ABNORMAL EVENT DETECTION IN SURVEILLANCE VIDEOS

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Abstract- This is an approach to detect anomalous activities from surveillance videos. Anomalous activities are the activities which are unusual to occur, it can be due to violation of rules and regulations or other unexpected incidents. The proposed approach can detect any such anomalies happening in a stationary surveillance camera video frame. We use unsupervised Learning here because abnormal events are rare to occur. We use convolutional auto encoder to train the model with normal frames in the stationary camera. We train our convolutional autoencoder to give high reconstruction cost for anomalous frames. We use USCD datasets to test and evaluate our method. Currently manual supervision is inefficient. It is important to detect abnormal events occurring in day-to-day life.

I.INTRODUCTION

We might be having plenty of surveillance cameras that work 24x7. Many of these cameras are placed in public and private sectors where people are bound to certain rules and regulations. There may be many possibilities of abnormal events occurring such leading to violation of law.If we can describe an example driving a bicycle in a park where vehicles are not allowed is violation.

Definition of anomaly differs from place to place depending on their rules and regulations. It is necessary to detect anomalies for better security and surveillance.In Practice anomalies are hard to detect. Analyzing frames of videos is a vital part of detection. There are huge efforts in developing anomaly detection systems with higher accuracy and prediction techniques. In supervised learning methods we have to manually label the training data which is not applicable here due to mainly two reasons. they are

1. Abnormal events data are difficult to find in the real world.
2. There are plenty of different kinds of anomalies in the real world and we cannot manually find all the instances and labelling is hard.

Due to the above reasons we are using autoencoder which is an unsupervised learning technique.
The work in this paper is aimed to create an approach which is suitable for regulating

rules in public and private sectors, also our approach can be deployed in systems which have lesser computation power and faster run time by avoiding other computationally complex steps by considering our use case.

III.RELATED WORK

In process of detach the low variations and noise in the background,we try to extract motion descriptor of the foreground by combining background subtraction with the binary operations of surveillance videos.In training stage, in order of gaining low ranked dictionary based on extremely similarly matching of training values and a isolate cluster for reconstruction coefficient vectors covering in a specific time,we try to put forward the optimized form of nuclear-norm and 1-norm and l2,In the process of detection ,we try to get a huge gap between the errors of reconstructions and some of regular samples,here we constrain the reconstruction vectors coefficient of some abnormal frames to issue so that look of normal by evaluating an 12 model,1-norm problem[1].We put forward a novel based on autoencoder to capture informational portrayal to detect anomaly in frames of videos by constructing a motion autoencoder,which receives successive frames as a seed of input and Difference in RGB as the output in order to simulate the optic flow[1]. Hence the considered model is much faster quick than any other past flow based learning method,where the mean time in this approach is fps of 32.We do not take consideration about the variance module to itself assign its importance weight to the speeding part of surveillance videos,it will improve the performance of the autoencoder.We create a cluster to autoencoder to outcomes the closed motion and looks describing.The cluster is trained to handle normal occuring,the path between the abnormal portrayal dates greater than the patterns of normal.The possibility is the error of reconstruction and path cluster are joined to access the abnormal event[3, 6].

III.METHODOLOGY

We can import a video using OpenCV libraries functions and loop through the frames. For processing and storing frames also we got functions in the opencv library to convert each frame into required dimensions and store them in the required data structure. Training an Autoencoders by passing the normal video frames for extracting features and fitting it such that it gives less reconstruction cost for normal frames. Once this model is ready we pass the testing dataset video frames and calculate the reconstruction cost. The detailed explanation is explained below.

Training Stage: We use set of only normal frames as the training set, We train a convolutional autoencoder by giving these frames as input.Since the trained model is fit for normal frames, we expect a high reconstruction cost from the autoencoder when we try to give an abnormal frame as the input

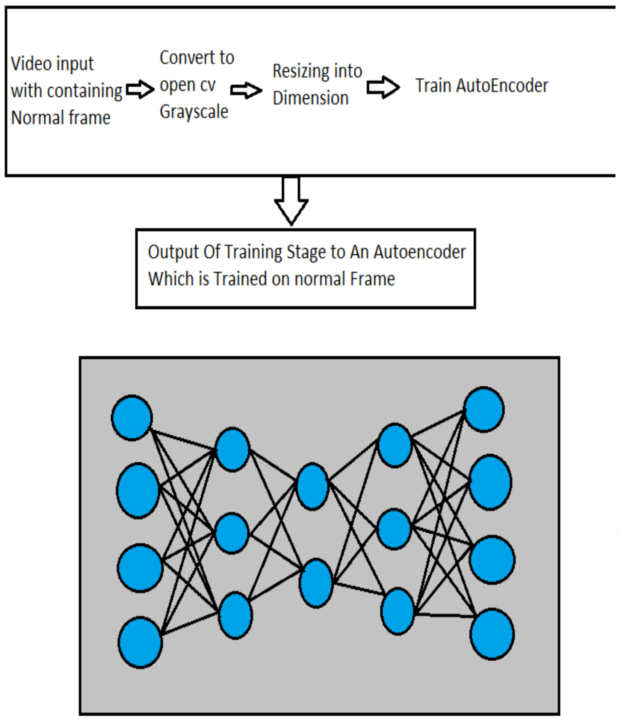

Fig 1: Flowchart for Training Stage

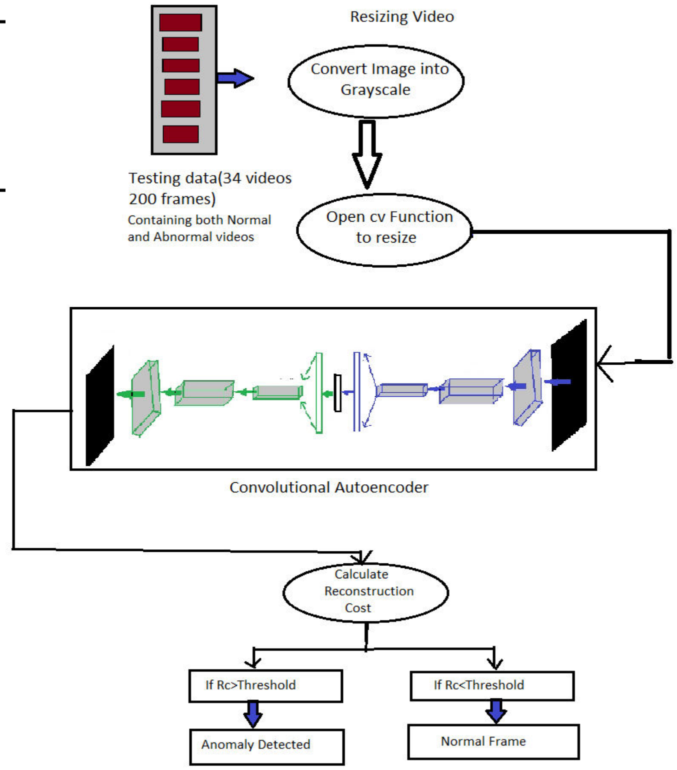

Fig 2: Flowchart for Testing stage

Testing Stage: Since the trained model is fit for normal frames, we expect a high reconstruction cost from the autoencoder when we try to give an abnormal frame as the input. So for the frames which have anomalies by setting a threshold for the reconstruction error we can detect an anomaly. The frames which give reconstruction cost higher than the threshold are considered as abnormal events/Frames.

IV.FLOWCHART

Fig 1 Shows the flow diagram of the training stage: The output of the process is a trained autoencoder model . Fig 2 shows the flow diagram for the testing stage, when we pass our video input to the trained model we reach an if condition which gives our final prediction for each frame.

V.RESULTS

We have given 36 Testing Videos as inputs which contain 200 frames. We create a simple convolutional autoencoder with eight hidden layers and the other is a convolutional autoencoder. We show that autoencoders are better than other image processing systems. The trained convolutional model gives reconstruction cost for each frame in each video. The graph plot denotes along x-axis frames count and along y-axis reconstruction cost as shown. Here it is a pedestrian's walkway. In the normal videos that we used for training the model, people were walking through the

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street which is considered as a normal event. The abnormal events our model detected are cyclists, people walking across the grass, people running too fast, moving vehicles in the street.
As shown above figure 3 there are instances causing the anomaly such as a car and a bicycle passing in the park. From the graph it shows values from 0 to 54 it is normal and it is observed that reconstruction cost is a low value. Later on the value of the reconstruction cost has huge fluctuations in the reconstruction cost values thus, it represents that anomaly is occurring.
To evaluate our model we compared it to the optical flow based [1, 4], LSTM based [2, 7] both of these methods need huge amounts of computation power to both train and test as we are aiming for a wide range for computing devices across. Also the binary subtraction method [1] can lead to inconsistent predictions in the beginning of video, since background detection algorithms need multiple frames in the beginning to figure out the background.
In the practical world we need more accurate true alarms when an anomaly happens and less importance to false alarms. F1 score has got less contribution from false alarms, so we used F1 score to evaluate our model.

$$F1 = 2 \times \frac{\text{Precision x Recall}}{\text{Precision + Recall}} = \frac{TP}{TP + \frac{1}{2}(FN + FP)}$$

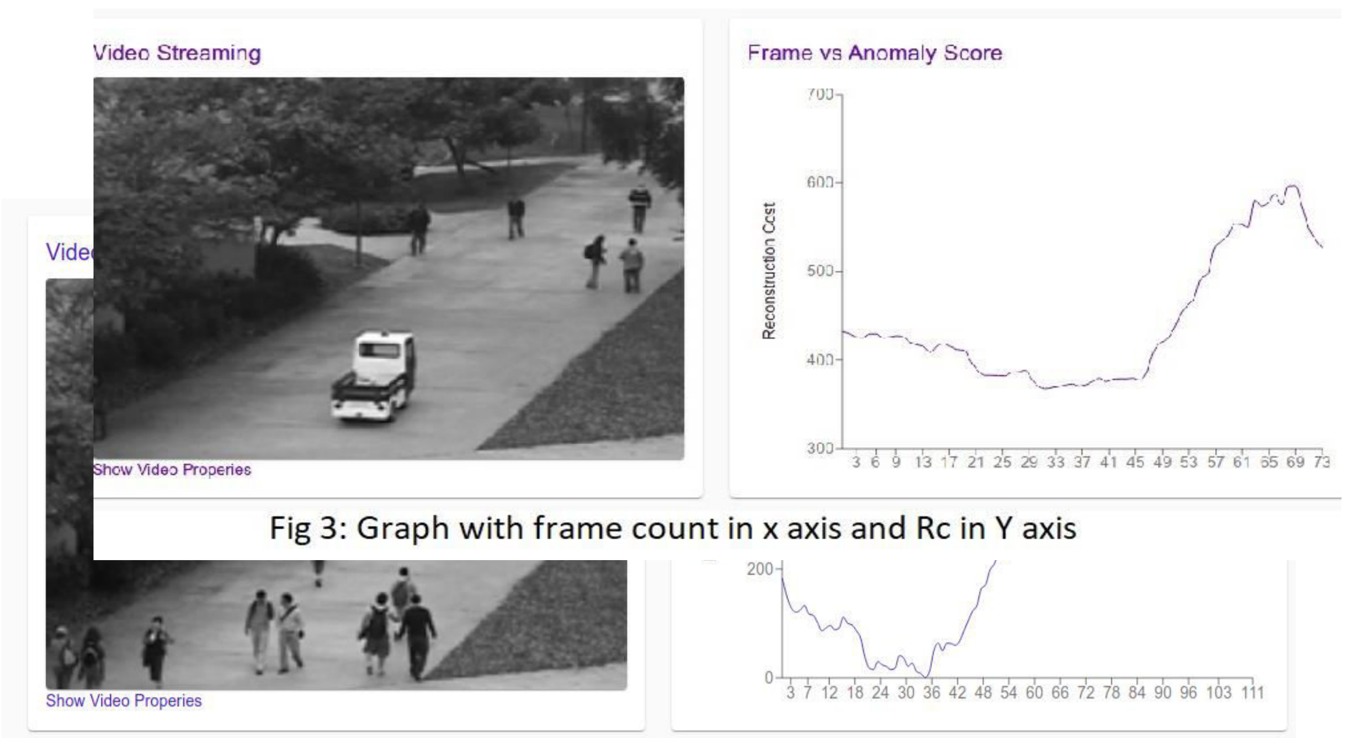

Fig 3: Graph with frame count in x axis and Rc in Y axis

Our papers also show the prediction graph which gives a clear picture of the occurrence of anomaly through the number of video frames and reconstruction cost.

VI.APPLICATIONS

The application of this technology can be implemented in many places such as public parks, traffic roads, streets, and even in public sectors, since detection plays a vital role it will be very useful to the public and private sectors in monitoring any anomaly. It can be used in any monitoring systems as it might be helpful in detecting guides to abide by the rules and regulations of certain organisations.

VII.CONCLUSION

This paper is basically on a machine learning system that can be used in detection in surveillance cameras. We are trying to reach maximum and accurate computation as possible and approximate may be precise detetections. Day to Day there are huge anomalies happening in real world situations which should be under monitoring and sorted out .We can use better models and datasets,compute the anomalies. Anomalies occur in different versions in nature may theft,fraud many can be recorded and found in anomalies.

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