Recent Advancement in Anomaly Detection in Surveillance Videos

Priyanka Patel, Amit Thakkar

Abstract*: Detection of Anomaly is of a notable and emergent problem into many diverse fields like information theory, deep learning, computer vision, machine learning, and statistics that have been researched within the various application from diverse domains including agriculture, health care, banking, education, and transport anomaly detection. Newly, numbers of important anomaly detection techniques along with diverseness of sort have been watched. The main aim of this paper to come up with a broad summary of the present development on detection of an anomaly, exclusively for video data with mixed types and high dimensionalities, where identifying the anomalous behaviors and event or anomalous patterns is a significant task. The paper expresses the advantages and disadvantages of the detection methods the experiments tried on the publically available benchmark dataset to assess numerous popular and classical methods and models. The objective of this analysis is to furnish an understanding of recent computer vision and machine algorithms methods and also state-of-the-art deep learnings techniques to detect anomalies for researchers. At last, the paper delivered roughly directions for future research on an anomalies detection.

Index Terms*: Anomaly, Detection, Surveillance, Locality, Outlier Detection, Unseen Pattern Detection, Video Understanding.

I. INTRODUCTION

Anomaly detection is of major attention to many different areas within deep learning, statistics, machine learning. The main objective to detect and identify those areas of the region whose pattern or behaviors do not conform to expected in that dataset. These unexpected events which are remarkably different from an observation data set, these are called anomalies. Unobserved pattern or novelty fluctuation in data is also a anomaly [9]. In spite of this, still, there is a no solid standard definition of this concept. An abnormality is likewise alluded to as a special case like an exception, outlier, variation conflicting object and it's by and large relying upon various applications. To detect or identify outliers or unexpected patterns are significant in numerous domains including business intelligence, machine learning, deep learning, decision making, network transmission, transport, production. For example, an abnormal event is accrued in the surveillance video, and unexpected block in the brain veins which can be a precursor of a brain tumor. As a result of this reality, anomaly discovery has a wide scope of domain. They are a fraud in credit card, health care, Agriculture, computer network, cleaning of data, video surveillance. After developing in machine learning the deep learning techniques has performed a vital role. Nowadays due to the wide range of smart gadgets are used, due to these information gathered from the real world are increasing and bigger which is likewise vast by size and Dimensionality. The property of the high-dimensional makes the data objects nearly equidistant to one another. Which will indicate that any data objects become very close as the dimensionality of data increases, resulting in the insignificant nature of their respective distances. Due to this nature, the standard methods for detecting anomaly cannot impressively manage high-dimensional data. Standard anomaly detection methods work better on the same type of patterns or features. But in real-world applications often have different types of patterns and features like nominal, binary, numerical, or categorical. This types of an anomaly lead to increased difficulty in detection of an anomaly in the dataset. Since many potential applications of detection of anomaly has been proposed and a wide range of detection algorithms are also developed from the past many years. In this paper, the concise audit of the present works and spot unique spotlight on the ones for that complicated video information with high dimensionalities and mixed types. Almost from the century, people are working on the security, to detect anomalies from surveillance video is a not a trivial job, to find anomaly is exceptionally important, specifically for video surveillance. Detection of Anomaly events in surveillance video refers to the task of finding observations that do not conform to the normal or predictable behavior. At the present time, many devices and measurements have been anticipated based on hand-crafted features. On the other hand, it remains challenging to efficiently distinguish abnormal entity from normal ones.

II. ANOMALY AND ANOMALY DETECTION

Anomalies are pattern or observation in the data that do not conform to the normal or expected behavior. Detection of Anomaly is an approach to discovery the patterns from given dataset whose behavior is not normal on expected. These unexpected behaviors are characterized as the outliers or anomalies.

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Anomaly some time also referred as Noise and detection of anomaly is referred as noise removal [8]. Removal Represents anomalies in a simple two-dimensional dataset as shown in Figure 1. In the whole dataset, there are two normal regions which are S1 and S2, since almost all observations fall under these two regions. Pints G2, G3, & G4 are far away from R1 and R2 region. R1 & R2 are considered as normal regions. Here the G1 region is also anomalies as it does not fall under normal regions R1 & R2.

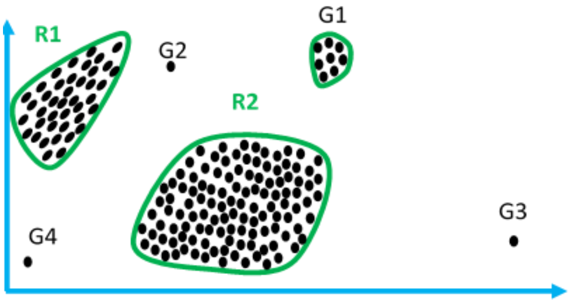

Figure 1 Example of G1-G4 Anomalies in 2D dataset

III. BACKGROUND INFORMATION BACKGROUND ASPECTS OF ANOMALY DETECTION

In this section, we have discovered almost all available previous research that sort of data are there refer figure 2. What types of methods, which video based anomaly detection techniques are available, what sort of labels on the instance, and models [1, 5].

A. *Type of Data*

The idea of properties decides the appropriateness of abnormality identification systems. The fundamental key part of any anomaly detection method is the idea of information as you taking as input. The information is commonly a gathering of information examples which alluded to a point, record, object, vectors, design, occasion, case, tests, perception, and substance. Refer figure 3.

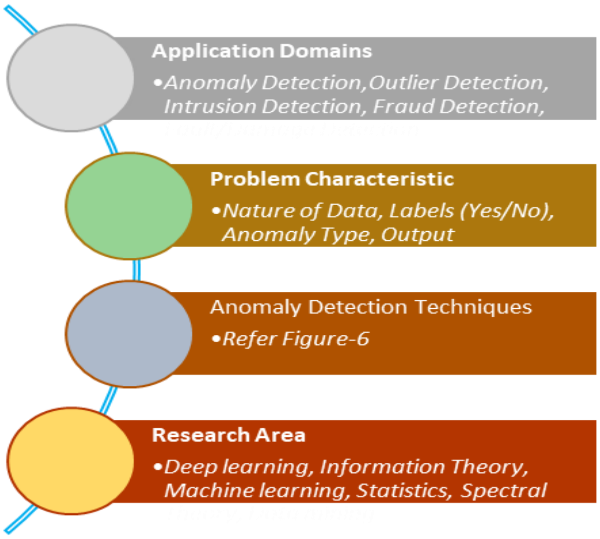
Application Domains
•Anomaly Detection,Outlier Detection, Intrusion Detection, Fraud Detection,
Problem Characteristic
•Nature of Data, Labels (Yes/No), Anomaly Type, Output
Anomaly Detection Techniques
•Refer Figure-6
Research Area
•Deep learning, Information Theory, Machine learning, Statistics, Spectral

Figure 2 Aspects of anomaly detection problem

B. *Nature of Data*

Dataset Description:1)UCSD-total 98 videos are available which acquired pedestrian walkway. A stationary camera fixed at an elevation, supervising whole pedestrian path. 2) Caltech Pedestrian Detection dataset- 2300 unique pedestrians in 10 hours video. 3) Crowd activity datasets- University of Minnesota multiple dataset for monitoring human activity. 4) USC's dataset- USC's School of Engineering, A number of fairly small pedestrian datasets taken largely from surveillance video. 5) Anomalous Behaviour Data Set- it's a multiple dataset for anomalous behaviour detection in video. 6) Virat- Approx. A8.5 hours of videos which surveillance data for human activity/ event detection. 7) McGill University Dominant and Rare Event Detection Data- 3 video clips (43, 96 mins) - it's a video surveillance data for dominant and rare event detection captured by cameras from a subway station. 8) UCF Crime dataset-biggest dataset total 128 hours with 13 classes and 1900 videos. Untrimmed surveillance videos with 13 real world anomalies like arson, arrest, abuse, assault, road accident, burglary, explosion, fight, stealing, shooting, etc...

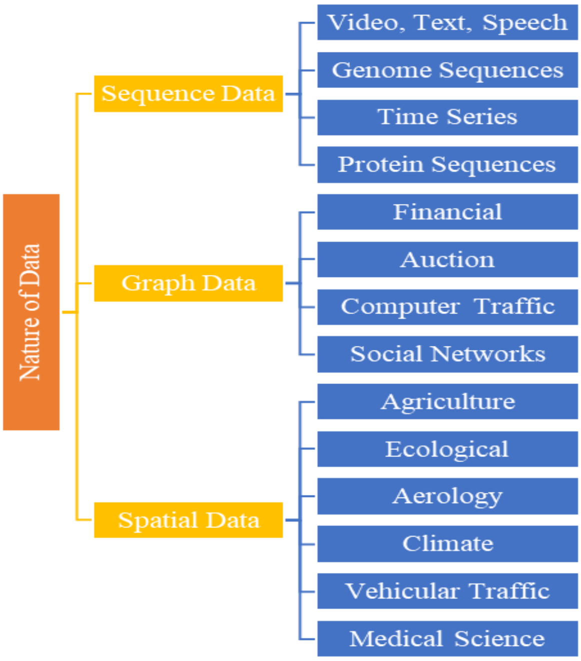

Figure 3 Nature of data

C. *A deep learning architecture with respect to the dataset*

Table 1 A deep learning architectures with respect to the dataset

Type	Example of Data Type	Deep learning Architecture
Sequential	Video, Text, speech, time series, signal, protein sequence, Genome Sequences	Convolution Neural Network, Recurrent Neural Network, Long Short-Term Memory

Type	Example of Data Type	Deep learning Architecture
Graph	Financial, Auction, Computer Traffic, Social Networks	Convolution Neural Network, Deep Convolution Neural Network, Deep Graph Convolutional Neural Network
Non-Sequential	Image, sensors, other	Convolution Neural Network, Auto encoder and its modifications
Spatial	Agriculture, Ecological, Aerology , Climate, Vehicular, Traffic , Medical Science	Convolution Neural Network, Deep Convolution Neural Network

D. *Type of Labels on Instance in Anomaly Detection*

I. *Supervised*

- Training dataset with labelled instance (normal and anomaly). To propose a predictive model for abnormal and normal classes. So any unnoticed action or instance will further match and compare with the model to determine the classes (Anomaly/Normal).Issues with this method:
- Issues with this method:
  - ○ During Training time: Anomalous instance are far fewer than Normal instance due to this imbalance classes distribution may occurred.
  - ○ It is usually challenging for obtaining exact and representative labels, especially for anomaly classes.
- Supervised Anomaly detection problem is as same as building predictive model.

II. *Unsupervised [15]*

- This method do not required training data.
- It is mostly based on the assumptions that normal instance are far more frequent than anomalies in the dataset. Due to these sometime this technique suffers from high false alarm rate.
- Numerous semi-supervised techniques can be adjusted to work in an unsupervised mode by utilizing a sample of the unlabelled dataset as preparing data.

III. *Semi Supervised*

- Training Data- With assumption that only normal class are labelled in training data.
- Do not require labels for anomaly class.
- More significant technique than supervised.
- Build a model for normal class and use it to identify Anomaly class.

E. *Type of Anomaly*

It can be shared into below mention types: Point, Contextual, and Contextual Anomaly.

I. Point/ Global anomaly: It has been observed during reviewing previous research work and it is well explored in literature, the point anomaly is a commonest and most used type. Figure-2 illustrate the point G1 is measured as point anomaly and arena G2 is measured as global anomalies as both are outside of R1 and R2 region. This type of anomalies also can be defined as an individual object/entity which is measured as anomalous with regards to other data in region and it is also known as global outliers as like point arena G2[1]. Means a data point is considered a global anomaly if its value is far outside the entirety of the data set in which it is found. For example: A employer who normally deposits salary of one employee is 450000 per month in checks at a local ATM suddenly makes two cash deposits of 100000 each in the span of two weeks is a global anomaly, because this event has never before occurred in this employee's history. The time series data of their weekly deposits would show an unexpected recent spike/point. Such a drastic change would raise alarms as these large deposits could imply illegal commerce or money laundering.

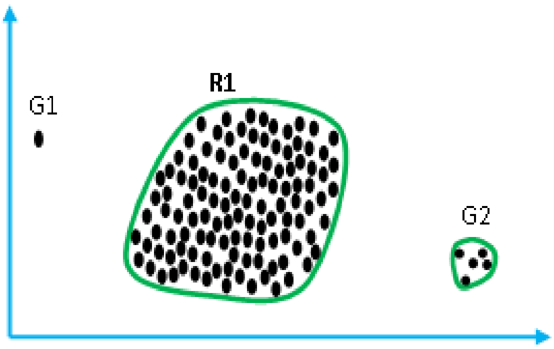

Figure 4 G1 & G2 are Global Anomaly for Normal Region R1

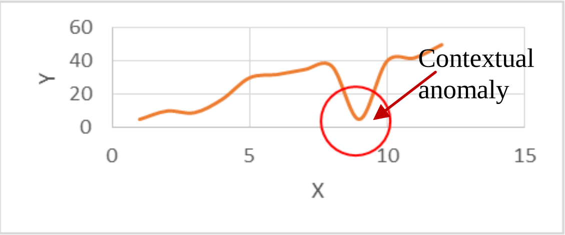

Figure 5 example of conditional anomaly

I. Contextual Anomaly: It may be characterized as in some particular condition or context in the event that a data instance is an outlie, at that point, it is a contextual anomaly. In spatial data and time series data, these types of anomalies are usually discovered. Some time it is also denoted to as outlier or conditional anomaly.

II. Collective Anomaly: A collection of related data instances is anomalous. Requires a relationship among data instances like Sequential Data, Spatial Data, and Graph Data. The individual instances within a collective anomaly are not. Collective anomaly are Anomalous by themselves.

F. *Type of Output*

Finally, the model produced output with two types: 1) Label: It will assign a Normal and Anomaly labels to each instance. 2) Score: The score will assign to each instance of the test data and after depending upon that instance is considered as an anomaly. This method creates a Rank list of anomalies an examiner may pick initial 5-10 abnormalities or may pick through some threshold values to select anomalies.

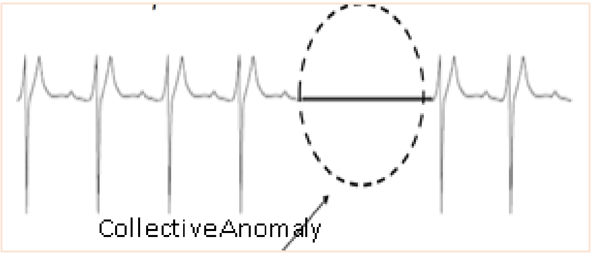

Figure 6 Example of collective Anomaly

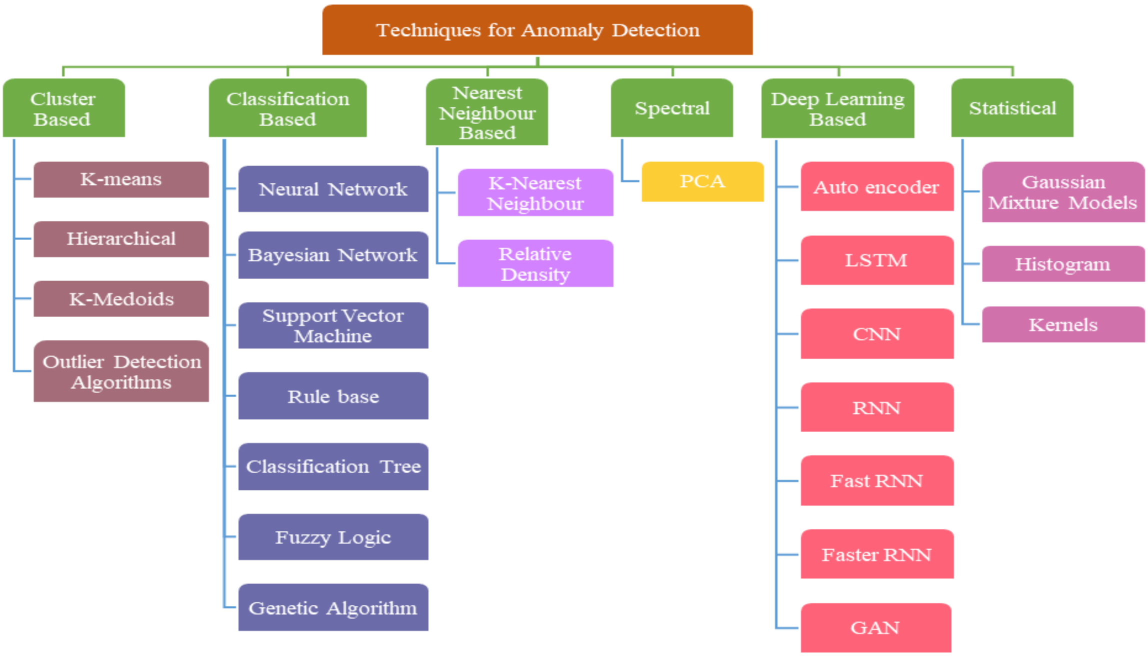

Figure 7 Anomaly Detection Techniques Classification

G. *Type of Techniques*

Various existing anomaly detection techniques has been classified in figure-5 that are generally used for detecting anomalies in various domains and mainly five different classes for different applications domains are listed. Paper focused on video surveillance domain and in surveillance domain various open applications including computer network, land transport, banking, agriculture, education, and security. Some deep learning techniques are also available for anomaly detection is also available including Auto-encoders, Long Short Term Memory Networks, Restricted Boltzmann Machines, Deep Neural Networks Gated Recurrent Unit, Recurrent Neural Networks, Convolutional Neural Networks, Variation Auto-encoders, Generative Adversarial Networks. Nowadays, deep learning techniques achieves good performance and flexibility by learning to represent the data as a nested hierarchy of concepts within layers of the neural network. Deep learning outperforms the traditional machine learning as the scale of data increases as illustrated in Figure 7[5].

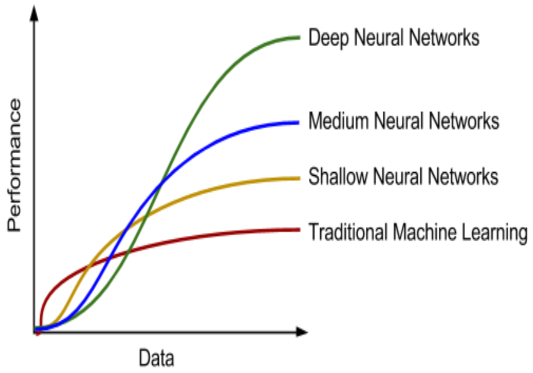

Figure 8 Performance Comparison of Deep learning-based algorithms Vs Traditional Algorithms Alejandro [2016].

IV. RELATED WORK

Table-1 shows the survey of techniques and application domain of resent trends. Despite of application domain and particular traditional techniques nowadays researchers are using hybrid approach to solve the problems.

During 2006 and afterwards people are more doing research on how deep learning methods are used to solve different types infect despite of any domain how it will work. The advance techniques of deep learning has impressed the researchers because these techniques gives better results and good accuracy but to achieve those benchmark result one need to high performance GPUs.

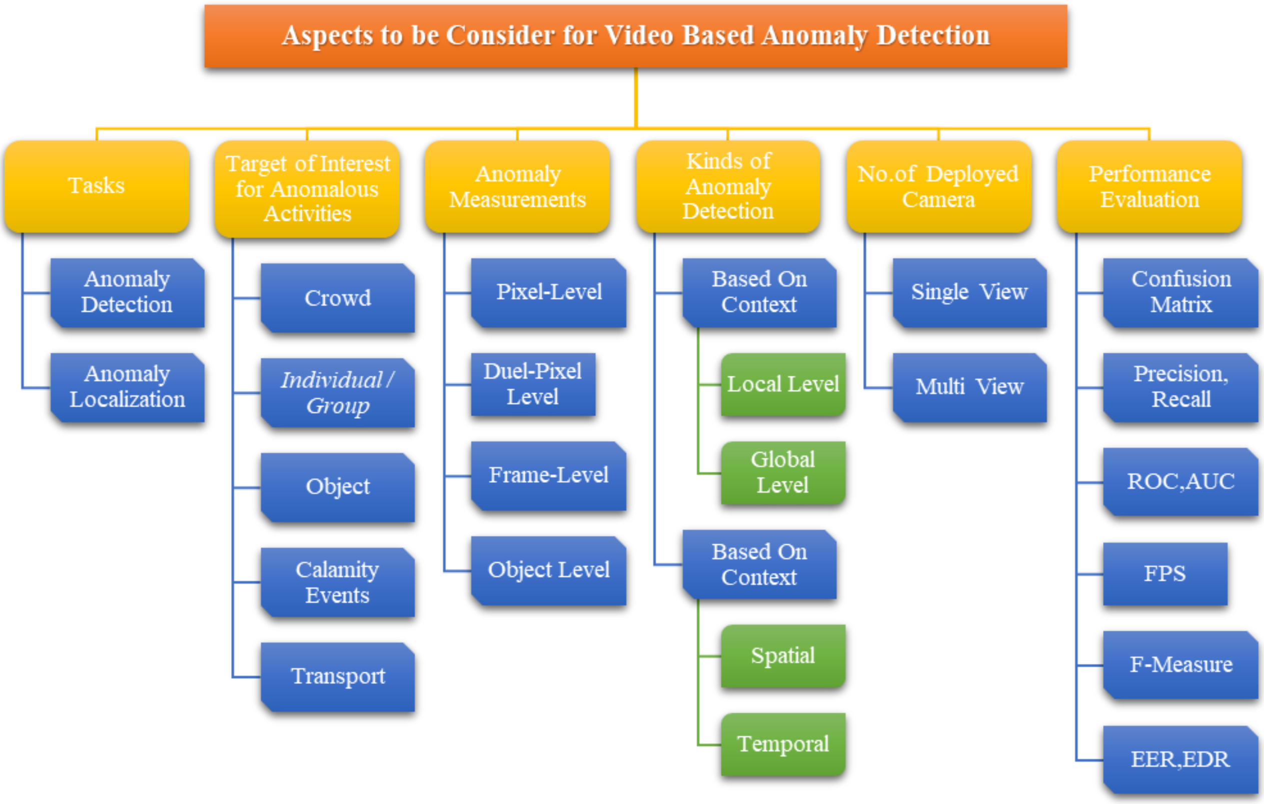

Figure 9 Anomaly detection approaches

Table 2 Comparison of our Survey to Related Survey Articles. 1 - Landi, Federico, Cees GM Snoek, and Rita Chuchvara [2019][4,10,11], 2- Lebichot, Bertrand, et al.[2019][4], 3 - Niculescu-Mizil, Alexandru, Eric Cosatto, and Felix Wu.[2018], Joshi, Shilpa, and R. K. Kulkarni [2019], Wu, Xiaohua, and Yan Nei Law [2018], 5- Mohammadi, Sara, et al. [2019], Kwon and Donghwoon Kwon et al. [2017], 6-Alnafessah, Ahmad, and Giuliano Casale [2019] 7 —Geert and Kooi et.al Litjens et al. [2017]. Rodriguez, Aitor Corchero, and Mario Reyes de los Mozos[2010], 8- Erfani, Sarah M., et al.[2016], 9- Xie, Junyuan, Linli Xu, and Enhong Chen.[2012],.10- our Survey.

		1	2	3	4	5	6	7	8	9	10
Techniques	Supervised	✓	✓							✓	✓
	Unsupervised	✓									✓
	Semi Supervised	✓									✓
	Hybrid Models	✓	✓							✓	✓
	Neural Networks									✓	✓
	Deep Neural Network	✓	✓					✓		✓	✓
	one-Class Neural Networks							✓	✓		✓
	Deep Learning	✓						✓			✓
	Data Mining						✓	✓			✓
Applications	Video Surveillance	✓									✓
	Fraud Detection		✓								✓
	Medical Anomaly Detection			✓							✓
	Product Damage Detection				✓						✓
	Cyber-Intrusion Detection					✓					✓
	Big-data Anomaly						✓				✓
	Detection										
	Log-Anomaly Detection							✓			✓
	Deep anomaly detection								✓		✓
	Image Processing									✓	✓

V. IMPLEMENTATION DETAILS FOR PROPOSED MODEL

The anomalies can't be always classified as an assault however it tends to be surprising action which is earlier not known. It might possibly be outliers. Detection of Anomaly is of a notable and emergent problem into many diverse fields like information theory, deep learning, computer vision, machine learning, and statistics that has been researched within various application from divers' domain including agriculture, health care, banking, education, and transport anomaly detection. Nowadays, at the point when information must be examined so as to discover a relationship or to predict known or unknown, classification, regression, and clustering, machine learning based, data mining based, and deep learning based strategies and techniques are utilized. To achieve a higher level accuracy rate (Sensitivity), and find Specificity rate of detected anomalous event or action from the information or data. Currently deep learning based hybrid approaches are also being developed and explored.

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The proposed methodology is abridged in Figure 10, the flow of the model first starts with collecting video data and convert them first into frames.

Segmented frames further divided into two categories normal class and abnormal class. Here normal means negative class. And abnormal means positive class. The normal class having all normal frames and one in abnormal class must have at least one anomaly action or event should be present. Next step is to create features set from below display model (refer figure 10). Once received the feature set further proceed for object segmentation. The training of anomaly detection model using the proposed deep multiple instance learning (DMIL).

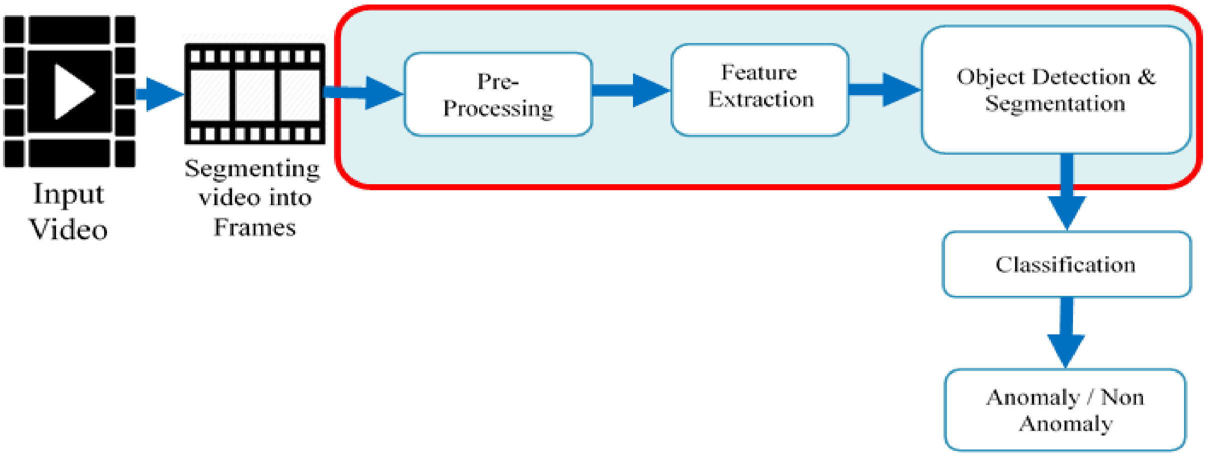


Figure 10 Flow of Detecting Anomalies from Surveillance Video Using Deep Learning

VI. RESULTS

Refer below results of model which can detect and recognize the object. Some statistics given here based on own dataset. Here the comparison statistics are not mention. But the performance evaluation is done through above mention permeates (refer figure 9).

Confusion Metrix:

True positives (TP): These are cases in which we predicted yes.

True negatives (TN): These are cases in which we predicted No.

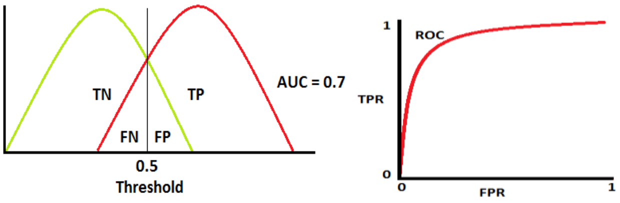
False positives (FP): Also known as a Type I error.

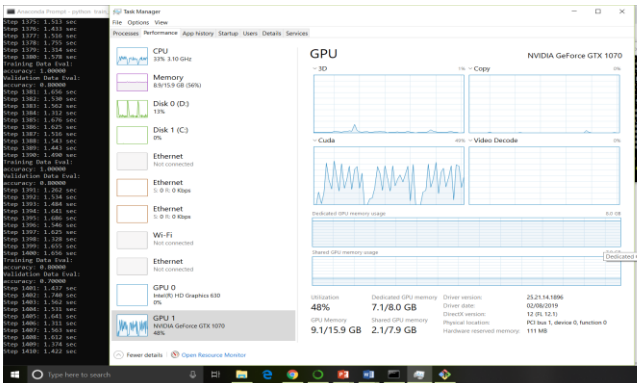
False negatives (FN): Also known as a Type II error.

Table 3 Confusion Metrix

	Predicted: NO	Predicted: YES
Actual: NO	**TN**	**FP**
Actual: YES	**FN**	**TP**

Accuracy: (TP+TN)/total
Misclassification Rate :(FP+FN)/total
True Positive Rate / Recall:TP/actual yes
False Positive Rate: FP/actual no
True Negative Rate/specificity: TN/actual no
Precision: TP/predicted yes
Prevalence: Actual yes/total
ROC Curve, AUC:



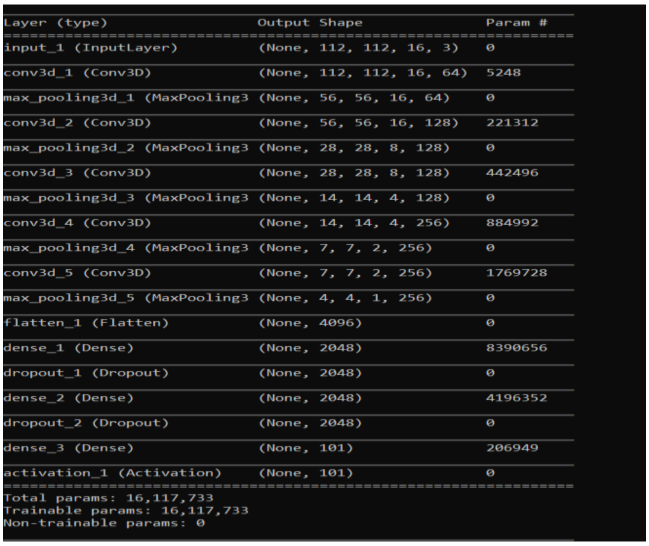


```
Step 1375: 1.513 sec
Step 1376: 1.433 sec
Step 1377: 1.516 sec
Step 1378: 1.755 sec
Step 1379: 1.314 sec
Step 1380: 1.578 sec
Training Data Eval:
accuracy: 1.00000
Validation Data Eval:
accuracy: 0.80000
Step 1381: 1.656 sec
Step 1382: 1.530 sec
Step 1383: 1.562 sec
Step 1384: 1.312 sec
Step 1385: 1.676 sec
Step 1386: 1.625 sec
Step 1387: 1.516 sec
Step 1388: 1.543 sec
Step 1389: 1.443 sec
Step 1390: 1.490 sec
Training Data Eval:
accuracy: 1.00000
Validation Data Eval:
accuracy: 0.80000
Step 1391: 1.262 sec
Step 1392: 1.534 sec
Step 1393: 1.484 sec
Step 1394: 1.641 sec
Step 1395: 1.686 sec
Step 1396: 1.546 sec
Step 1397: 1.625 sec
Step 1398: 1.328 sec
Step 1399: 1.655 sec
Step 1400: 1.656 sec
Training Data Eval:
accuracy: 0.80000
Validation Data Eval:
accuracy: 0.70000
Step 1401: 1.437 sec
Step 1402: 1.740 sec
Step 1403: 1.562 sec
Step 1404: 1.531 sec
Step 1405: 1.641 sec
Step 1406: 1.311 sec
Step 1407: 1.563 sec
Step 1408: 1.612 sec
Step 1409: 1.374 sec
Step 1410: 1.422 sec
```

CPU 33% 3.10 GHz
Memory 8.9/15.9 GB (56%)
Disk 0 (D:) 13%
Disk 1 (C:) 0%
Ethernet Not connected
Ethernet S: 0 R: 0 Kbps
Ethernet S: 0 R: 0 Kbps
Wi-Fi Not connected
Ethernet Not connected
GPU 0 Intel(R) HD Graphics 630 0%
GPU 1 NVIDIA GeForce GTX 1070 48%

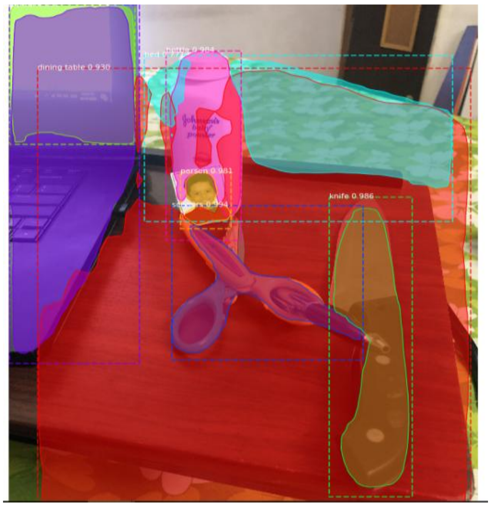
GPU NVIDIA GeForce GTX 1070

Utilization 48%
Dedicated GPU memory 7.1/8.0 GB
GPU Memory 9.1/15.9 GB
Shared GPU memory 2.1/7.9 GB
Driver version: 25.21.14.1896
Driver date: 02/08/2019
DirectX version: 12 (FL 12.1)
Physical location: PCI bus 1, device 0, function 0
Hardware reserved memory: 111 MB



```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 112, 112, 16, 3)   0
_________________________________________________________________
conv3d_1 (Conv3D)            (None, 112, 112, 16, 64)  5248
_________________________________________________________________
max_pooling3d_1 (MaxPooling3 (None, 56, 56, 16, 64)    0
_________________________________________________________________
conv3d_2 (Conv3D)            (None, 56, 56, 16, 128)   221312
_________________________________________________________________
max_pooling3d_2 (MaxPooling3 (None, 28, 28, 8, 128)    0
_________________________________________________________________
conv3d_3 (Conv3D)            (None, 28, 28, 8, 128)    442496
_________________________________________________________________
max_pooling3d_3 (MaxPooling3 (None, 14, 14, 4, 128)    0
_________________________________________________________________
conv3d_4 (Conv3D)            (None, 14, 14, 4, 256)    884992
_________________________________________________________________
max_pooling3d_4 (MaxPooling3 (None, 7, 7, 2, 256)      0
_________________________________________________________________
conv3d_5 (Conv3D)            (None, 7, 7, 2, 256)      1769728
_________________________________________________________________
max_pooling3d_5 (MaxPooling3 (None, 4, 4, 1, 256)      0
_________________________________________________________________
flatten_1 (Flatten)          (None, 4096)              0
_________________________________________________________________
dense_1 (Dense)              (None, 2048)              8390656
_________________________________________________________________
dropout_1 (Dropout)          (None, 2048)              0
_________________________________________________________________
dense_2 (Dense)              (None, 2048)              4196352
_________________________________________________________________
dropout_2 (Dropout)          (None, 2048)              0
_________________________________________________________________
dense_3 (Dense)              (None, 101)               206949
_________________________________________________________________
activation_1 (Activation)    (None, 101)               0
=================================================================
Total params: 16,117,733
Trainable params: 16,117,733
Non-trainable params: 0
```

VII. MATH



VIII. CONCLUSION

The Proposed multi-instance learning model is a way to deal with identifying inconsistencies and abnormalities in surveillance videos. Because of the complexity of realistic anomalies, through only normal data may not be optimal for anomaly detection, the nature of these practical abnormalities, utilizing just normal class may not be ideal for discovery of the abnormal event. Here endeavor design for both positive and negative class videos. To avoid labor-intensive temporal annotations of anomalous segments in training videos, try to learn a general model of anomaly detection using Multiple Instance Learning frameworks with weakly labelled data. For validation, an introduce verity of anomaly dataset having different types of an anomaly. The exploratory results of object segmentation on some benchmark dataset and private small dataset demonstrate that the proposed abnormality identification approach performs essentially improved.

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