International Journal of Scientific Research and Engineering Development-– Volume 2 Issue 3, May –June 2019

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Abnormal Events Detection in Surveillance Systems

Varuna S[1], Shreyas P Bhat[2], Kiran T S[3], Mrs. Sumana C[4]

[1](Undergraduate student, Computer Science and Engineering, Jyothy Institute of Technology, Bengaluru
Email: sathyavaruna@gmail.com)

[2] (Undergraduate student, Computer Science and Engineering, Jyothy Institute of Technology, Bengaluru
Email:shreyasbhat.bhat@gmail.com)

[3] (Undergraduate student, Computer Science and Engineering, Jyothy Institute of Technology, Bengaluru
Email: kirants540@gmail.com)

[4](Assistant Professor, Dept. of Computer Science and Engineering, Jyothy Institute of Technology, Bengaluru
Email: sumana.c@jyothyit.ac.in)

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Abstract:

The detection of abnormal events has an essential role in video content analysis and is a challenging task in order to monitor the surveillance fields. In this paper, we proposea way to train the neural network through abnormal, anomalous and normal videos with clipping them as video segments and extracting the features. The anomaly detecting model trained, predicts probability scores for the testing video segments.

Keywords **—anomaly event detection, video surveillance, computer vision, activity recognition, feature extraction.**

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I. INTRODUCTION

Video surveillance systems are important field monitoring systems for security and law enforcement.Smart video surveillance is a very popular research topic in computer vision applications.As surveillance cameras are increasingly used, real world anomalous events are necessary and are harder to detect.Detecting anomalous events such as traffic accidents and crimes from the videos is a challenging and laborious task. Developing an intelligent system to detect these types of events alleviatesthe waste of labor and time.As it is difficult to list all of the possible anomalous events, it is desirable that an abnormal detectionalgorithm does not rely on any prior information aboutthe events. State of the art anomaly detection based on sparse coding[1,2]produceshigh false alarm rates for different normal behaviours as, itassumes that only a small initial portion of a video contains normal events, and thatinitial portion is used to build the normal event dictionary.However,surveillance cameras can change drastically over time based on different times of the day.

The above mentioned sparse codingapproach considers any pattern that deviates from the learned normal patterns as anomalous i.e. untrained normal videos are predicted as anomalous. We propose using deep neural networks framework by treating normal and anomalous surveillance videos as bags and short segments/clips of each video as instances in a bag. Based on training videos, we automatically learn an anomaly ranking model that predicts high anomaly scores for anomalous segments in a video. During testing, a long-untrimmed video is divided into segments and fed into our deep network which assigns anomaly score for each video segment such that an anomaly can be detected.

II. RELATED WORK

Abnormal detection is one of the most demanding and challenging to accomplish in computer vision. Several attempts have been made in surveillance systems to detect anomalous behaviour[3].Yihao Zhang*et al.*proposes anomaly detection in traffic video with the information provided in the HEVC compressed domain.In High Efficient Video Coding (HEVC)[4].Tian Wanga *et al.* propose event detection based on moment feature descriptor and classification. The feature descriptor extracts the optical flow and computes the histogram of optical flow orientations(HOFO).The hidden Markov model(HMM) is proposed to classify the events due to the probabilistic property. HOFO feature descriptor is based on the movement and if the index of the HOFO is at a low level [5].

Lazaros Lazaridis*et al.*proposed a crowd behavior analysisthat uses crowd density heat maps and optical flow information to classify abnormal events.Filters of different sizes in order to produce density heat maps.Optical flow algorithms calculate the displacement of motion of objects, surface and edges in a video from one frame to other [6].Zhipeng Wang*et al.* proposed an abnormal event detection in video via motion information entropy.Calculation of the frame level motion entropy which is used to describe the confusion of a scene based on that motion entropy, the second component calculates the Gaussian distribution of normal scene. And then it uses the truncated probability to detect whether the frame is abnormal or not [7].Yu Zhao*et al.* proposed approach using the spatio-temporal feature and nonnegative locality-constrained linear coding (NLLC) isproposed to detect abnormal events in videos[8].

Fan Jiang*et al.* propose a multi-sample-based similarity measure, where HMM training and distancemeasuring are based on multiple samples. These multipletraining data are acquired by a novel dynamic hierarchicalclustering (DHC) method[9].Xun Tang*et al.* present a method based on sparselycoded motion attention for detecting abnormal events in crowded scenes[10].

III. METHODOLOGY

The proposed approach first divides the surveillance videos into two sets, anomalous and normal set. Videos clipped in segments for feature extraction and train the abnormal detection model.

A. Dataset

The dataset used for the proposed approach is University of Central Florida(UCF) anomaly detection dataset. The dataset contains total of 1692 surveillance footages that are divided into, 900 abnormal videos and 792 normal videos. The abnormal videos covers 13 real world anomalies and abnormal events classified such as, Arrest, Arson, Assault, Accident, Burglary, Explosion, Fighting, Robbery, Shooting, Stealing, Shoplifting, and Vandalism.Table 1 provides the additional information about the UCF dataset.

B. Feature Extraction

Table 1	**No. of videos**	**Average no. of frames**	**Example anomalies**
UCF Dataset	1692	7000	Arrest, arson, assault, accident, burglary, fighting, explosion

The initial step before training the abnormal event detection model, visual features of the dataset videos are extracted from fully connected FC6 of Convolution 3D neural networks. Each video frame is resized to240 x 360 pixels at 30 frames per second framerate.Each video is divided into clips, each clip contains 16 frames. Feature extracted values are saved to a text files for corresponding video clips.

C. Training Abnormal Event Detection (AED) Model

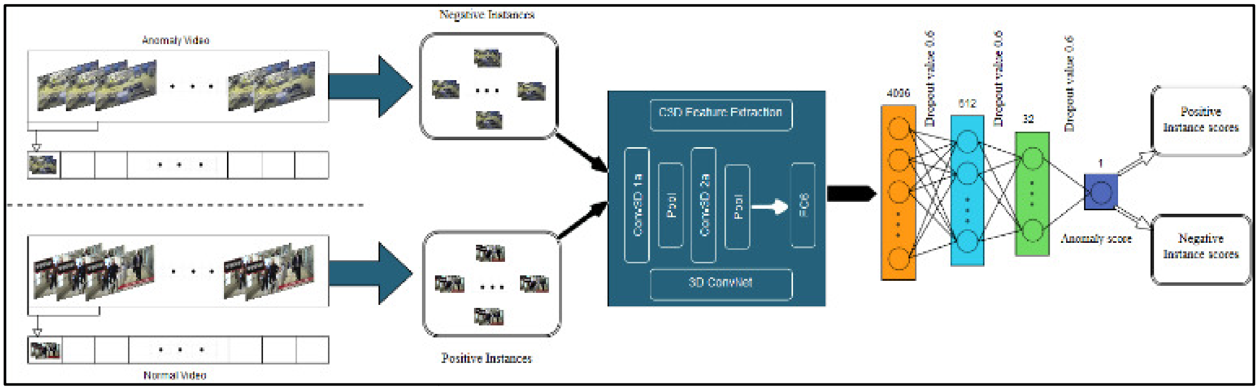

Figure 1. The flow diagram of the proposed anomaly detection approach

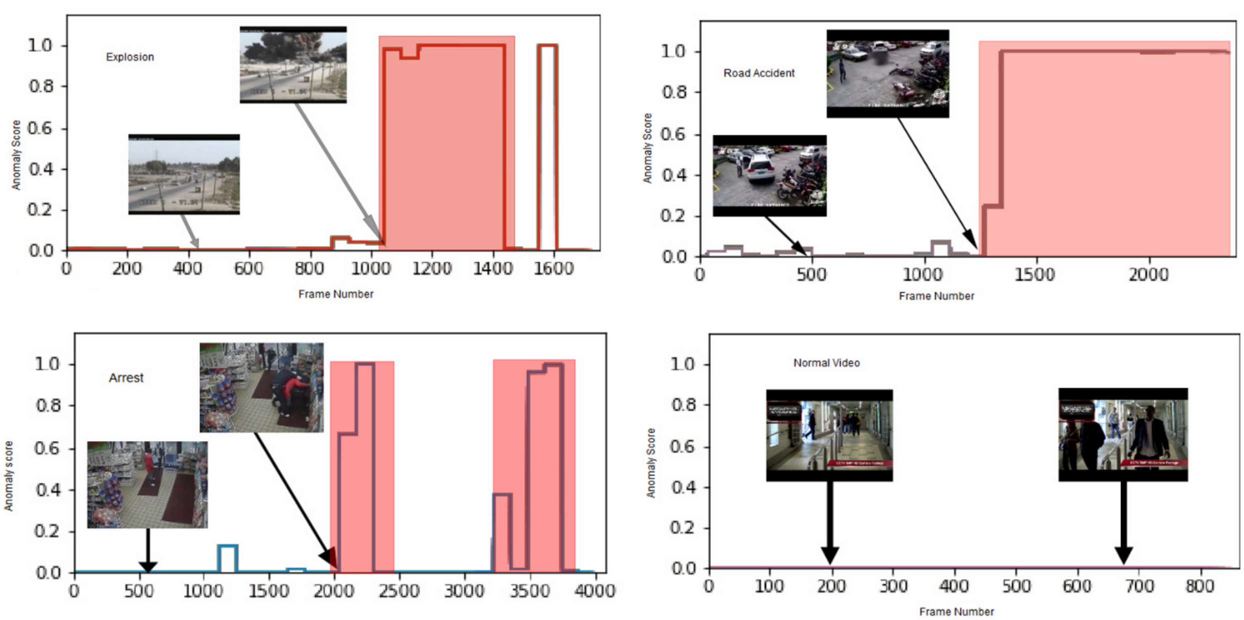

Figure 2. Results of anomaly detection model on testing videos. The testing videos represent explosion, road accident, arrest and normal video.

The extracted features of datasets are inputs to the 3-layer fully connected neural network. The videos segments are divided as positive set and negative set and input to the 3-FC network. The first layer has 512 units, second layer has 32 units and third layer has 1 unit, with 60% dropout regularization between each of the fully connected layers. The training produces scores or weights for the abnormal event detection model.Then we compute loss based equations provided by Waqas Sultani et al.[].Next step here is to back-propagate the loss for the whole batch and repeat the process for an appropriate number of epochs/iterations so that over-fitting of the model is minimal.Figure 1 shows the flow diagram of the proposed abnormal detection approach.

D. Testing AED Model

The AED model uses the trained weights for detecting abnormalities in test videos. The test video is divided into clips, each clip containing 16 frames similar to training. The divided clips are feature extracted. Extracted features are fit to the AED model, to produce positive and negative probability scores for each video clips. A graph of the scores and their corresponding frames is output. Anomalous frames values will have anomalous probability detection spikes in the graph.

E. Abnormal Activity Recognition Results

Untrained videos can be tested for abnormality, the classification probability output graphs foreach video clips generated are converted to gif format with video playback. The Figure 2 shows some of the anomaly activity recognition results.

IV. CONCLUSIONS

The abnormal event detection in surveillance systems proposes a deep learning neural network that uses convolution neural networks for feature extraction for training the AED model. A large dataset of videos is obtained by UCFanomaly detection dataset, used to train deep neural network proposed. The experimental results on the dataset show that AED model performs better than other traditional anomaly detections methods. The future enhancements of the proposed method are reducing the over-fitting of the model and increasing the number of real world anomalies represented in the dataset.

ACKNOWLEDGMENT

This project was supported by Principal of Jyothy Institute of Technology,K. Gopalkrishna,Head of the Department,Dr. Prabhanjan S, and our project guide,Mrs. Sumana C.

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