hit ratio analysis, are examined. The results show significant differences when compared to the traditional F-RAN model. The results show that the suggested model outperforms the current model in both simulation results.

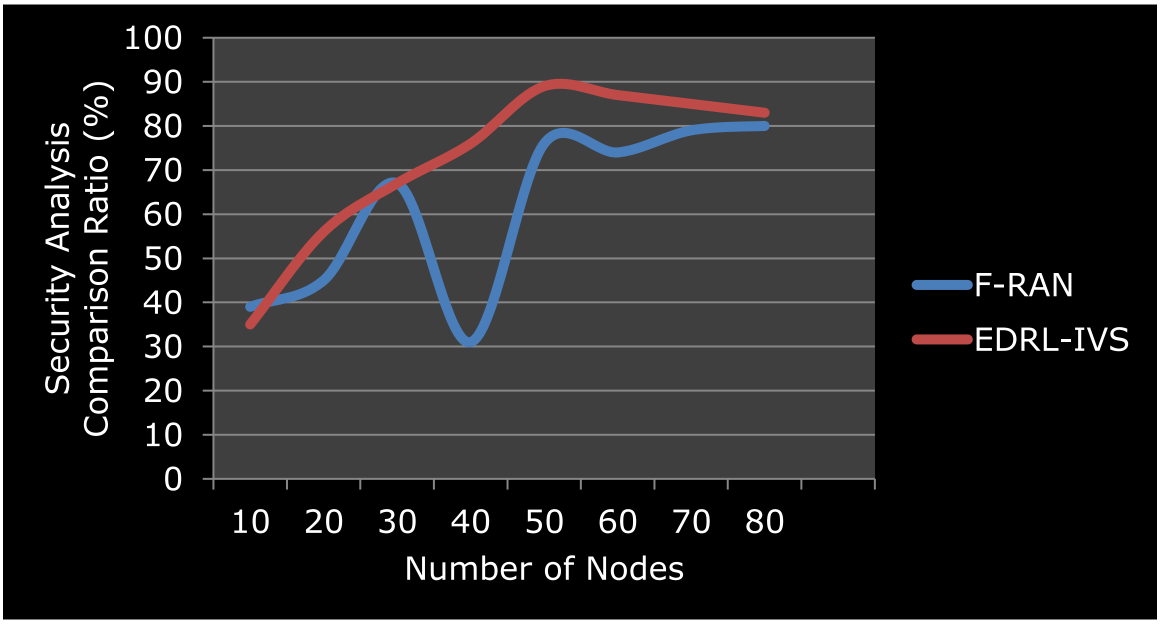

Figure 7: Analysis of security comparison

Video mobility analysis is a method for extracting data about objects in motion from recorded footage. Using a high-speed camera and computer software to perform motion analysis on video footage captured at high speeds is common. These are compared and analyzed with the conventional method F-RAN in figure 7 above. The performance of EDRL-IVS is higher than the existing method. Performance comparison OF EDRL-IVS in Table2.

Table 2: Performance comparison OF EDRL-IVS

NUMBER OF NODES	PERFORMANCE ANALYSIS RATIO (%)	
	RSSWN	SD-EDC
10	28	46
20	31	51
30	35	57
40	37	60

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50	39	64
60	42	69
70	46	71
80	49	75

Simulated results of the proposed EDRL-IVS system are shown in table 2. Simulation nodes range from 10 to 80, and results like the number of nodes detected and the performance ratio are scrutinized. There is a comparison between the proposed EDRL-IVS system's simulation results and the current model. The outcome is shown in the above table. According to the findings, the suggested EDRL-IVS system is more effective than the existing RSSWN model under all circumstances.

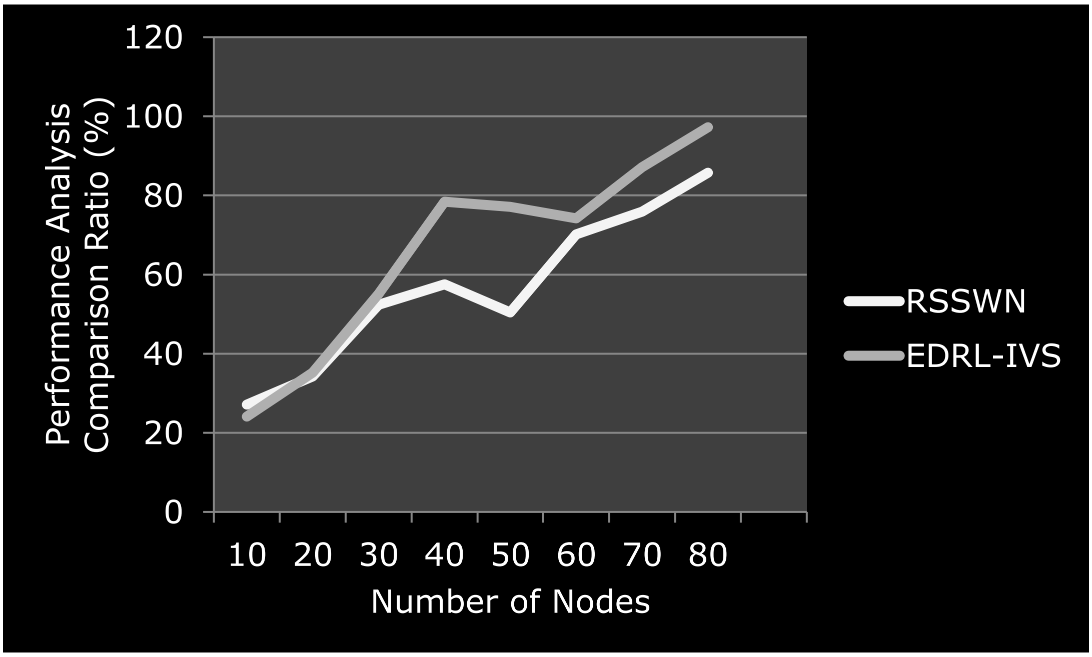

Figure 8: Performance comparison of EDRL-IVS

Performance Analysis is a highly specialized field that uses systematic observations and visual feedback to provide objective statistical data to improve performance and decision-making. RSSWN is compared with the proposed method, EDRL-IVS, which outperforms the old performance in figure 8.

4.1- Accuracy Analysis of IVS With Existing Methods

Table 3 shows a comparison of EDRL-IVS vs. traditional methods, with the latter yielding superior outcomes. The three methodologies discussed above allow us to calculate the average task delay based on the number of IoTs, computing quantity, data volume, and processing capacity of the DRL server.

Table 3: Accuracy Comparison Of EDRL-IVS

NUMBER OF NODES	F-RAN	RSSWN	DRL-ML	MEC-VSS	DDPG	EDRL-IVS
10	21.21	24.54	18.76	28.76	27.13	24.10
20	12.65	45.36	73.56	32.45	34.25	35.23
30	26.33	53.66	48.23	46.76	52.39	55.13
40	18.98	35.97	53.26	30.12	57.54	78.43
50	36.78	61.78	31.03	51.34	50.43	77.11
60	31.87	49.74	45.69	67.87	70.17	74.20
70	56.21	71.23	77.89	50.65	75.89	87.15
80	49.21	31.43	69.31	70.12	85.74	97.24

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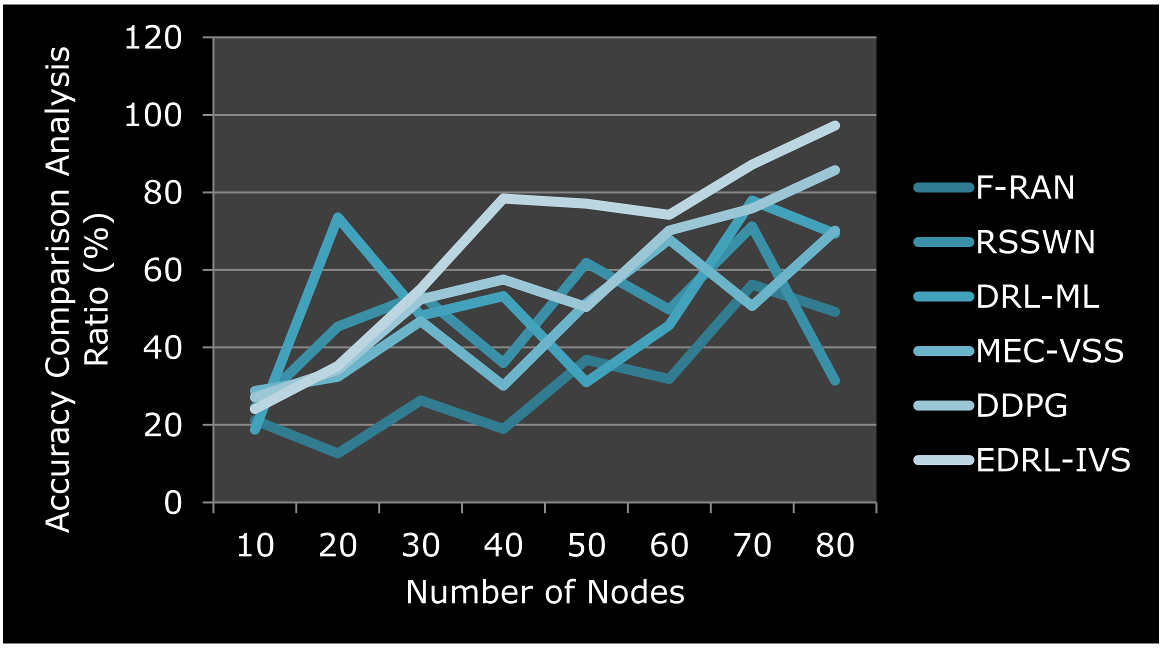

Figure 9: Accuracy comparison of EDRL-IVS with other methods

Figure 9 shows that industry and science are interested in the Internet of Things to improve production efficiency and provide better resource management information for video surveillance. EDRL-IVS is experiencing a spectrum constraint for digital devices due to the rapid proliferation of end devices and information flows.

However, there is a small performance disparity between DRL and the suggested method and the computer-generated random method or intelligent video surveillance methodology with the best probability. Our proposed method, EDRL-IVS with state information, reward function, and action vector design, were used to create the mobile edge computing process in this research instead of the method provided by IoT.

5- Conclusion

The study presented a IoT service-learning technique that utilizes deep reinforcement learning for intelligent video surveillance. This approach involves labeling a limited number of data points while leaving the rest unlabeled, and using the EDRL-IVS model to determine the optimal behavior regulations. The proposed deep reinforcement learning model is compared to a conventional supervised model and found to be better at generalizing positioning policies for environments with a mix of labeled and unlabeled data. This study demonstrates the potential of using deep reinforcement learning for fusion optimization in intelligent systems for information fusion, including fusion in robotics and decision-making. Additionally, this technique could be applied in multimedia data fusion applications and E-Systems data fusion. Future research could explore the potential of fuzzy approaches and optimization algorithms for data fusion applications utilizing deep learning models. In general, several cameras can be used to keep an eye on strange activity; this can record instances of people entering and leaving the place, while cameras can catch unsupervised situations at abnormal situations. When suspicious behavior is detected, the camera operator must be notified to take action. All monitoring operations will be automated in the future, thanks to effective deep learning. As an added benefit, using a mathematical tool increases learning efficiency by 97.24% and yields better results than DL. The functionality will be used to further improve DRL performance in the future.

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