A NEW ANOMALY ACTIVITY DETECTION USING CNN & RNN

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ABSTRACT

With the great use of closed-circuit tv (CCTV) surveillance structures in public areas, crowd anomaly detection has come to be an an increasing number of imperative component of the wise video surveillance system. It requires staff and non-stop interest to figure out on the captured event, which is challenging to operate via individuals. The reachable literature on human motion detection consists of a variety of procedures to observe bizarre crowd behavior, which is articulated as an outlier detection problem. This paper provides a unique evaluate of the latest improvement of anomaly detection strategies from the views of pc imaginative and prescient on exclusive handy datasets. A new taxonomic organisation of current works in crowd evaluation and anomaly detection has been introduced. A summarization of current evaluations and datasets associated to anomaly detection has been listed. It covers an overview of extraordinary crowd concepts, which include mass gathering occasions evaluation and challenges, sorts of anomalies, and surveillance systems. Additionally, lookup tendencies and future work potentialities have been analyzed.

INDEX TERMS:Anomaly,surveillance,imaginative,taxonomic.

1. INTRODUCTION

The World Health Organization (WHO) clarifies significant gathering events as any occurrence, whether planned or unplanned, that attracts a substantial number of participants to strain the neighborhood, city, or nation hosting the event's planning and response resources. The heterogeneous composition of the crowd in terms of color, age, language, and culture presents several administrative issues for local organizers focused on ensuring the event's efficient management. Administrative authorities are more concerned with understanding the crowd mechanics that explain what could harm large crowds. An anomaly detection system is a monitoring program that automatically identifies and considers the signs of abnormal or irregular actions directly. With the widespread usage of video surveillance techniques, manual evaluation of vast quantities of video data gathered from crowd surveillance CCTV cameras has become complicated, time-consuming, and ineffective in the case of large crowds. It requires workforce and continuous attention to decide if the captured actions are normal or abnormal. Therefore, an automatic anomaly detection functionality is necessary for surveillance systems to accurately identify and detect anomalies in crowd scenes. Detecting abnormal behaviors rapidly and automatically in crowded environments is significant for improving safety, preventing risks, and guaranteeing quick response. Anomaly detection in surveillance systems is critical for assuring safety, security, and in some cases, the prevention of possible disasters. Anomaly detection intends to discover the anomalies in a quick time automatically. Recently, intelligent monitoring systems have become crucial for effective crowd management. Due to their importance, computer vision, video analysis, and automated crowd anomaly detection have become popular research topics.

With the many emerging challenges in public management, security, and safety, there is an increasing need for monitoring public scenes through surveillance cameras. At first sight, it seems an easy job for a human to monitor surveillance cameras feed to extract essential and helpful information from behavioral patterns, detect abnormal behaviours, and provide immediate response. However, due to severe limitations in human ability, it is hard for a person to monitor simultaneous signals. It is also a time-consuming task requiring many resources such as people and workspace. Therefore, an automatic detection method is crucial to this end. One of the sub-domain in behaviour understanding from surveillance cameras is detecting anomalous events. Anomaly detection in surveillance cameras is a challenging task that might face several problems: (1) abnormal events rarely happen; therefore, it is hard to find massive datasets of such events. This lack of samples might lead to some difficulties in the learning process. (2) Generally, everything that does not follow a specified pattern (or rule) is called an "anomaly". As a result, we cannot dedicate a model for abnormal events. (3) An action can be normal or abnormal in different situations. It means that even a global abnormal event (GAE) can be a routine activity in a particular situation like shooting in a gun club. The act of "shooting" is generally considered abnormal, while it acts normal in a shooting club. On the other hand, some behaviour is not intrinsically abnormal, but it would be an anomaly in a specific location and condition called local abnormal event (LAE). Besides, Varadarajan in proposed abnormal events as "an action done at an unusual location, at an unusual time".

From a learning standpoint, anomaly detection can be divided into three approaches: supervised, unsupervised, and semi-supervised, as a significant and well-known categorizing for learning methods. In supervised learning, there are two different approaches by considering whether the model is trained by only one category or all existing categories [7]. In other words, in single model learning, the model is trained by only normal(or abnormal) events, whereas in multi-model learning, both normal and abnormal events need to be trained. In the single model learning, anomalous events distinguished from normal ones by learning a threshold for normality definition, learning of a multidimensional model of normal events within the feature space and learning rules for model definition. While, for the multi-model learning approach, which is particularly used when there are several groups of anomalies, each class will be trained dependently or independently. On the other hand, an anomaly detection problem is generally considered as an unsupervised learning problem. This technique deal with unlabeled data in which it is assumed that Normal events frequently occur while Abnormal events rarely happen in data. Considering all rare events as anomalous is one of the drawbacks of this learning. Several clustering algorithms in unsupervised learning consider normal and abnormal events should be well separated in the feature space. Besides, the semi-supervised Anomaly detection approach neither is too reliable on labeled data like the supervised approach nor have a low accuracy as unsupervised models. This model tries to diminish the differences between supervised and unsupervised techniques. Several works take advantage of the properties of semi-supervised learning schema such as in. This paper proposes the anomaly detection problem as a multiple scene formulation in a supervised learning schema. Numerous abnormal behaviours in the real world depend on our definition of an anomalous event to label it as an anomaly. However, here, we focus on the UCF-Crime dataset, including much abnormal, illegal, and violent behaviour captured by surveillance cameras in public places, which can lead to severe problems for individuals and a society population. Our proposed model used ResNet50 as a Convolutional Neural Network (CNN) for feature extraction. Then, due to working with the video dataset, we add an RNN, ConvLSTM, to the model architecture, which can work efficiently on such data to our model. Then, the model returns whether the input video includes illegal behaviour or not. This model can save humans time and money and increase the accuracy of detecting irreparable damages.

2.LITERATURE REVIEW

With the widespread use of surveillance cameras and the emerging need for automatically abnormal event detection, several methods have been proposed to solve various types of anomaly detection in video datasets. Supervised learning methods aim to separate data classes, whereas unsupervised techniques explain and understand data characteristics. Between the two, supervised anomaly detection techniques outperform unsupervised anomaly detection techniques using labeled data. In supervised anomaly detection, the separating boundary is learnt from training data, and then test data are classified into either normal or abnormal classes using the learned model.

In 2015, Tran et al. presented a model for learning spatiotemporal features with 3D convolutional networks. This model is called C3D, and in this model, each segmented video goes through a three convolution layer 3D

ConvNet to classify different actions. After four years, Sultani et al. [30] used this model with multiple instance learning (MIL) in their paper to find abnormal events.

However, deep neural network architecture has recently been successfully used in various computer vision tasks, including anomaly detection problems. Mainly, supervised deep learning for anomaly detection includes two parts: a feature extraction network followed by a classifier network [31]. This paper implements Convolutional Neural Networks (CNN) to extract essential features from each input video data frame. By taking advantage of the Recurrent Neural Network (RNN) structure, the system can investigate a series of frames to find any abnormal events.

Nowadays, deep learning has been widely studied, since it learns features automatically from raw data. In many computer vision applications, deep learning has shown impressive performance, such as image segmentation, object detection, and activity recognition. These works mainly focus on supervised scenarios. However, in the field of anomaly detection, labeled abnormal events are seldom available for training. Fortunately, unsupervised deep learning approaches have also been studied in recent years to address important tasks, such as image classification and object tracking. The reason why deep learning conducts inspiring performance is that multi-layer non-linear transformations can adaptively extract meaningful and discriminative features. Nevertheless, deep learning is seldom studied for abnormal event detection, expect for and.

In Ref, appearance, motion, and their joint representations are learned with three stacked denoising autoencoders. Then anomaly scores are predicted by three one-class *support vector machines* (SVMs) on these learned features, respectively. Finally, detection results are fused with an automatically learned weight vector.

In Ref., Fang et al. represent appearance and motion features with salience maps and multi-scale HOFs. After that, a deep learning framework named *PCA network* (PCANet) is used to extract high-level features. As, a one-class SVM is adopted in Ref. to detect abnormal events.

In this paper, a different deep model is designed for abnormal event detection. Firstly, 3D gradient features are computed to describe video events, due to their simplicity and effectiveness. Specifically, the gradients at horizontal and vertical directions represent the appearance features. Meanwhile, motion characters are described by gradients at the temporal direction.

Subsequently, a PCANet is trained to generate high-level descriptors from these 3D gradient features. In order to model normal video events, the *Gaussian mixture model* (GMM) is generally used to learn normal event patterns. Since video events are quite complicated, it always requires massive Gaussian components to model these event patterns. Unfortunately, this brings about plenty of parameters and increases the complexity. In order to deal with this problem, this paper develops a deep GMM method to explore video event patterns. The deep GMM method is provided with high representation power while having relatively few parameters.

Several surveys regarding crowd anomaly detection methods already exist. For example, Borja et al. presented a short review of deep learning methods aimed at understanding group and crowd behaviors. Similarly, Afiq et al. offered a review of algorithms published between 2013 and 2018. Khan et al. summarized seminal research works on crowd management published between 2010 and 2020. Suarez et al. compiled a survey of deep learning solutions for anomaly detection in surveillance videos, considering articles published between 2016 and 2020.Braham et al. performed a comparative study of crowd analysis algorithms, taking into account some previous reviews and various studies published between 2017 and 2020. Elbishlawi et al. assembled deep learning-based methods for crowd scene analysis methods that were published up to the time of writing (until 2020). Mohammadi et al. conducted an in-depth literature survey into deep learning-based anomaly detection methods for both images and video (the studies were mainly published between 2010 and 2020). Mu et al. focused their review on deep learning methods published until 2020. Sharma et al. contrasted the deep learning literature published between 2017 and 2020 with earlier research published between 2011 and 2017 by studying 93 research articles from reputed databases published between 2011 and 2020.

3.EXISTING SYSTEM

Detecting the abnormal activities or anomalies of a crowd in real-world surveillance videos is considered an important yet challenging task because prior knowledge about anomalies is usually very limited or unavailable. Moreover, in real-life situations, both abnormal events and behaviors may take place at once in the crowd, and they both need to be detected. No generic definition currently exists for abnormal events, which are usually dependent on the scene under consideration. For example, a car passing on the road is a normal activity but it becomes abnormal when it passes in the pedestrian lane. A typical approach for addressing such a scene’s context dependency is to consider a scene’s rare or unforeseen events as abnormal. Nevertheless, this may result in classifying unseen normal activities as abnormal. In general, it may not be possible to know all the normal and abnormal activities during training. It is only possible to have access to subsets of normal and abnormal activities. The lack of a generic definition and insufficiency in the data make it extremely hard for any learning algorithm to understand and capture the nature of an anomaly. The results of the related literature report some success stories along with several convincing studies, which are mostly conducted in constrained conditions. Under uncontrolled scenarios, the task of crowd anomaly detection is still challenging for the research community

4.PROPOSED SYSTEM

In recent years, Deep Learning (DL) approaches have become the state of the art in time series modeling. In particular, the combination of a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN) have shown promising results in multi-time series classification problems as they are able to work directly over raw data and thus no pre-processing nor additional domain knowledge is required. However, little research has been done in the anomaly detection domain using the CNN–RNN architecture. Hence, our aim is to investigate new techniques for supervised multi-time series anomaly detection based on this architecture. In this paper, we propose a new CNN-RNN architecture where the CNN is used to extract meaningful features from raw sensor data and the RNN is applied to learn temporal patterns. Unlike other approaches [26], [32], [33], we utilize an independent CNN to process each sensor data. Throughout the paper, we refer to each convolution as a convolutional head, thus forming a Multi-head CNN. Processing each sensor data on independent CNN entails a number of advantages: (1) the feature extraction is enhanced by focusing only on one particular sensor rather than on all at once, (2) each convolutional head can be adjusted to the specific nature of each sensor data, and (3) it makes the architecture flexible to adapt it to new sensor configurations as the convolutional heads can easily be added, modified or removed. Furthermore, instead of processing the entire time series resulting from sensor data, they are divided into smaller portions using a sliding window. Hence, the feature extraction is done window by window for each time series, meaning that it can focus on the different phases existing in a time series. Finally, the features coming from all convolutional heads are processed together window by window by the RNN side to classify the entire event. We will refer to the proposed architecture as Multi-head CNN–RNN.

5.SYSTEM ARCHITECTURE

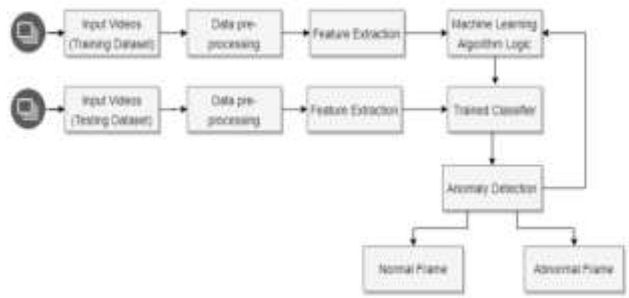

Fig.1 System Architecture

6.RESULT

Fig.2 In above screen click on ‘Generate Image Train & Test Model’ button to generate CNN model using LBP images contains inside LBP folder.

Fig.3 In above screen we can see CNN LBPNET model generated. Now click on 'Upload Test Image' button to upload test image.

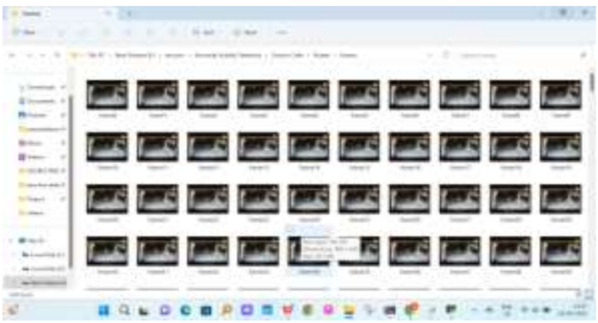

Fig.4 In above screen we can see two faces are there from same person but in different appearances. For simplicity I gave image name as synthetic and real to test whether application can detect it or not. In above screen I uploaded synthetic image.

Fig.5 And now click on 'classify Picture in Image' to get below details

Fig.6 In above screen we are getting result as image contains synthetic face. Similarly, you can try other images also. If u want to try new images, then u need to send those new images to us so we will make CNN model to familiar with new images so it can detect those images.

7.CONCLUSION

This paper defines a novel structure combining ResNet50 and ConvLSTM to detect abnormal behaviour in the UCF-Crime dataset. There are several limitations that we faced in implementing this model. The dataset we used is in different illumination, speed, and subjects. For instance, some anomalies happened in the video, while we could not see any person in some videos (i.e., car accidents). Besides, we need to deal with another limitation of our dataset. The abnormal events may only take one or two seconds to happen, and even in 10-second videos, more than 80 per cent of the video length shows it is normal behaviour. Despite all mentioned limitations, our proposed method outperforms other methods on the UCF-Crime dataset. In addition to using all 14 categories of UCF-Crime, binary classification, and dividing into four major categories, we also trimmed the original video of three different anomalous events. We have both abnormal and normal events with the same background and objects.

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