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REAL-TIME VIOLENCE DETECTION USING DEEP REINFORCEMENT LEARNING

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Abstract – Violence is on the rise these days, and in this research, violence that takes place in public spaces is referred to as trembling violence. A real-time violence detection model is needed to monitor people's behavior and take appropriate action when abnormal activities occur in order to prevent these abnormal actions. This work introduces a real-time violence detection system that uses a human intelligence simulation to identify violence in the vast volume of streaming data. The Apache Spark method is used to analyze a vast amount of real-time video feeds from several sources that make up the big data. This approach divides the frames and uses the histogram-of-oriented gradient (HOG) algorithm to get each frame's attributes. Then, based on their characteristics, each frame is categorized as either violent or non-violent. In terms of deep reinforcement learning (DRL), this categorization is carried out using a double dueling deep Q-learning network (**D3Q net**). When compared to the current deep neural networks, the suggested architecture achieves the best and most accurate results. For real-time violence detection, this model has a classification accuracy rate of 95.08%.

Keywords: *Big data, Apache spark framework, Histogram of Oriented Gradients (HOG), Deep Reinforcement Learning (DRL), Double Dueling Deep Q-learning network (D³Q net)*

1. INTRODUCTION

In the contemporary world, surveillance is a fundamental need for people's safety and property protection. Computer vision experts find it difficult to analyze the vast amounts of video or visual data that this monitoring system regularly produces [1]. Since anomalous actions are rare and have a reduced likelihood in real-world surveillance, it is challenging to manually search these massive video streams for them. Computer vision specialists are interested in anomaly detection, such as fighting, grabbing, and robbery, because of its daily surveillance applications. A deep learning method that can effectively classify normal and abnormal behaviors without the need for human interaction is used to identify these anomalous actions [3,5]. In addition to being essential for inspection, such an automated system reduces the amount of human labor required to maintain round-the-clock monitoring. analyzing the constantly generated data streams in real-time to get quick insights [12]. Big data is used because of the technology's exceptional computational power, which allows it to analyze stream data more quickly and handle enormous volumes of data. Complex and effective data stream processing systems have been made possible by big data frameworks like Apache Spark. It integrates with several components, including Spark Core, streaming, MLlib, SQL, and GraphX [15], and it is shown

in fig.1.

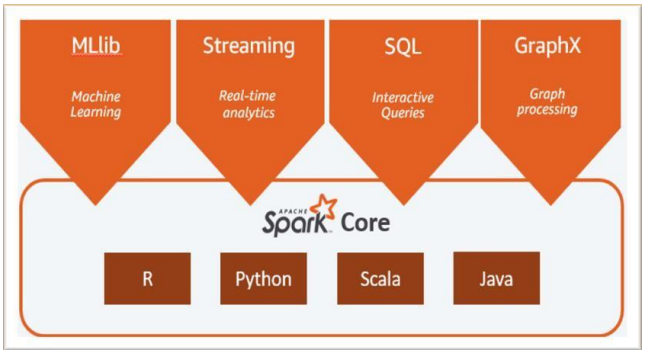


Figure 1. Apache Spark ecosystem

The concept of deep learning uses a vast amount of data to dynamically recognize trends and extract features from complicated unstructured data without any human interaction, making it a useful resource for big data analysis. Big data analytics helps to analyses and interpret the data by identifying trends and patterns. Machine learning can expedite this process with the assist of decision-making techniques. It can classify input data, discover trends, and convert the information into useful business insights. Reinforcement learning (RL) is the subject area of machine learning (ML) that examines how intelligent agents should respond in each environment to optimize the concept of rewards [18]. RL is continuously learning through a trial-and-error process to achieve optimum results, while deep reinforcement learning (DRL) is learning from old dataset and adapting it to a new dataset. The DRL [22] is a technique to help machines learn from their actions like the way humans learn from experience. This technique can be used to solve the issue of interpreting data streams for real-time prediction in surveillance networks.

The remaining portions of this work were divided into the following five sections. The existing works are summarized in Section 2, and the Section 3 includes the proposed model using big

data framework namely Apache spark and deep reinforcement learning (DRL) with the Double dueling deep Q-learning neural network (D^{3}Q net), Section 4 includes with outcomes and discussion and Section 5 encloses with conclusion.

2. RELATED WORK

In recent days several deep learning techniques were introduced by the researchers mainly to enhance the accuracy of detecting the real-time violence. In 2021 W.Ullah., *et al.,* [1] had designed a bidirectional LSTM network to detect the real time anomaly in the surveillance network. It provides smart anomaly detection based on deep features that can execute in surveillance networks with less computation time. In this system the spatiotemporal features are extracting from a series of frames by CNN, and it was passed to BD-LSTM to classify normal and anomalous events.

In 2020 Pujol., *et al.,* [3] had designed a soft computing approach for detecting the abnormal activities in the smart cities. This model proposes the establishment of a technique for identifying violent in videos by integrating multiple features that calculate the momentum caused within two video sequences with radon transform or optical flow and SVM. This model yields the accuracy rate between 85% and 97% based on the complexity of the datasets, since it is not applicable in real-time videos.

In 2019 F.Ullah., *et al.,* [3] had established a framework to detect the violence by using the surveillance camera in the smart cities. In this method, a three-staged end-to-end DL violence identification method is proposed. The individuals are first spotted in the video streams of the surveillance camera using light weighted CNN and this frame sequences were forwarded to 3D CNN, which extracts the spatial temporal properties of the progressions and feeds them to the softmax classifier and optimized.

In 2018 Shayan., *et al.,* [4] had designed a deep learning technique along with big data for enhancing public safety and liveability in cities. The proposed method mainly focused on distributed cyber infrastructure for smart cities. The cars that involved in an illegal activity it was difficult to track the crime sequence from the video streams. This issue was overcome by this method with deep reinforcement learning to recognize the cars and categorize them into the accurate data of vehicle and also identified the suspicious behaviour and crime action from the video streaming.

In 2019 Ji Li., *et al.,*[5] had developed a deep learning model to detect the real-time violence on basis of 3D CNN without using hand-crafted and temporal information. The proposed model has number of parameters and can acquire the spatiotemporal aspects of violence effectively. It saves computational resources, and very efficient to analyse the data in real time, although it requires numerous read-write storage operations.

In 2020 A.Jain., *et al.,* [6] had introduced a technique with deep learning method for detection of violence by extracting the motion features from the dynamic image. The datasets were publicly available from movies, hockey stadium and real time violence were gathered. The prediction was performed by tuning the Inception-Resnet-V2 model using the violent content stream of RGB-DI and it achieves better accuracy in the detection of violence and non-violence activities.

In 2021 Demertzis.K., *et al.,* [7] had developed a Darknet system to traffic monitoring and network management system based on weight agnostic neural networks (WANN) to automate the harmful intents identification in real time. It is a precise and efficient computational intelligent analytics tool for traffic analysis, and real-time encrypted traffic identification. This method lowers the abilities and effort barriers that protect many firms from preserving their most valuable assets.

In 2020 Rohit and Rajdeep [8] had introduced a lightweight computational model for classifying violent and non-violent activities. This model was based on deep learning techniques collaborated with CNN and BiLSTM for detecting violence in the real time surveillance. It was extensively utilized in hockey fights, movies and violent flow video datasets while preserving the accuracy range of 99.27%, 100% and 98.64% for classification. However, the detection of many violent activities including weapons was difficult.

In 2019 Marius., *et al.,* [9] had established an efficient deep learning approach for automatic real time identification intended for video sensor networks. It attains real-time processing on a Raspberry PI-embedded model along with time domain classifier and the input feature vectors are extracting from MPEG encoded video streams. This model yields high accuracy with comparatively low computational cost, but it never detects the weapons used for violence and terrorist attacks.

In 2019 Sumon., *et al.,* [10] had presented a AI to detecting the violence and non-violence in the crowd. This model is lightweight model that deployed easily in security cameras such as CCTV cameras and UAVs. It is integrated with CNN and LSTM have been tuned based on the violence scenes in movies and acquires the accuracy rate of 95.67%. However, this model not performed well in this particular dataset.

From this study, the researchers work on different AI methods in supervised and unsupervised learning for learning the multilevel representation of features for identifying and classifying the objects. In the proposed system, deep reinforcement learning (DRL) along with big data is used to detect the real-time violence in surveillance networks while preserving the high accuracy with low computational cost.

3. PROPOSED MODELLING

3.1. Big Data analysis using Apache Spark

The big data frameworks are used to store and analyses huge amount of data generated by different sources in a dependable and effectual method. It is an open-source framework and fastest tool for big data processing used to achieve high speed and easy to use in sophisticated analyzing in processing the large dataset. The Apache spark framework is used for analyzing the input as massive amount of video feeds from various sources. The videos from several camera sources are sent as an input into the spark framework. These video streams are modified into non-overlapped sequences (i.e., images) from the videos. This module receives the streaming video block as an input patch streams, and these patches are fed to HOG function for extracting the features. The stream patches may be executed rapidly and efficiently. It is used to perform advanced analysis processing in massive data at a high speed and with ease. It initiates stream processing is scalable, high capacity, and highly reliable.

3.2. Feature extraction using HOG

The feature extraction is a vital role in extracting the spatiotemporal features from the input frames are done in histogram of oriented gradients (HOG). In the spark system, the frame is divided, and the characteristics of each video frames are retrieved through HOG. It is mostly utilized in proposed technique for object detection. To recognize video streams with high accuracy, features are taken from the peers of the identified point of interest using HOG. The video frames are fed into the shift register frame by frame. After processing the image patches, it is transformed into 8x8 pixels cells and gradient oriented is generated for every cell.

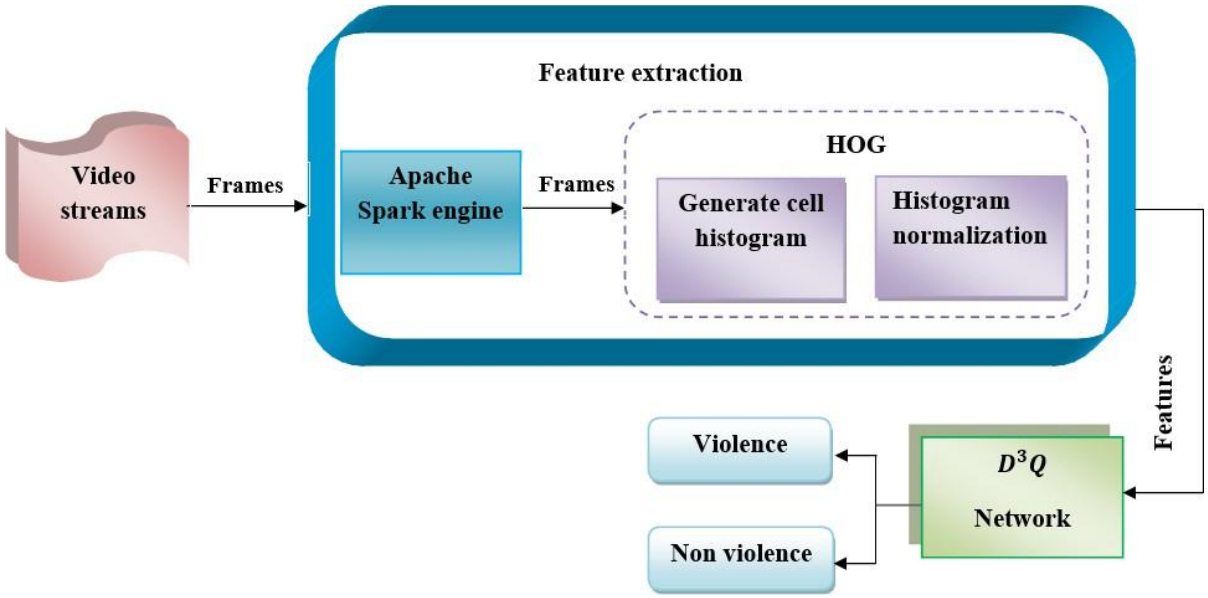


Figure 2. Schematic representation of proposed methodology

Then the input frames are received by the gradient calculator for determining gradient magnitude and direction. Histograms are created utilising the magnitude and direction of gradients that have been computed, as well as the total of gradient magnitude for each cell. Finally, the histograms are then standardised by using neighbouring pixels and extracting the pixels from the image patches. These image patches are labelled as violence and non-violence approaches based on the actions. It employs a technique known as Bit-Map HOG, which locates uneven object shape and speeds up the method.

3.3. Double dueling deep Q-learning neural network (D³Q net)

The DRL is a technique to help machines learn from their actions like the way humans learn from experience. This technique can be used to solve the issue of interpreting data streams for real-time prediction in surveillance networks. In DRL, this network has some key concepts that include agent, action (ac), reward (re), state (st), punishment, policy, a environmental model and DNN implementation. The agent is a self-evolved neural networks model that takes observations as input and produces the output. The state that includes important observations and the actions refers to the navigation decision made by the agent.

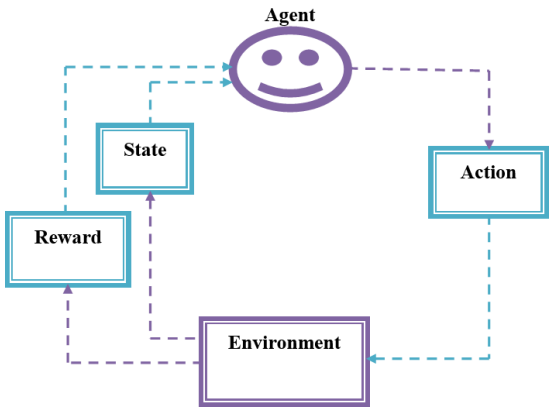


Figure 3. Framework of Deep reinforcement learning

Since the neural network is combined with Q-learning algorithm and reinforcement learning named as deep Q-learning network (DQN). This network takes the input as pre-processed video streams near to the present instance. The inputs are converted non-linear data using convolution layer and fully-connected layer, yielding a Qvalue for every action in the resultant layers. To mitigate the instability issue DQN employs the experience replay mechanism to deal with the acquired transfer data instantly and it generates the targeted Q value using a different network. DQN minimises the rewards and error values to a narrow time period, which assure that the Q-values and the gradient values are within a proper range, which increases the steadiness of the method. This model includes the deep dual Q-network, the deep Q-network based on supervised learning, the deep Q-network based on prioritized samples, and the deep Q-network. The double duelling deep Q-learning network (D³Q net) is used to minimize overestimation by breaking down the maximum target operation into action selection and action evaluation and decouples the selection and evaluation of actions and the architecture is shown in fig.4.

S is a set of states and $st_t \epsilon S$ denotes the agent's position; A is a set of agent implementation operations and $ac_t \epsilon A$ denotes the action taken by the agent at the time period t. The reward function is denoted by $\rho: S * A \rightarrow R$ and $r_t \sim \rho(st_t, ac_t)$ denotes the agent's instant rewards at the state s_t while performing an action ac_t. The probability distribution function for the state transitions id denoted by $f: S * A * S \rightarrow [0,1]$ and $st_{i+1} \sim f(st_t, ac_t)$ refers to the likelihood of an agent changes states from s_t to s_{t+1} while performing an action a_t. In DRL strategy $\pi: S * A$ is a map, that the agent chooses action ac_t in the state st_t, perform the action, and transform to the next state $st_{t+1}$with the prospect $f(st_t, ac_t)$ while receiving reward $re_t$from the response of the environment. Suppose that the instant rewards for every future instance must be increased by multiplying the discount factor x at time t to end time t' and the sum of the rewards is defined as,

$$R = \sum_{i=t}^{t'} \gamma^{i-t} re_i \quad (1)$$

Where $\gamma\epsilon[0,1]$ is employed to calculate the effect of future reward on the total rewards. The state action value is $Q^{\pi}(st, ac)$ denotes the action ac in the present state st and competes on the basis to the end point, where the total yield is calculated by the agent is defined as,

$$Q^{\pi}(st, ac) = EN[R_t|st_t = st, ac_t = ac, \pi] \quad (2)$$

If the expected return of all the other approaches is larger than π^*, for all state action pairings, the approach is termed the optimal strategyπ^*. Although there may be several best strategies, they all have the same state action value function and it is deriving as,

$$Q^{\pi}(st, ac) = max_{\pi}EN[R_t|st_t = st, ac_t = ac, \pi] \quad (3)$$

It is known as optimum state action value function and the optimum state motion value function is derived by using Bellman optimum equation are as follow,

$$Q^{\pi}(st, ac) = EN_{st':st}[re + \gamma max_{ac'}Q(st', ac')|st, ac] \quad (4)$$

The MSE of the gathered Q-values of the network to the targeted Q-values as the loss rate. The mini-batch gradient is utilized to separate the information into smaller patches and calculate the error by updating the coefficients. The loss function is derived as,

$$LF = \frac{1}{2n}\sum[Q^*(st, ac) - Q(st, ac)]^2 \quad (5)$$

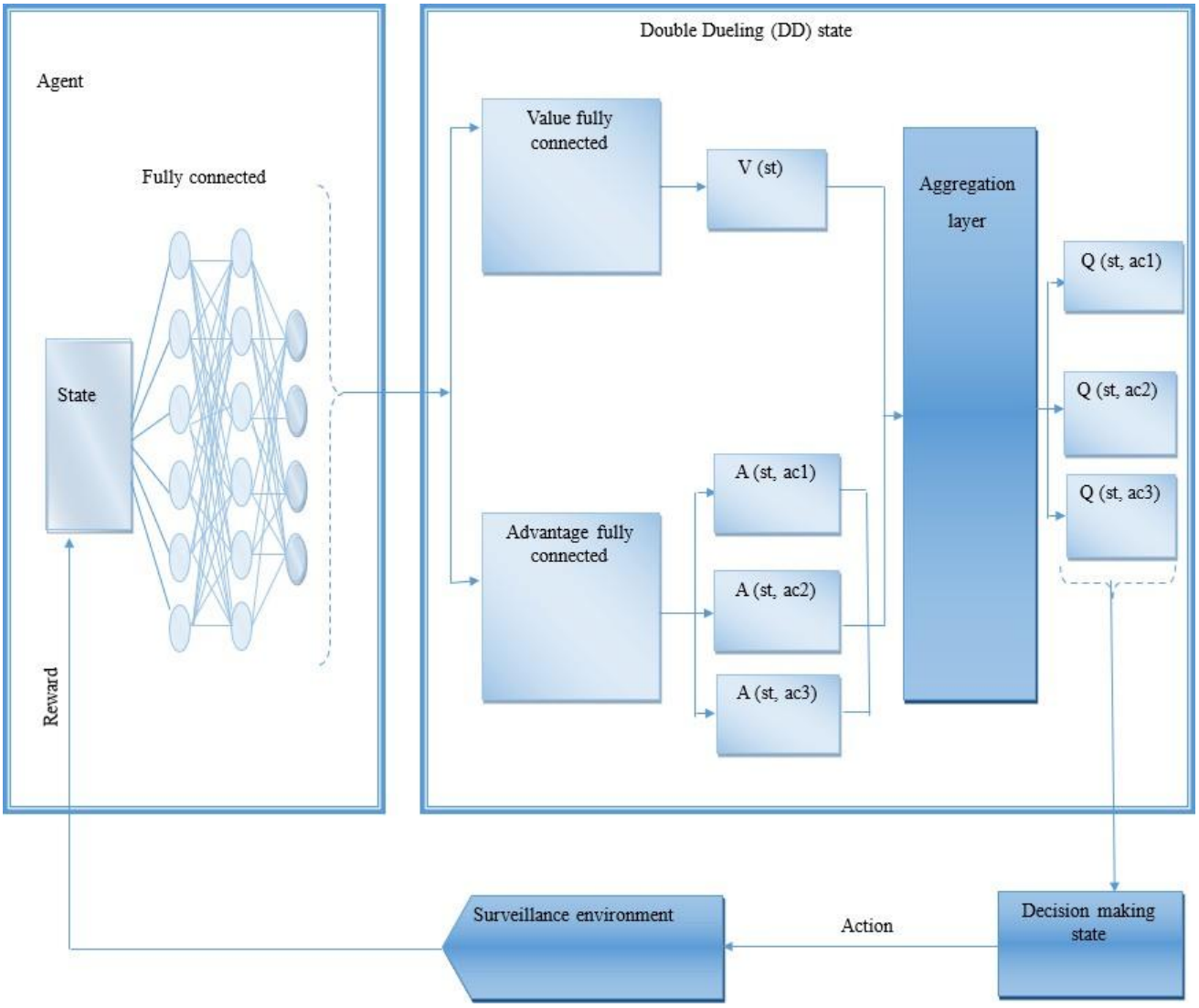


Figure 4. The architecture of Double dueling deep Q-learning neural network

In classical reinforcement learning, the recursive Bellman equation is used to obtain the Q-value function and it is defined as,

$$Q_{i+1}(st, ac) = EN_{st':st}[re + \gamma max_{ac'}Q_i(st', ac')|st, ac] \quad (6)$$

where $\rightarrow \infty, \pi^*$; by the continuous iteration of the state action value function will gradually converges, and the best approach will emerge as (7) is obtained.

because the approach of an iterative Bellman equation is too intensive for calculating the Q-value in the large state space. To handle this, a linear function estimator is typically utilised in the RL algorithm to estimate the state action value function.

$$Q(st, ac|\theta) \approx Q^*(st, ac) \quad (9)$$

In addition, deep neural networks and other nonlinear function

$$\pi^* = argmax_{ac \in A} Q^*(st, ac) \quad (7)$$

The target value is derived as,

$$Q^*(st, ac) = R' + \gamma max_{ac+1} - Q(st', ac') \quad (8)$$

However, determining the optimal strategy by iterative updating equation (6) is not clearly viable for practical issues, estimator can be utilised to approximate the value function or strategy. This model achieves robustness and high accuracy while preserving stability by avoiding over fitting of video streams in surveillance for real time violence detection.

Algorithm.1: Deep Q-learning algorithm

initialize replay memory M to capacity n; action-value function Q with θ;
and target-value function $\hat{Q}$ with $\theta^{-} = \theta$
for episode=1, X do
repeat
observe state s
with probability ∈ select ac random action ac_t
otherwise select $ac_t = argmax_{ac}\, Q\,(st, ac, \theta)$
execute action ac; observe reward re and next state st'
store transition (st, ac, re, st') in M
sample random minibatch of transitions from M
if st'_i is terminal then
$x_i \leftarrow re_i$
else
$x_i \leftarrow re_i + \gamma max_{ac}\, Q(st'_i, ac', \theta)$
end
if episode > 10 then
perform ac gradient descent step on $(x_i - Q(st_i, ac_i, \theta))^2$ with
respect to the network parameters θ
end
until simulation is terminal
every X steps reset $\hat{Q} \leftarrow Q$
end

4. RESULTS AND DISCUSSIONS

In this section, the proposed model is experimentally assessed with various data and compared with other existing model for anomaly detection.

Here the videos from the surveillance cameras mainly in public places are used to classify the violence and non-violence incidents. The gathered videos are processed as images to tune the network and based on this learning the network that classifies the violent scenes from the non-violent scenarios and that different scenarios are depicted in fig.5.

The above figure illustrates the video images captured by the CCTV camera, in which the green bordered images indicates that there is no violence and the red bordered images indicates the violence. Figure (a) and (b) shows that there is no violence in the behaviour of the people, (c) and (d) shows that there is fighting sequence between the youngsters, then (e) and (f) represents the chain snatching scenario in the public place and finally (g) and (h) shows the accident a crime sequence that captured in the traffic signal camera.

4.1. Performance analysis

In this work the efficiency assessment is calculated in terms of accuracy, specificity, and sensitivity. The sensitivity is used to evaluate the accurate results by grouping the sample data identified as true positives in the videos and it is estimated as,



Figure 5. Sample images of violence and non-violence scenarios captured in surveillance camera

$$Sen = \frac{T_p}{T_p + F_n} \quad (10)$$

$$Sp = \frac{T_n}{T_n + F_p} \quad (11)$$

The accuracy is the measure of representations of true positives

Table 1. Performance evaluation of D³Q net

Class	Sensitivity	Specificity	Accuracy
Violence	95.4	93.1	94.6
Non violence	92.3	95.4	93.4

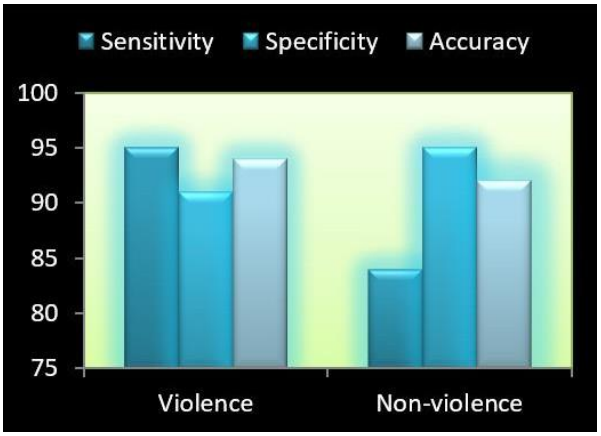


Figure 6. Performance evaluation of D³Q net

The performance analysis shows that the proposed

model achieves high accuracy rate, in violence detection it achieves 94.6% as and in non-violence detection it achieves 93.4%. The overall accuracy rate gained by the proposed

model is 95.08%. For example, the model detects figure (c) as non-violence and its graphical representation is depicted in fig.7, then the figure (d) is detected as violence scenario and its representation is depicted in fig.8.

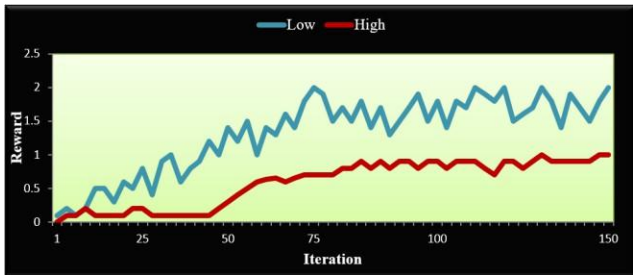


Figure 7. Graphical representation of figure(c) considered as non-violence

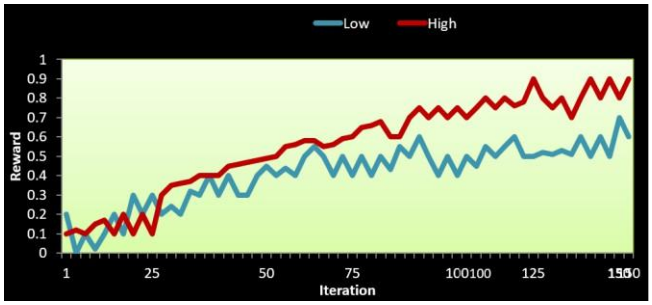


Figure 8. Graphical representation of figure(c) considered as violence

4.2. Comparative analysis

The efficiency of each network was assessed to display that the outcome of the proposed method is more effectual. the mini-batch gradient descent strikes a balance among stochastic gradients robustness and batch gradient efficiency. The model PROGRESS rate is greater than batch gradient descent, allowing for even more stable descent and the avoidance of local minima with the consequence of an additional features or parameters. The comparison is performed between the proposed model, 3D CNN [5], CNN-BDLSTM [1] and CNN-BiLSTM [8].

Table 2. Comparative analysis of three existing model with the proposed model

Models	Movies Violence	Movies Non-violence	Real-time Violence	Real-time Non-violence
CNN-BDLSTM [1]	95.3	93.5	82.7	87.6
3D CNN [5]	96.2	96.4	94.5	92.4
CNN-BiLSTM [8]	98.3	96.3	91.2	89.3
Proposed method	98.5	97.2	94.6	93.4

From the above evaluation that the existing model is achieved in terms of the videos streams of hockey fights [5, 8] and crime datasets [1] with training and obtain the proper rate of accuracy in classification. The comparative efficiency of each technique is demonstrated in table.2 and graphical comparison is portrayed in figure.9 and 10, classifies based on violence and non-violence scenarios. However, the existing models not perform well in real data from the surveillance cameras. The proposed model outperforms in this site and acquires higher accuracy in the real-time datasets since it works on the reinforcement learning i.e., without any human intermission.

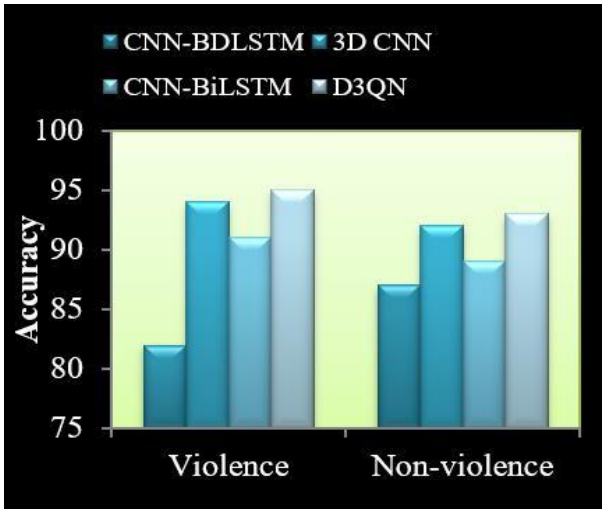


Figure 9. Accuracy acquired by different models with movie datasets

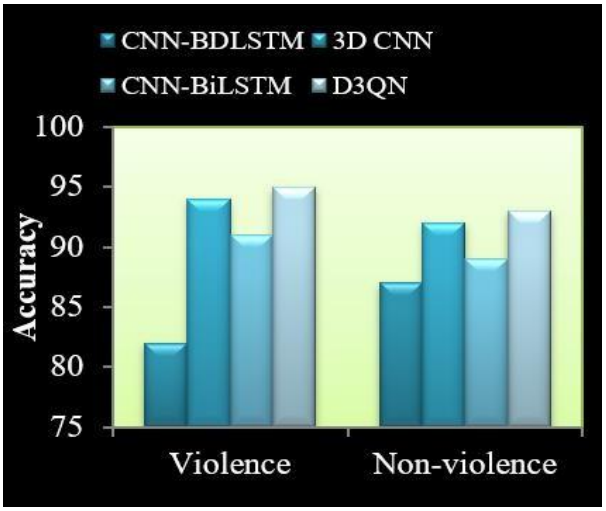


Figure 10. Accuracy acquired by different models with real-time datasets

There are certain limitations in the proposed system, the difficulty in big data analysis is the divergent composition and the input gathered from multiple perspectives is in different formations such as structured, unstructured, and semi-structured datasets. The gathered data from the surveillance network is almost colorless i.e., black and white. Since the colored images have gathered and processed in future work for acquiring higher accuracy.

5. CONCLUSION

In recent years big data and deep learning are two methodologies continuously improving for handling real-time problems. Several video-based surveillance system automation methods have sufficient prior training data for detecting violence activity. To address this flaw, the current study proposes a technique to find the risk rating at a given moment using instant training data, which combines the context model with continuous mode using DRL. In the proposed system instead of pre-training data, it includes dynamically learning in human-to-human interactions and human moving manner. Another intriguing feature is that it finds a solution to the present incident while training itself. The accuracy can be improved and the limitations or challenges are

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