Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

LITERATURE / REVIEW ARTICLE

Survey on Abnormal Event Detection and Signalling in Multiple Video Surveillance Scenes Using CNN

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Received: 19 April 2023 / Revised: 25 April 2023 / Accepted: 8 May 2023

DOI: 10.5281/zenodo.7937989

Abstract — With the growth of urbanisation, the flow of people is increasing steadily every year. The likelihood of stampedes in public areas rises as a result of this trend. Monitoring the audience for the occurrence of odd circumstances and acting quickly to prevent them is necessary. Crowd analysis is typically done for purposes of security and public safety. It is difficult to continually handle for human operators to continuously scan the visual screens for any occurrence of interest. There has been a lot of study done in the area of anomalies identification in crowds by the computer vision and signal processing groups, which pushes researchers to design an autonomous system for doing so and assisting the operators. Recent attempts have been made to avoid using any labour-intensive hand-crafted feature extraction and processing methods by utilising deep learning models. There are shortcomings such ground truth availability, anomaly type, etc. that are highlighted in despite the extensive research and achievement in this area. The development of effective anomaly detection systems still presents numerous difficulties for the computer vision community. This includes the lack of cameras, bad weather, problems with night vision, etc. We have used several special methods that enhance the system's overall performance.

Index Terms — Convolutional Neural Network, Anomaly Detection, Generative Adversial Network, Deep Reinforcement Learning.

I. INTRODUCTION

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning method that can take in an input picture, give various elements and objects in the image importance (learnable weights and biases), and be able to distinguish between them. Comparatively speaking, a ConvNet requires substantially less pre-processing than other classification techniques. ConvNets have the capacity to learn these filters and properties, whereas in basic techniques filters are hand-engineered.

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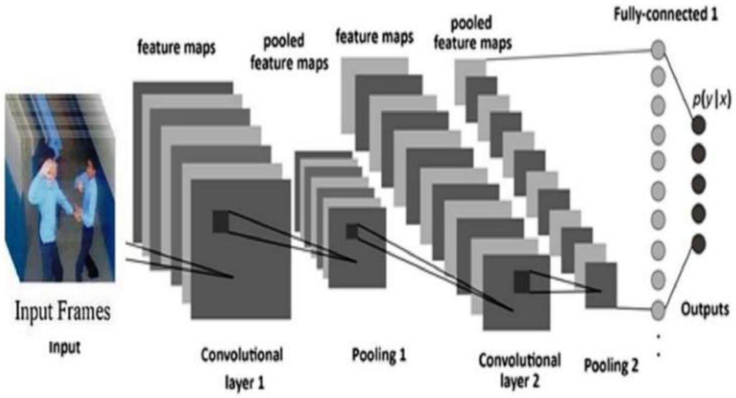

Fig. 1. The architecture of a ConvNet

Fig. 1. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known asthe Receptive Field. Using a convolutional neural network, patterns can be found in an image. You accomplish it by adding confusion to an image and searching for patterns. Lines and corners can be recognised in the first layers of CNNs, but as we go deeper, we can pass these patterns on to our neural network to recognise more complicated characteristics. A convolution is a two-function integration that demonstrates how one function changes the other. The input picture, the feature detector, and the feature map are the three crucial components to be mentioned in this procedure. The picture being detected is the input image.

A matrix, typically 3x3 but perhaps potentially 7x7, serves as the feature detector. A kernel or filter are other names for a feature detector. Intuitively, a feature map, also known as a convolved feature or an activation map, is created by multiplying the matrix representation of the input picture element-by-element with the feature detector. The purpose of this step is to reduce the image's size and facilitate processing. In this step, some of the image's characteristics are lost. The primary aspects of the image that are crucial for image detection are kept, though. These characteristics are what make that particular thing identifiable. For instance, each animal has distinguishing characteristics that let us recognise it. Having numerous feature maps allows us to avoid losing image data. Every feature map locates certain features in the picture.

Background

The task of detecting aberrant events in surveillance recordings is one that is rapidly developing in the field of video analysis. There has to be further research into discriminating techniques or motion information because both normal and aberrant occurrences share certain similarities. We suggested using deep learning to identify the categories of crimes. Convolutional Neural Networks (CNNs), a type of artificial neural network used mostly for image recognition and processing because of its capacity to spot patterns in images, are the name of the deep learning technique we are applying in this proposed system.

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A CNN is a strong tool, but it must be trained using millions of labelled data points in order to improve accuracy and correctly identify the material's identity.Arson, burglary, fighting, explosions, and other aberrant actions must be monitored by an intelligent surveillance system that can automatically sound an alarm or alert.

Problem Statement

In this paper, we provide an answer to the question whether a method exists that can detect unusual activities like murder, street fighting and other situations such as fire wherein we need to call the concerned department. The continuous monitoring of the CCTV is done as to detect these abnormal activities using the Convolutional Neural Network as shown in Fig. 1. A major question here is whether there exists a method that:

- Can the method be time efficient to send an alarm to the concerned departments on time?
- How to achieve the accurate analysis of the video and detect the abnormal activity?
- Is it flexible enough to be implemented all over the city for it's best use?

The aim of this paper is to propose an method that can identify abnormal activities like murder, street fighting, and other situations where we need to contact the relevant department also existence of such a mechanism that can convey an alarm to the relevant departments in a timely manner.

Objectives

We consider the various approaches that are available and work to choose the best one that will work for our problem statement. We address the standard methods of detection in papers [1] and [2]. Problems with activity recognition have frequently been solved using statistical learning techniques. Classifier can manually track down and find motion in order to recognise it. However, they had to rely on manually created features because discriminative features were difficult to come by. In paper [4], we employ GAN training because it was found to produce superior outcomes. In order to develop features for human activity recognition, heuristic feature extraction techniques such symbolic representation, statistics of raw data, and transform coding are frequently used.

II. LITERATURE SURVEY

In [1] The problem of abnormal event identification in video surveillance is critical. In this research, we offer a unique method for real-time 150 frames per second (FPS) detection of anomalous occurrences. The two steps of our methodology are feature extraction and anomaly detection. We employ a deep neural network to learn spatiotemporal characteristics from the input video for feature extraction. Then, it suggest a Gaussian mixture model-based method for finding anomalies. Our approach is capable of identifying a wide range of aberrant occurrences, such as crowd behaviours, item motions, and interactions between people and objects. It tests our methodology on two difficult datasets, and the findings show that it surpasses cutting-edge techniques in terms of detection accuracy and speed.

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The problem of abnormal event detection in video surveillance is crucial. It entails spotting instances like fighting, theft, or falling that depart from customary behaviour patterns. The time-consuming and labor-intensive constructed characteristics used by conventional approaches for anomalous event identification frequently fall short of capturing the intricate spatiotemporal dynamics of real-world situations. Deep learning has recently demonstrated considerable promise in this area since it can automatically identify high-level characteristics from unstructured data. In this study, we provide a unique method for 150 frames per second real-time detection of anomalous occurrences. The two steps of our methodology are feature extraction and anomaly detection. We employ a deep neural network to learn spatiotemporal characteristics from the input video for feature extraction. Then, we suggest a Gaussian mixture model-based method for finding anomalies. This approach is capable of identifying a wide range of aberrant occurrences, such as crowd behaviours, item motions, and interactions between people and objects.

In this paper [2], Due to the richness and variety of real-world situations, anomaly identification in large-scale video collections is a difficult challenge. In this study, we offer a discriminative framework that takes advantage of the spatiotemporal context of video data to discover anomalies in huge films. The two steps of our method are feature extraction and anomaly detection. We employ a deep convolutional neural network to extract characteristics from the input video and teach it discriminative features. Then, for anomaly detection, we suggest a one-class support vector machine-based approach. This technique is capable of spotting a wide range of abnormalities, such as irregular crowd behaviour and strange item behaviours as well as unusual object appearances. We test our strategy on two sizable video datasets, and the findings show that it beats state-of-the-art approaches in terms of both detection and recognition along with the accuracy and speed. For many applications, such as video surveillance, population monitoring, and anomaly identification in medical imaging, anomaly detection in large-scale video datasets is an essential job. The complex spatiotemporal dynamics of real-world situations are frequently difficult to represent by the handmade characteristics used in traditional approaches for anomaly identification.

Deep learning has recently demonstrated considerable promise in this area since it can automatically identify high-level characteristics from unstructured data. In this study, we offer a discriminative framework that takes advantage of the spatiotemporal context of video data to discover anomalies in huge films. The two steps of our method are feature extraction and anomaly detection. We employ a deep convolutional neural network to extract characteristics from the input video and teach it discriminative features. Then, for anomaly detection, we suggest a one-class support vector machine-based approach. Our technique is capable of spotting a wide range of abnormalities, such as irregular crowd behaviour and strange item behaviours as well as unusual object appearances. In [3] This paper states that the abnormal event detection does not depend solely on the information presented by the extracted frames but is also determined by the presence of objects as well as their movements. The dataset containing normal videos is given as the training set to the model and the outliers are classifies as abnormal events.

There are 3 subprocesses: Spatio-Temporal features processing, GAN training and Optical flow images analysis. Preprocessing includes extraction of the appropriate features in the foreground, edge detection of objects and patch extraction. A 3-D model is developed as the output which has visual

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presentation as well as motion features. Patch extraction is done using a grid overlay and minimum number of pixels are selected to avoid noise and irrelevant data. The output patches are given as an input to the network. The output of the Gunner-Farneback optical flow algorithm helps us to identify hues and intensities which represent the direction and speed respectively. To identify the motion abnormalities, we use sorted histograms. The first 5% of the hues having the lowest frequencies are considered to be abnormal. The dataset comprising normal videos input to the generator of GAN gives patches as the output. These patches are input to the discriminator network which is a pre-trained VGG-16 CNN network that determines the originality. The accuracy is feedback both to the generator to identify fake accuracy and to the discriminator to distinguish between real and fake videos. The generator has 4 layers and the discriminator has two parts – VGG-16 in the input layer and the two fully connected layers are concatenated with the first layer. Python and Keras are used to implement GAN.

The roc_curve function from sklearn library of Python is used to determine the area under curve (AUC). The proposed method has lower Equal error rate (ERR) and Higher AUC compared to all the other approaches. It is also time effective as the overall execution time is 0.312 seconds. A major limitation of this approach is that it is not applicable to process and analyse real-time videos having more than 30 frames per second(fps). In paper [4] This paper makes use of Variational Autoencoder (VAE) which is an end-to-end deep learning framework to detect anomalies in the video frames. It follows an assumption that all the normal training instances conforms to the Gaussian distribution. High dimensional dataset is provided as an input to the VAE which then transforms it into low dimensional data in hidden layer representation. The hidden layer representation constraints the lower dimensional data to conform to the Gaussian distribution. Precisely, original pixels are given as an input to VAE which learns the Gaussian distribution in the hidden layer. When the hidden layer representation of a test dataset is provided as an input to VAE, it calculates the probability in the Gaussian Distribution.

If it is below a threshold, it is classified as an abnormal event, i.e., Abnormal events have a low probability in the Gaussian distribution while Normal Samples have a much higher probability in the Gaussian distribution. In this approach, event representation and anomaly detection model are combined into one making the model highly optimized and effective. This method even provides a strong generalization ability. The suggested approach has been implemented on UCSD Ped1 and Avenue Datasets. This approach has a frame-level AUC of 93.1% and a pixel-level AUC of 66.9%. Due to it’s low accuracy, it is not guaranteed to yield effective results when implemented on complex databases. Paper [5] This paper presents an unsupervised learning method to analyse and interpret videos. The videos input to the model are parsed into spatio-temporal regions to detect all types of anomalies. Usually, the normal video instances are dominant and hence have less focus as it doesn’t draw special attention to any unusualness unlike the abnormal video instances. It employs pixel by pixel analysis. Spatio-temporal video volumes (STV) which are highly dense are used to create compositional graphs that are both local and global at all volumes. No training sets are utilized but the Bag of Video words (BOV) lookup tables are continuously updated. Using one or two seconds of the video, an adaptive model of dominant behaviour is constructed to detect abnormalities. Initially, STVs are constructed and grouped to construct the codebook which reduces the search space.

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The uncertainties in codebook construction are taken into consideration in the hierarchical structure. It codes the information about the video volumes and then analyses them as either spatial or temporal or as spatio-temporal. The relationships between the STVs are determined using a probabilistic framework. STVs are clustered using Fuzzy clustering and dominant videos are used to build the model. Precisely, high level behaviours detect anomalies. A single algorithm comprises both a high-level activity model and a low-level pixel change. It extracts patterns from videos in an online manner. The major advantage of this algorithm is its extendibility using hierarchical clustering. A major limitation is that long term behaviours are not learnt as it doesn't account for trajectories. In [6], This paper presents a method for detecting anomalous events in dashcam videos. The abstract highlights the need for automated systems to detect anomalous events in dashcam videos, as these events can be critical for safety on the roads. The proposed method uses a combination of deep learning and computer vision techniques to detect anomalies in the video. The approach involves preprocessing the video frames to extract visual features, followed by training a convolutional neural network (CNN) on the extracted features. The CNN is trained on a large dataset of normal driving videos to learn the patterns of normal driving behavior.

The trained CNN is then used to detect anomalous events in new dashcam videos by identifying deviations from normal driving patterns. The method is evaluated on a dataset of dashcam videos, and the results show that it can effectively detect anomalous events with high accuracy. The use of data-driven anomaly detection techniques from deep learning to improve driver safety systems using dashcam videos. The existing hand- crafted pipelines are inadequate due to the long-tailed distribution of road hazards.Using a dataset of truck dashcam videos, called RetroTrucks, which includes both normal and anomalous driving scenes. However, there is almost no literature on applying anomaly detection to moving cameras, and a lack of relevant datasets. This paper also includes potential applications of the proposed method in real-world scenarios, such as in-vehicle monitoring systems and autonomous vehicles and proposed method has the potential to improve safety on the roads by detecting and alerting drivers to anomalous events in real-time. This paper [7] Learning Regularity in Skeleton Trajectories for Anomaly Detection in Videos" is a research paper that proposes a new approach for detecting anomalies in videos based on the regularity of human skeletal movements. The paper presents a method for learning the regularity of human skeletal movements using a deep learning approach, and then uses this learned model to detect anomalies in new video data. The paper begins by discussing the importance of anomaly detection in video surveillance systems and the challenges associated with this task. The authors argue that the detection of anomalies based on human skeletal movements is a promising approach, as it can capture important cues related to human behavior. The proposed method consists of two main components: a regularity learning module and an anomaly detection module.

The regularity learning module uses a deep neural network to learn the regularity of human skeletal movements from a large dataset of labelled videos. The anomaly detection module then uses this learned model to detect anomalies in new video data by comparing the observed skeletal movements to the learned regularity model.The authors evaluate the proposed method on several publicly available datasets and compare it to state-of-the-art methods for anomaly detection in videos. The results show that the proposed method outperforms existing methods in terms of detection accuracy and false positive rates.Overall, "Learning Regularity in Skeleton Trajectories for Anomaly Detection in Videos" presents a promising approach for detecting anomalies in video surveillance systems based on human skeletal movements. The paper highlights the importance of learning the regularity of human behaviour for effective anomaly detection and demonstrates the effectiveness of a deep learning approach for this task.

Paper [8] The "Spatio-Temporal Action Graph Networks" survey paper provides an overview of the state-of-the-art research on Spatio-Temporal Action Recognition (STAR) using Graph Neural Networks (GNNs). STAR is a challenging task in computer vision that involves detecting and recognizing actions from video data.The paper introduces the concept of Spatio-Temporal Action Graphs (STAGs) that represent the structure and dynamics of actions in video sequences as a graph. The STAGs capture the spatial and temporal relations between different regions of interest (ROIs) in video frames and how they change over time.The paper presents various approaches for modeling STAGs using GNNs, including Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), and Graph Isomorphism Networks (GINs). These methods learn the features and relations between ROIs in STAGs to perform action recognition tasks.The survey paper also discusses the challenges and limitations of current STAG-based methods, such as the need for large-scale annotated datasets, the lack of interpretability of GNN-based models, and the difficulty in modeling long-term temporal dependencies. Overall, the "Spatio-Temporal Action Graph Networks" survey paper provides a comprehensive review of recent research in the field of STAG-based action recognition using GNNs, highlighting the potential of this approach for improving the performance of action recognition systems in real-world applications.

Paper [9] In this paper it discusses the problem of video anomaly detection, which is the automatic identification of unusual events in video surveillance. The main challenge is to distinguish anomalous events from normal ones, which can be accomplished by using one or more training videos from the same scene containing only normal events. The goal is to develop algorithms that can automatically identify anomalous events and flag them for human inspection, reducing the amount of video that needs to be monitored by humans. There are different formulations of the problem, including single-scene and multiple-scene, and different evaluation criteria, including spatial and temporal localization and false-positive counting. The paper presents a new dataset for single-scene anomaly detection, called Street Scene, and two new evaluation criteria, as well as two novel algorithms that outperform state-of-the-art algorithms on this dataset. It describes two detection criteria, namely the track-based detection criterion and the region-based detection criterion. The track-based criterion measures the rate of detecting anomalous tracks against the number of false positive regions per frame. The region-based criterion measures the rate of detecting anomalous regions over all frames in the test set against the number of false positive regions per frame. It also discusses two variations of a novel algorithm for video anomaly detection, one based on the foreground mask, and the other based on optical flow fields. The algorithm involves dividing the video into spatio-temporal regions, storing exemplars for each region, and using the distance from a testing video patch to the nearest neighbor exemplar as the anomaly score.

In [10] The paper discusses a proposed anomaly detection method that uses deep multiple instance learning to train a model using positive and negative bags in surveillance videos. It relaxes the assumption of having accurate temporal annotations and instead uses video-level labels to detect anomalies. It describes the construction of a new large-scale dataset for evaluating an anomaly detection method. The dataset

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consists of 1900 untrimmed surveillance videos covering 13 real-world anomalies that have a significant impact on public safety. The videos were collected from YouTube and LiveLeak using text search queries and were pruned to remove edited, prank, news, and hand-held camera videos. The videos were then annotated by multiple annotators to determine the temporal extent of each anomaly. The dataset was divided into training and testing sets containing all 13 anomalies at various temporal locations. The evaluation metric used was the frame-based receiver operating characteristic (ROC) curve and corresponding area under the curve (AUC). The method was compared with two state-of-the-art approaches for anomaly detection. Experimental results show that the proposed method for anomaly detection outperforms the state-of-the-art approaches, and the dataset is very challenging, providing opportunities for future work.

III. CONSOLIDATED TABLE

SL.NO	REFERENCE	YEAR	DESCRIPTION	LIMITATIONS
1	[1]	2019	• Efficient sparse combination learning frame-work. • The short running. • Time is guaranteed.	• The detection speed is muc larger than in working environment.
2	[2]	2019	• Independent of the order in which anomalies appear. • Requires no separate training sequences.	• Anomalous frames Need be distinguishable in th space.
3	[3]	2020	• Abnormal event detection does not depend solely on the information presented by the extracted frames but is also determined by the presence of objects as well as their movements.	• It is not applicable to process and analyse real-time videos having more than 30 frames per second(fps).
4	[4]	2021	• Makes use of Variational Autoencoder (VAE) which is an end-to-end deep learning framework to detect anomalies in the video frames.	• Due to its low accuracy, it is not guaranteed to yield effective results implemented on complex databases.
5	[5]	2021	• Uses unsupervised learning method to analyse and interpret videos.	• Long term behaviours are not learnt as it doesn’t account for trajectories.
6	[6]	2020	• Two detection criteria, the trackbased detection and the regionbased detection. • It divides the video into spatio temporal regions, and uses the distance from a testing video patch to the nearest neighbour exemplar.	• Limited camera viewpoints. • Limited number of anomalies.

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7	[7]	2021	• Uses deep multiple instances learning to train a model. • Dataset consists of 1900 untrimmed videos, and 13 realworld anomalies. • Evaluation metric used was the frame-based receiver operating characteristic (ROC) curve and corresponding area under the curve (AUC).	• More Complexity of Scene and Objects. • Lack of interpretability.
8	[8]	2019	• Highlights the importance of learning regularity in skeleton trajectories, which can be used to detect anomalies in the video.	• Focuses on anomaly detection using skeleton trajectories, and does not consider other modalities such as RGB or depth images. • Do not provide a detailed discussion on the limitations of the datasets used in the studies.
9	[9]	2020	• A new framework called Spatio-Temporal Action Graph Networks (STAG) for action recognition in videos. • Describes the architecture of STAG, which consists of multiple components including a graph convolutional network, a tempor convolutional network, and a self-attention mechanism.	• Does not provide a comprehensive evaluation of the robustness of STAG to different types of noise, occlusion that can occur in real- world video data.
10	[10]	2019	• Proposes a framework for anomaly detection in dashcam videos, whi are videos captured by cameras mounted on the dashboard of a vehicle. • Dashcam provide rich visual information that can be used to detect abnormal events such as accidents, road violations, and pedestrian crossings.	• The proposed framework is computationally intensive, and its practical application in real- world scenarios may require significant computational resources and time.

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IV. CONCLUSION

In this paper, we outline the numerous approaches put out for spotting anomalous activity as well as their individual benefits and drawbacks. We have considered every issue and are working to develop an anomaly detection technique that minimises complex, unavoidable human errors. maximum use of available human and material resources. aids in developing a safety system for smart cities. the prompt arrival and notification of the departmental authorities of any ongoing abnormal events. decreases crime rates as a result of the system's strong effects.

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