Turkish Journal of Computer and Mathematics Education Vol.12 No.12 (2021), 738-743

Research Article

Crime Detection In Videos And Alerting System Using Artificial Intelligence

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Article History: Received: 11 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 23 May 2021

Abstract: During the last few decades, surveillance cameras have been installed in different locations just to watch manually. Object detection and analysis of the information captured using these cameras can play effective roles in event prediction, monitoring video feeds and goal-driven analysis applications including anomalies or intrusion detection. Large number of Artificial Intelligence techniques has been used to detect anomalies; amongst them Convolutional Neural Networks (CNN) using deep learning techniques improved the detection accuracy significantly. The goal of this article is to propose a new method based on deep learning techniques for Crime detection in video surveillance cameras. The proposed method has been evaluated in the UCSD dataset, and showed an increase in the accuracy of the Crime detection

Keywords: Computer vision, Artificial Intelligence, Deep Learning, C N N (Convolutional Neural Networking algorithm).

1. Introduction

Crime scene detection with the use of unsupervised machine learning techniques is still an open debate in the field of machine learning. Crime means the occurrence of events or behaviors which are unusual, irregular, unexpected and unpredictable and thus different from existing patterns [1]. Detecting anomalies by learning from normal data can have important and different applications [2]. And also, an Crime detection process is completely dependent on the environment, context and Crime scenario [3, 4]. In different scenarios, anomalies will accordingly be different [1]. Existing supervised methods for Crime detection such as simple CNN based methods require labels which are difficult to attain due to the video high dimension information. High dimension of video affects representation and creation of a model [5]. In this, Crime detection is based on videos of surveillance cameras. It should be noted that detection in videos is more difficult than in other data since it involves detection methods and also requires video processing as well [6].

2. Literature survey

Due to the existence of rich and analytical information in videos and their easy accessibility, scientific researchers have been interested in the analysis and processing of these kinds of data. One of the challenges in analyzing video data is objects detection in video frames [9]. Also, video crime detection has been one of the controversial research topics within the recent years. In the last few years, deep learning approaches have also been introduced for the implementation of crime detection methods. In all crime detection approaches, learning is achieved solely through normal data. Another important point regarding the anomalies is that abnormal events are usually rare events that occur comparatively less than other normal incidents [2].

The challenges for detecting anomalies in videos include speed, online alerts, and localization. It should be mentioned that crime localization is very crucial and most of the existing systems and data lack it. In some approaches, the localization is performed in the pre-processing step which is usually based on video frames comparison. This will increase the accuracy [10, 11]. In other words, most of the existing approaches and available datasets only indicate the presence of anomalies and do not specifying their location [12]. The current methods also lack appropriate training data and correct crime description along with their high cost of extracting features which directly affect detection [6].

One of the widely used methods for detecting anomalies is the use of a binary classifier which has two normal and abnormal classes. The normal class contains data whose occurrence frequency is high, while the other class contains rare and unseen events in accordance with the data pattern [2].

Like other machine learning methods, deep learning based crime detection techniques can also be divided into three categories of supervised, unsupervised and semi-supervised. Supervised crime detection needs labeled data which is difficult because of the volume and dimension of data. In a supervised approach, the main operation is decision rules based or model based which can distinguish between two classes [13]. And also unsupervised methods need complex computing [2]. Unsupervised methods are also known as data driven crime detection [13].

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3. Objectives

10. Divide video into frames and divide test frames to defined patches
11. Train the model to analyze the test data and detect the threatening object or crime.

12. Send SMS to the control station about detection of abnormal or threatening objects with Location of the place.

The proposed methodolgy

The proposed method of this paper is based on deep learning techniques for detecting anomalies in video. Two main components are considered for this method. The first component is the extraction and learning of the feature and the second component is the detection of anomalies. Apart from these two components, there is a pre-processing step which is related to background estimation and removal. Like all machine learning approaches, this method also has two main train phase and test phase. In train phase, features are trained by train parts of dataset which contains only normal frames, and trained model in test phase is used by other parts of dataset which contain abnormal frames.

The third feature is motion which is based on the flow of objects between patch frames and it generates optical flow and a sequence of video then used for another score on anomaly. The last feature is scene which is based on patch frames and reconstructing a scene from learned model. The combination of these features is also used for detection and creation of scores.

Algorithm

i. Source input
ii. Preprocessing
iii. Feature extraction
iv. If matched points > threshold value
v. True -> weapon detected
vi. False -> System initialization
vii. Repeats from step 3 until weapon is detected

Pre-Processing:

The first step before starting extracting and learning features is to estimate and remove the background. The background is indeed different for different scenarios as there are various methods for its removal. For instance, the background might include empty spaces or street borders. In this method, the background estimation is based on most occurrence of frequency (MOF) between video frame patches [9]. For the background estimation steps at first, a histogram is generated for each frame of the video which is based on pixels and their location in the image. Then the histogram of the frames in each patch is compared with each other, and the maximum values per patch are identified as background and are thus grayed. Removing the background will reduce the cost of the computing and the processing time. This step is considered as a part of train network.

Feature Extraction and Learning Component

In addition to background estimation, train network has four main components. The deep network for extracting appearance feature uses a stacked denoising auto-encoder (SDAE) with 6 encode layer and the same structure of decode layer .Each frame is convolving to network with 1*1 window size and it includes stride and padding. All frames normalize in binary mode. This SDAE has 6 encode layers and 6 same structure in decode layer which is deeper than the existing methods. The output of this step is detected objects which are called appearance representation. This output is used in detecting phase and also is utilized as an input to density estimation component in order to increase the accuracy of estimation.

4. Block Diagram

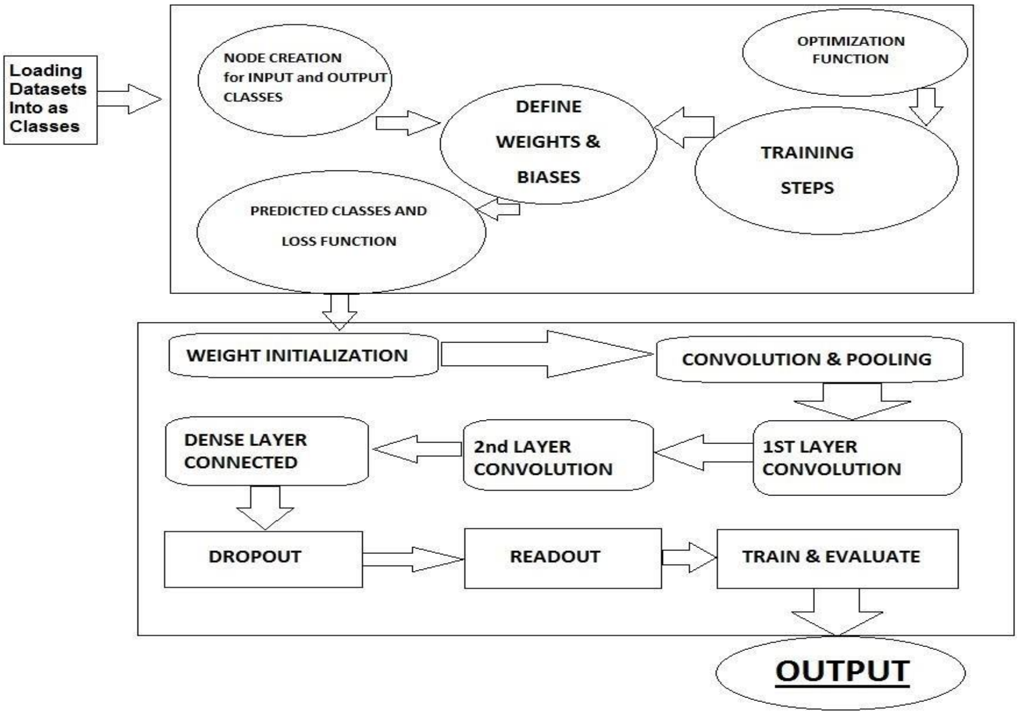

Fig 4.2 Block diagram of CNN model.

Density Estimation is carried out by convolutional neural network with 8 * 8. Windows filter. This network is shown in Figure 4.2 the output of this component is feature map and the loss function is computed based on square error. In the estimation of the density, the sectors associated with the background are considered zero.

5. Feature Extraction

The third component is motion feature extractor [17, 23]. It performs a feature extraction based on the direction of moving objects in the scene of video patches. This deep network also has a similar structure to appearance feature extractor but it is based on frames patches. After entering the patch frame into the network, computing optical flow will be done based on comparison of frames in a patch. The output of this step is Motion Representation which is used for future detection.

The last component is Scene Reconstruction which is based on reconstruction network [26]. The structure of this reconstruction network is based on convolution Auto- Encoder with the same CNN generator and discriminator networks. Generator part regenerate the scene which has 10 layers to reconstruct frames based on the previous and the next frame in same patch and the discriminator compares the generated scene with original one in order to compute the reconstruction error. It should be mentioned that discriminator part has the same structure as that of the generator. A high reconstruction error during test indicates anomalies. The reconstruction error in train network is low and this will be a measure for detecting anomalies.

	Testing Data	Training Data
BLOOD	200	196
KNIFE	200	184
MACHINE GUN	200	203
REVOLVER	200	210
SHOTGUN	200	189
GUN IN HAND	200	156

TABLE 1 : DATASET COLLECTION INFORMATION

At the end of the training step, a set of learned and combined features is created in order to achieve Crime detection.

Two other combination features are Motion Feature and density map. These are two complementary features and the direction of motion must be equal to the transfer of density direction.

6. Conclusion

In the detection component, learned features which are generated in train network are given to a classifier with two classes of normal and abnormal. Features are given as individual and combined feature to these networks. Reconstruction error and appearance features are given to network as a combined feature since the appearance feature or object detection with a reconstruction error can be a strong feature for the detection of anomalies. The lower reconstruction error for the corresponding frame can make the detection more accurate. In future, work will be the same.

7. Result

The CNN is implemented using Tensor flow (open –source platform) to achieve **90.43% accuracy** for tested dataset as an output.

A new approach in this paper has been enhanced to detect Blood knife and Various types of Guns available. The following table shows the analysis report of weapon detection using CNN algorithm.

Hence, we can see that the weapon objects recognized in the video can easily be detected; this identification is further passed on to informing the authorities of the Crime scenario by informing in monitor screen alert pop up window with the percentage of accuracy of identifying the object of Weapon.

	Weapon	**Accuracy (90.43%)**
	Pistol	97%
	Blood	94%
	Assualt rifle	91%
	Machine Gun	81%
	Knife	79

	Short Gun	87
	Gun in hand	71

TABLE 2: RESULT OF ANALYSING WEAPONS WITH ACCURACY PERCENTAGE

8. Acknowledgements

We would like to express our gratitude towards Dr. Prameela Kumari N for guiding me throughout the project. We also feel thankful and express our kind gratitude towards our Director Dr. R. C. Biradar for allowing us to conducting this project. We thank all participants for their positive support and guidance.

We feel thankful to the college staff for giving me such a big opportunity. We believe that we will enroll in more such events in the coming future. We ensure that this project was done by us and is not copied.

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