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ABNORMAL EVENT DETECTION IN VIDEO SURVEILLANCE USING DEEP LEARNING

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ABSTRACT

In the recent years, the surveillance tasks have been on the rise worldwide. However, in the context of abnormal detection, only one normal event is available for the learning process. Therefore, the implementation of a generative learning method in an unsupervised mode to solve this problem becomes fundamental. In this context, we propose a new unsupervised deep one class learning architecture. It's capable of generating optical flow images from original videos and extracting compact spatio-temporal characteristics for anomaly detection purposes. It is designed with a custom loss function as a sum of three terms, the reconstruction loss (Rl), the generation loss (Gl) and the compactness loss (Cl) to ensure an efficient classification of the "deep learnning" class. We tested our method on very complex datasets called UCSD abnormal detection dataset and obtained results is surpassing existing technique.

Keywords*: Convolutional neural network, IoT devices, anomaly detection; UAV videos; deep Learning.*

1. INTRODUCTION

The use of drones is booming around the world with a large variety of potential applications: wireless acoustic networking for amateur drone surveillance. A videodrone protection system is a closed-circuit television CCTV system that describes a whole range of video surveillance technologies. Many factors can significantly reduce the effectiveness of CCTV systems, such as fatigue and lassitude caused by prolonged viewing of many surveillance videos. A possible solution to this problem would be the use of intelligent video surveillance systems. These systems must be capable of analysing and modelling the normal behaviour of a monitored scene and detecting any abnormal behaviour that could represent a security risk. In recent years, considerable technological advances in the fields of machine learning and computer vision have made it possible to process CCTV systems. Some of these are classics of machine learning: image classification, facial recognition, human pose estimation, natural language processing, automatic voice recognition and even more atypical tasks; machine translation systems, reading and automatic software code generation. Moreover, Deep Learning (DL) is a sub-domain of Machine Learning (ML), it aims to learn high-level abstractions in data using multi-level architectures. These different levels are obtained by stacking several nonlinear transformation modules. Each module transforms the data at a different level until a suitable representation is obtained to perform the target task. Deep learning has made it possible to go beyond the traditional model in certain application cases and to design efficient pattern recognition systems without in-depth expertise on the target elements. In fact, the most effective deep-learning methods are based on supervised learning, using large, labelled databases containing samples from different classes. To take advantage of these learning materials in an intelligent monitoring system, a large amount of training data representative of normal and abnormal events is required. Abnormal events are the rare events that does not appear redundantly at the scene. Thus, there are many barriers to the creation of such databases—for example, we can cite the following:

- The contextual aspect of the event. Indeed, an event is closely linked to its context, an abnormal event in one scene can be normal in another. This point makes it almost impossible to design common databases that can be used uniformly for different scenes.
- Risks and variability to reproduce some abnormal events make it impossible to identify and generate enough training samples.

Abnormal video events have been called by many names in the literature, such as abnormality, irregular behaviour, unusual behaviour, or abnormal behaviour. These different names will be used alternately without worrying about technical inconsistency. The detection of abnormal video events is also characterised by a variety of strategies for processing training data. The first approach is to carry out the training only on normal data and to consider any type of event outside the training phase as abnormal.

2. RELATED WORKS

H. Song, C. Sun, X. et al. [1] presented a paper on autoencoder coupled with attention model to discover normal patterns in videos via adversarial learning. Abnormal events are detected by diverging them from the normal patterns with the reconstruction error produced by the autoencoder. To this end, we build an end-to-end trainable adversarial attention-based autoencoder network, called Ada-Net, to make the reconstructed frames indistinguishable from original frames. O. Ye, J. Deng, et al. [2] presented a paper on abnormal event detection hybrid modulation method via feature expectation subgraph calibrating classification in video surveillance scenes in this paper. Our main contribution is to calibrate the classification of a single classifier by constructing feature expectation subgraphs. First, we employ convolutional neural network and long short-term memory models to extract the spatiotemporal features of video frame, and then construct the feature expectation subgraph for each key frame of every video, which could be used to capture the internal sequential and topological relational characteristics of structured feature vector. S. Lee, H. G. Kim et al. [3] presented a paper on BMAN learns spatio-temporal patterns of normal events to detect deviations from the learned normal patterns as abnormalities. The BMAN consists of two main parts: an inter-frame predictor and an appearance-motion joint detector. The inter-frame predictor is devised to encode normal patterns, which generates an inter-frame using bidirectional multi-scale aggregation based on attention. With the feature aggregation, robustness for object scale variations and complex motions is achieved in normal pattern encoding. T.Gupta, V. Nunavath et al. [4] presented a paper on a a framework named as CrowdVAS-Net for crowd-motion analysis that considers velocity, acceleration and saliency features in the video frames of a moving crowd. CrowdVAS-Net relies on a deep convolutional neural network (DCNN) for extracting motion and appearance feature representations from the video frames that help us in classifying the crowd-motion behavior as abnormal or normal from a short video clip. These feature representations are then trained with a random forest classifiera framework named as CrowdVAS-Net for crowd-motion analysis that considers velocity, acceleration and saliency features in the video frames of a moving crowd. CrowdVAS-Net relies on a deep convolutional neural network (DCNN) for extracting motion and appearance feature representations from the video frames that help us in classifying the crowd-motion behavior as abnormal or normal from a short video clip. Arif Ahmed, D. Prosad Dogra, S. Kim et al. [5] presented a paper on trajectory clustering, summarization or synopsis generation, and detection of anomalous or abnormal events in videos are mainly being exploited by the research community. This paper presents a survey of trajectory-based surveillance applications with a focus on clustering, anomaly detection, summarization, and synopsis generation. The methods reviewed in this paper broadly summarize the abovementioned applications. The main purpose of this survey is to summarize the state-of-the-art video object trajectory analysis techniques used in the indoor and outdoor surveillance.

3. PROPOSED SYSTEM

We have used different datasets to evaluate the proposed deep learning algorithm.detection method. The model was trained with only normal events contained in datasets, and then it was tested within different abnormal events. The used datasets are listed as follows:CCTV Video Dataset is a dataset filmed by a cctv in a car park. It is mainly used for events identification. It is composed of 30 videos captured in high resolution, with a duration up to 24 s each. The videos in CCTV were divided into three categories: normal, suspicious, and abnormal, and they are defined by the actions of the persons involved in the videos. The normal case is defined by several events, such as people walking, getting in their cars, or parking correctly. The abnormal cases are represented by people fighting or stealing. Finally,for suspicious cases, nothing is wrong, but people do suspicious behavior which could distract the surveillance staff. In order to use the MDVD dataset in unsupervised mode for anomaly detection, we split this dataset into: 10 videos for the training containing only normal samples, and 10 videos for the test containing both abnormal and normal events..

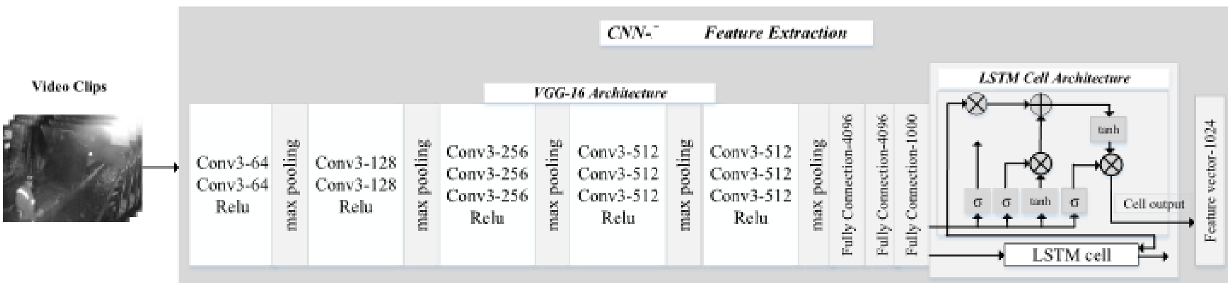

Figure 1: System Architecture of proposed system

IMPLEMENTATION:

The project constitute of below modules,

DATASET:

In this section, we present a method for detecting and localization of abnormal events in scenes, based only on training dataset of normal situations. Our work is divided into two main stages, the first one consists of extracting robust and discriminative features using the first two convolutional layers of a pre-trained CNN, and in the second stage, we use the resultant features to train a one-class nonlinear AlexNet algorithm Ex: videos will convertor 30 frames images

PRE-PROCESSING:

To reduce the variability in the Abnormal Event, the images are processed before they are fed into the network.All positive examples that are the Abnormal images are obtained by cropping images with frontal videos to include only the front view. All the cropped images are then corrected for lighting through standard algorithms.

4. CLASSIFICATION BASED ON FEATURE EXPECTATION

Interesting part of an image from where the required information's are extracted is called as feature extraction. Once the frames of video are represented using feature expectation sub graphs, we can use them to classify and recognize anomaly. In this section, we will combine with sconvolutional neural network classifiers and feature expectation sub graphs to calibrate the classification of a single linear convolutional neural network classifier.

5. RESULTS AND DISCUSSION

In this section, analyze the results of the proposed system which is implemented on the Python platform. The screenshots the experimental results our system. The abnormal Event Figure 3

Figure 3: abnormal Event

6. CONCLUSION

In this paper, we propose a new, unsupervised learning method based on deep one class architecture for the detection of abnormal in video surveillance . The main advantage of this method is its efficiency to jointly extract the optical flow features and to integrate a compactness regularization term during training. This method proves promising in terms of detection and localization of abnormal by surveillance and gives very high performance experimental results compared to state-of-the-art methods

REFERENCE

[1] H. Song, C. Sun, X. Wu, M. Chen, and Y. Jia, "Learning normal patterns via adversarial attention-based autoencoder for abnormal event detection in videos," IEEE Transactions on Multimedia, vol. 22, no. 8, pp. 2138–2148, 2020.

[2] O. Ye, J. Deng, Z. Yu, T. Liu, and L. Dong, "Abnormal event detection via feature expectation subgraph calibrating classification in video surveillance scenes," IEEE Access, vol. 8,pp. 97564–97575, 2020.

[3] S. Lee, H. G. Kim, and R. M. Ro, "BMAN: bidirectional multiscale Aggregation networks for abnormal event detection,"IEEE Transactions on Image Processing, vol. 29, pp. 2395–2408, 2019.

[4] T.Gupta, V. Nunavath, and S. Roy, ‘‘CrowdVAS-net: A deep-CNN based framework to detect abnormal crowd-motion behavior in videos for predicting crowd disaster,’’ in Proc. IEEE Int. Conf. Syst., Man Cybern. (SMC), Bari, Italy, Oct. 2019, pp. 2877–2882

[5] S. Arif Ahmed, D. Prosad Dogra, S. Kar, and P. Pratim Roy, ‘‘Trajectory-based surveillance analysis: A survey,’’ IEEE Trans. Circuits Syst. Video Technol., vol. 29, no. 7, pp. 1985–1997, Jul. 2019