A Review of Violence and Riot Detection Techniques

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Abstract

The world is changing every now and then at the speed of human thoughts arises in the mind. These thoughts can be shared on Internet and social media platforms and it may connect other people to the same thought. Whether it is the Internet world or Physical world, Security is vital and needs to be addressed carefully. In the Physical world CCTV Surveillance is an important way of security. It captures real time footage of the area that is under threat, whenever there is any unwanted activity under that area then that footage needs to be analyzed for detecting unwanted activities. Nowadays CCTV cameras are a prime source of securing any area that is under threat, so there is an increase in the number of Surveillance cameras so the size of recording also increases manifold. Now the challenge is how this Surveillance footage will be analyzed for timely action.

Detecting unwanted activities in video and images with the help of some automated system is the need of today's challenges of security. Machine Learning or Deep Learning may help us in detecting these unwanted activities in video and images in real time for sending timely notification and taking action against these activities. Action recognition is a broader aspect of violence detection that needs great effort and data. However my work is limited only to recognize violence activities like fighting, rioting, stone pelting and violence done by a group of people or a riot-like situation.

My whole motivation towards this work is because of 23 Feb 2020 Delhi Riots. These riots compelled me to find some technical solution to prevent and detect these riots. The intention of this research work is to study different methods and models to predict violence like behavior using Machine Learning or Deep Learning in video and images. This Paper discusses deep learning methods like Support vector machine (SVM), Convolution neural network (CNN) and recurrent neural network (RNN) to detect violence activities. Additionally, the video features and datasets that are used in the algorithms and are crucial to the recognition process are also covered. For better comprehension, the research methodologies' steps have been outlined here. The overall research results that may be useful for identifying prospective future work in this research field have been discussed.

Index Terms

Violence identification, support vector machine, deep learning, surveillance camera, computer vision, Riot, Fire, Stone Pelting, Crime, Neural Network, Convolution neural network, Recurrent neural network, Surveillance System, CCTV monitoring, Activity detection, Random Forest.

I. Introduction

CCTV Surveillance is a common way of security for any place that is under threat. It is very difficult to monitor them by human beings to detect anomalies or unwanted activities 24/7. With Increase in surveillance cameras, this challenge is increasing day by day. With human involvement there is a possibility of manipulation and we may also gain human error and also the need of a particular trained human-being in the first place. Public places like College, School, Restaurant and Roads are most vulnerable from a safety point of view. Normally these places are secured with surveillance cameras but how to detect anomalies and unwanted behavior from these surveillance videos is a challenge that motivates me to find some automated system that could analyze the video for any violence like activity.

Violence detection from surveillance video is a part of Activity recognition i.e. used for detecting activities like dancing, painting, singing and many more. Here I am restricting my Research Work to detect only disruptive or Violence activities.

The primary goal of this paper is to give a comprehensive systematic literature review of the methods of violence and Riot detection. In the last decade, different methods of violence and turmoil activity detection have been proposed. It is crucial to categorize and summarize the proposed methods. To conduct an in-depth research study, we select the base paper that is most relevant and appropriate with this area of Research. For making this research qualitative and significant we cover the past 10 years i.e. from 2012 to July-2022 Research Papers published in various resources like IEEE XPLORE, ACM and SCI HUB. Every Reference of this Research paper is explored and further second level references are also explored and continuing this with every reference only 40 papers that are most related with this area of research are selected for the purpose of this study.

Recently researchers have been attracted towards violence detection research area, as there is a similarity between action recognition and violence action recognition. Action can be categorized as normal and abnormal. Abnormal activities may include fighting, beating etc.
The Objective of this Survey is to contribute the Following.

- Classification of the existing models into diverse categories for better discussion.
- Critical review of each model in chronological order
- Sharing its novelty, main features and limitations.
- Exploration and ranking and significance of the video
- Features for violence detection.
- Discussion of the real-world datasets which are widely used.

II. Basic Concepts

We have listed some fundamental ideas in Table 1 in relation to violence, riots, computer vision, video features, and the recognition of activities using vision. Their brief descriptions are provided in Table. The variety of applications involving the analysis of pictures and videos attracted a lot of researchers to the field of computer vision. Analysis of images and videos includes the detection of objects and recognition of the activity that is performed by the object. The entire process of activity recognition begins with the capture of photos or the production of videos. Figure 1 depicts the fundamental architecture. Researchers have put out many approaches that exploit these traits in accordance with their own methodologies.

Table 1: Basic Concepts

Sl. No.	Feature	Description
1	Computer Vision	Computer vision make us able to derive relative information from digital images, videos and other visual inputs
2	Centroid	All point average position of an object shape or space dimension of an object is called the centroid [26].
3	Direction	Any object lies along a line from the point where the object is directed.
4	Dimension	Property of a space which measures in length, width and object thickness toward a given direction.
5	Acceleration of Images	Change of velocity or speed over the time unit [26].
6	Spatiotemporal	The feature related to time and space of objects.
7	Violence	Activities that are violent in nature like fighting, rioting, beating etc. are called Violence
8	Riot	A violent disturbance of the peace by a crowd.
9	Movement	An Action in which objects change their position in videos [26].

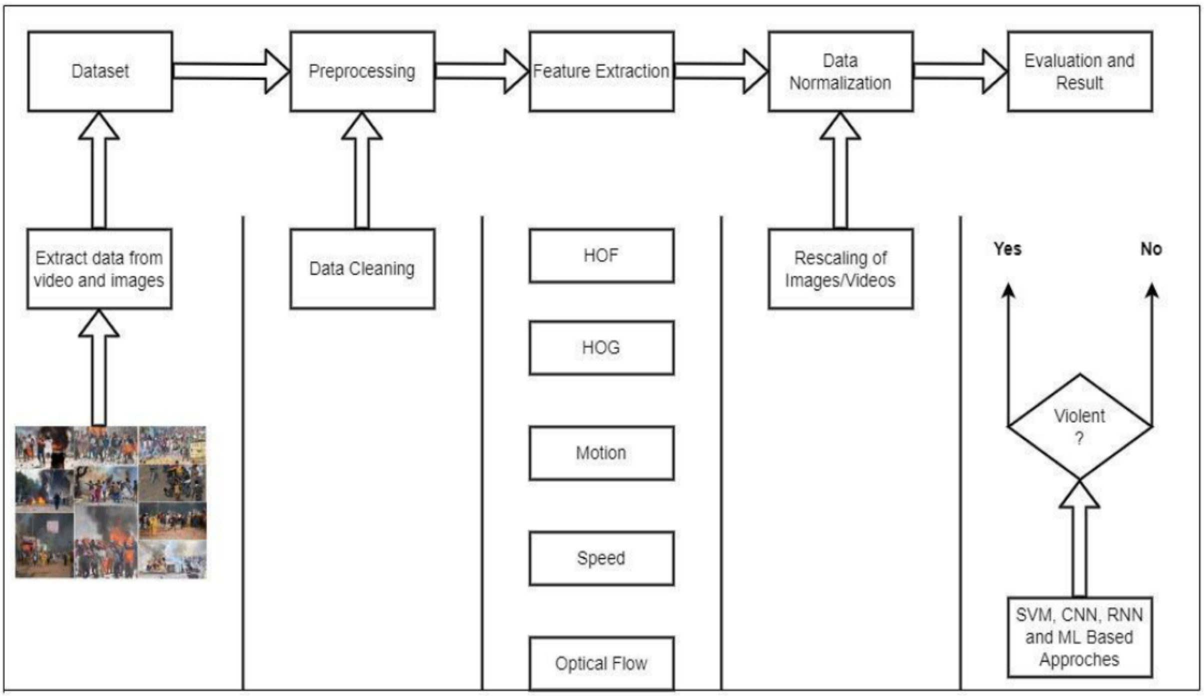

Figure 1: Typical Architecture of Violence Detection System

III. Research Methodology

The Purpose of this Review is to collect different methods and models to detect Violence and Riot activity in Video Surveillance using Computer Vision. In this area we analyze the available research with the help of systematic Research. Firstly a Base Paper is identified and selected then after its references were evaluated.

For finding the Base Paper and References use different digital databases, Science libraries and their search engines. Following are the some digital resources for finding the Related Research

- Science-Direct Elsevier (https://www.sciencedirect.com)
- ACM (DL) Digital Library (https://dl.acm.org)
- IEEE Xplore Access Digital Library (https://ieeexplore.ieee.org)
- Google Scholar and Google (https://scholar.google.com)
- Springer-Link Electronic Library (https://www.springer.com)

By exploring these Libraries on a Continuous basis and reading the different Research, We select Base Paper for further study and Research.

The primary focus is to investigate the most significant study of this vital domain. To extract relevant publications, the following criteria are established.

1. The Research publications from 2012 to July 2022 selected for the study.
2. Considered Only Conference Papers and Journal Papers for primary study.
3. Papers written in the English Language are selected, and Research papers published in other languages are excluded.
4. Research papers that have contributed in this area are selected for further study.

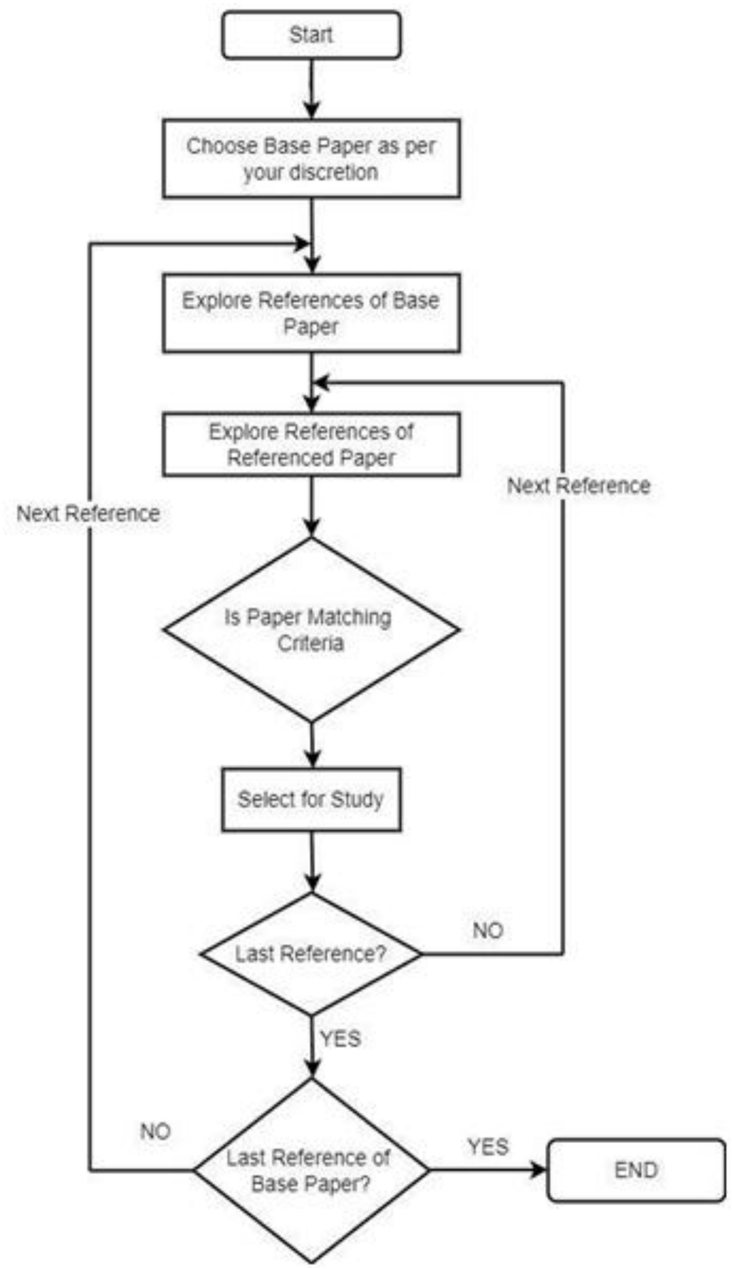

Figure 2: Research Paper Identification and Selection

By keeping the above criteria we explored all the references of Base Paper and the references of all referenced papers. Here Base Paper Contain 32 References and all the 32 Reference Papers contain 952 References so Total 1 + 32 + 952 = 985 Papers were identified and checked for above criteria. After evaluating all 985 Papers as per criteria only 40 Papers were selected for further study and Research. Figure-1 illustrates the methodology and selection criteria for selecting a Research Paper. It also shows overall iterations that I follow to go through all 985 Papers.

Identification of Base Paper should be aligned to Research Domain so that it could contribute and make your efforts most significant. Paper that we chose published on 26 Feb 2021 in Springer (https://doi.org/10.1007/978-981-16-0507-9_27). We went through the paper many times and also explored all references of this paper and finally got 40 papers that match the criterion. Figure 2 demonstrates the classification of Research Papers on the basis of years.

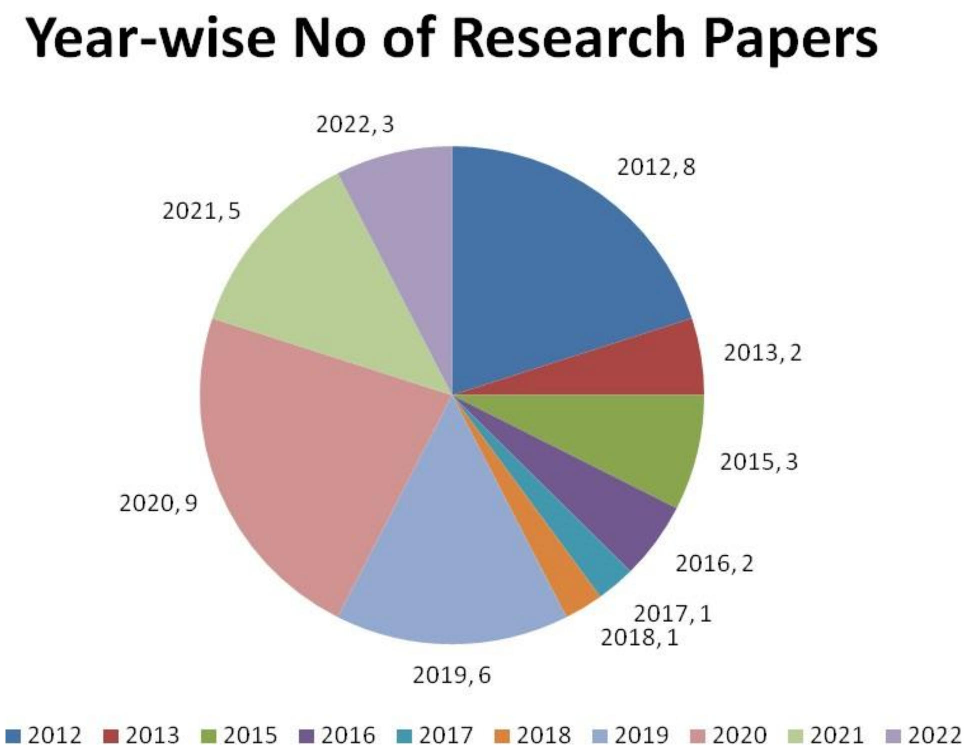

Figure 3: Classification of Research Papers on the basis of Year of Publication

IV. Classification of Violence and Riot Detection Techniques

Rapid growth in crime and violence has attracted the attention of Researchers in the past 10 years. There are a number of techniques which are used to identify anomalies or Violence activities in Surveillance videos through Computer Vision. Researchers have proposed various methods for violence detection; broadly these methods can be categorized into three categories Violence detection techniques using Machine Learning, Violence detection techniques using Support Vector Machine and Violence detection techniques using Deep Learning. Table 2 describes different methods of violence / Riot detection.

Table 2: Violence Detection Methods

#	Method	Object Detection Method	Feature Extraction Method	Classification Method / Activation Function	Scene Type	Accuracy %	Frame Size
1	Violence Detection using pre-trained ResNet-50 CNN along with ConvLSTM[1]	Pre-trained ResNet-50 along with ConvLSTM	ResNet-50	SOFTMAX	Less Crowded	89.90	256 X 256
2	Violence Detection Fast Sliding Window based Approach[2]	Sliding Window	CNN	Linear Support Vector Machine	Both	96.53	-
3	Real-Time Detection of Violent Crowd Behavior using ViF Descriptors and SVM[3]	ViF descriptors	Bag-of-Features	Linear Support Vector Machine	Crowded	Nil	-
4	Action Recognition with Trajectory-Pooled Deep- Convolutional Descriptors[4]	CNN	Trajectory Pooled Deep Convolutional Descriptor	-	Less Crowded	78.70	224x 224
5	Crowd Counting using CSRNet[6]	CSRNet (CNN)	CSRNet	–	Crowded	Nil	300 x450
6	Protest activity detection using 50-layer ResNet[7]	ResNet (CNN)	ResNet	–	Both	Nil	Nil
7	violence detection system using CNN and LSTM[8]	CNN along with LSTM	CNN	SVM and K- Nearest Neighbor	Less Crowded	97.43	200 X 200
8	Riot Detection using CNN and LSTM[9]	CNN along with LSTM	CNN	SOFTMAX	Crowded	82.75	224 X 224
9	Understanding the Highly Congested Scenes using CNN[11]	CSRNet (CNN)	CSRNet	–	Crowded	–	–
10	Violence Detection using Deep Learning[12]	MobileNet and SqueezeNet	Bag-of-Features	–	Less Crowded	Nil	256 X 256
11	Violence Detection using ConvNets[13]	CNN	CNN	–	Both	–	–
12	Video Anomaly Detection using KNN[15]	Nil	3D Markov Random Field (MRF)	KNN	Both	92.70	–
13	Histograms of Optical Flow Orientation for Visual Abnormal Events Detection.[16]	Nil	histograms of the orientation of optical flow	One-Class SVM	Both	97.00	120 X 160
14	Violence Detection in Videos by Combining 3D Convolutional Neural Networks and Support Vector Machines[18]	C3D (3D CNN)	CNN	SVM	Both	98.60	–
15	Real-Time Anomaly Detection using Gaussian classifier[22]	Feature Vector	Feature Vector	Gaussian Classifier	Both	99.60	–
16	Action Recognition with Improved Trajectories[24]	bag of features and Fisher vector	bag of features and Fisher vector	SVM	Both	91.20	-

17	Anomaly Detection in Video Using Predictive Convolutional Long Short- Term Memory Networks[26]	CNN along with LSTM	CNN	SOFTMAX	Both	–	224 X 224
18	Multi-view Learning for Visual Violence Recognition with Maximum Entropy Discrimination and Deep Features[27]	multi-view maximum entropy discriminant (MVMED+)	DSIFT, HOG, LBP	Maximum Entropy Discrimination	Both	90.60	256 X 256
19	Real time Violence Detection Framework for Football Stadium comprising of Big Data Analysis and Deep Learning through Bidirectional LSTM[28]	Bidirectional Long Short-Term Memory (BDLSTM) Network	HOG	SOFTMAX	Both	–	–
20	A novel video analysis method for violence detection in crowded scenes[29]	Top-ACLM	Top-ACLM	SVM	Both	100.0	360 x 280
21	Violence detection using pre- trained models[32]	ResNet50+NN, VGG16+NN	VGG16, ResNet50	Relu	Both	96.00	360 x 280
22	Violence Detection by Pretrained Modules with Different Deep Learning Approaches[34]	CNN along with LSTM	VGG16, VGG19 and ResNet50	SOFTMAX	Both	97.06	28 X 28
23	Violence Recognition from Videos using Deep Learning Techniques[35]	CNN along with LSTM	VGG-16 and LSTM responsible for spatial and temporal features extraction	SOFTMAX	Both		224 X 224
24	Violence Detection Using Spatiotemporal Features with 3D Convolutional Neural Network[36]	MobileNet CNN	3D CNN	SOFTMAX	Both	96.00	224 X 224
25	Real-Time Anomaly Recognition Through CCTV Using Neural Networks[37]	CNN and RNN	inceptionV3 created by Google (A- CNN)	SOFTMAX	Both	–	299 x 299
26	Abnormal Activity Recognition using CNN and LSTM[39]	Lightweight CNN and LSTM	YOLO-V4	SOFTMAX	Less Crowded	89.50	–
27	Detecting Crime Scenes using ML[40]	CNN	YOLO	SOFTMAX	Less Crowded	Nil	–

V. Datasets

Datasets are as vital as the model itself; datasets are collections of related information that can further be used to draw some insights and prediction. Here we are discussing some real world popular datasets that are mostly used for activity / Violence recognition. Table 3 summarizes the details of datasets related to activity recognition and violence detection

Table 3: Summary of Datasets

#	Dataset Name	References	No of Images/Clips
1	KTH	[1]	This dataset contains overall 600 videos with resolution 160 × 120
2	Hockey fight dataset	[1][2][39][8][18][29][32][35][36]	This dataset contains overall 1000 videos. Out of which 500 are violence and 500 are non-violence videos with resolution 720×576.
3	Violent-Flows	[1][2]	This dataset contains 200 videos. 100 videos are from violence and other 100 are from non-violence with resolution 320x240
4	Movie Fight Dataset	[2][8][18][32][36][35]	200 Video Clips (100 Fight and 100 non Fight)
5	pilgrim's	[39]	Nil
6	HMDB51	[4][24]	6766 video clips with 51 action categories
7	UCF101	[4]	13320 Video clips with 101 action classes
8	ShanghaiTech	[6][11]	Nil
9	UCLA Protest Image	[7]	40764 images
10	UCF Crime dataset	[8][24]	CCTV Footage of Violence
11	BEHAVE	[12]	11872 frames of different action like Attack, Group, Run, Walk
12	UCSD	[13][15][22][25]	This dataset contains 34 training videos and 36 testing video samples. Video represents persons who are going towards and away from the camera.
13	UMN	[15][16][22]	This dataset contains crowd activity 11 videos in number. Out of which 3 videos contain indoor and outdoor scenes. Videos contain a

			pattern of an initial part of normal behaviors and ends with abnormal behaviors of escaping.
14	PETS	[16]	This dataset contains 37 category pet images with 200 images of each class.
15	Crowd Violence	[18]	Surveillance video footage of crowd violence, The data set contains 246 videos. This dataset includes videos of non violence and violence activities
16	Violence Image /Recognition	[27]	5974 violence images and 11516 non-violence images
17	Violent Interaction	[28]	containing 2314 videos with 1077 fight ones and 1237 no-fight ones
18	ImageNet	[35] [37]	ImageNet is a large database or dataset of over 14 million images

VI. Conclusion

The demand for such systems that automatically recognize violent incidents grows as more surveillance cameras are installed to monitor human activities in many spheres of life. Activity recognition, such as the detection of aggressive action, becomes a popular topic in computer vision to attract new researchers. Numerous scholars have proposed various methods for finding such activities in videos. This systematic review's main objective is to investigate the field of violence and riot detection research. This systematic study included information on systems based on SVM, CNN, and machine learning for detecting violence and riots. These methods are thoroughly discussed, along with the benefits and drawbacks of each. Additionally, all of the datasets and video attributes that are employed in the algorithms and are essential to the recognition process are listed in tables. The accuracy depends on the object identification, feature extraction, and classification techniques used, as well as the dataset being used. Our study primarily focuses on the strategies and procedures for spotting violent behavior in surveillance footage. This study makes video surveillance techniques more useful. There is always room to make technology more human-centric and to benefit humans most.

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