# Abnormal Events Detection in CCTV Surveillance Systems

Group - 5

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# Introduction

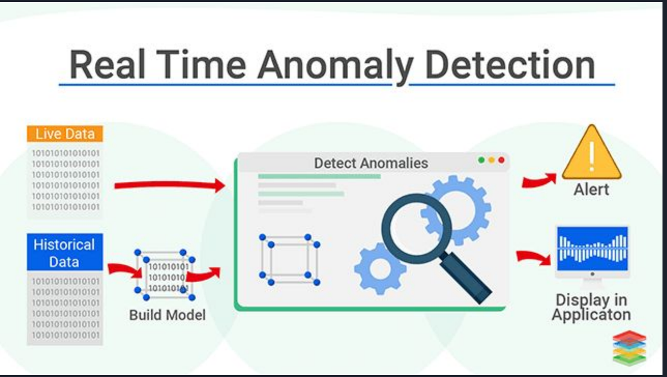
- Increased use of cameras for surveillance

- Main task for these surveillance is to detect anomalies
    - Examples: Illegal Activities, Crimes, Fire etc.

- Anomalies occur for a short period of time compared to normal events

https://images.firstpost.com/wp-content/uploads/2016/02/CCTV-Camera_380_getty.jpg

# Problem Statement



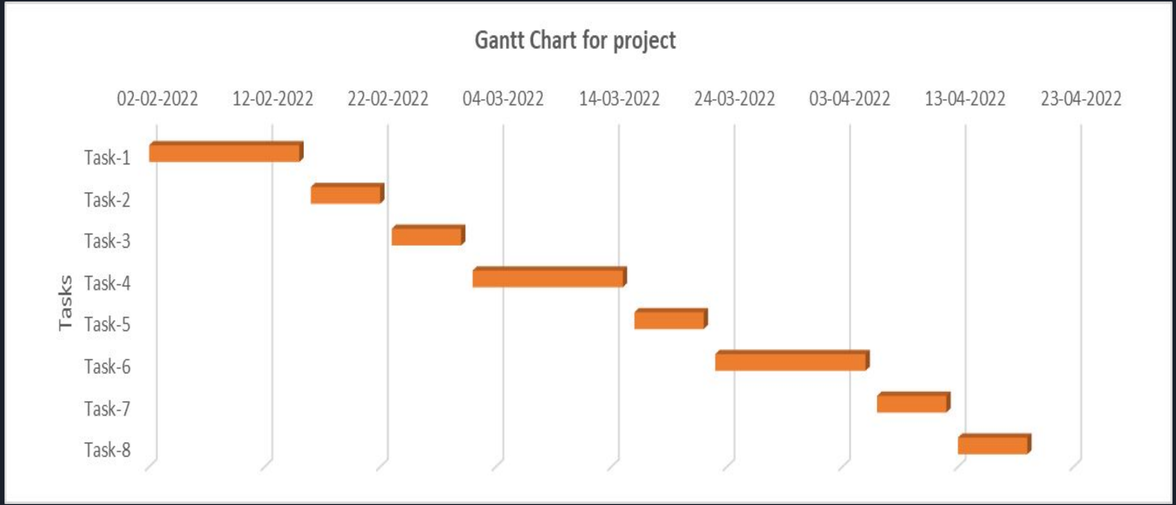

https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.xenonstack.com%2Fblog%2Freal-time-anomaly-detection&psig=AOvVaw2f3jaVBKZyH7SQ3W4gNV1A&ust=1648544483625000&source=images&cd=vfe&ved=0CAsQjRxqFwoTCIjKyfW46PYCFQAAAAAdAAAAABAL

- Importance of abnormal events detection in video content analysis.

- Anomalous events v/s Normal events
  - The need for development of intelligent computer vision algorithms.

- The goal of this project is to develop a practical anomaly detection system is to timely signal an activity that deviates normal patterns and identify the time window of the occurring anomaly

# Gantt Chart for project work timeline




| Task-1 | Task-2 | Task-3 | Task-4 | Task-5 | Task-6 | Task-7 | Task-8 |
|---|---|---|---|---|---|---|---|
| Understanding the research paper | Started feature extraction | Completed feature extraction | performed sampling over all the videos | started feature extraction for a larger dataset | Training the model against larger dataset with hyperparameters tuned | Started research for another model which could be better than C3d | Trained the I3d model with smaller dataset to check its performance |
| Gaining more understanding about the dataset | Faced some errors in feature extraction | Understood how MIL and C3D works | started training and improving the results | | Tested the model with this larger dataset and generated the results | Looked for more research papers which implemented this same | Tested the model and generated the results |
| Gaining more insights about the model | | | | | | Found an I3d model which was quite better than C3d | |

# Existing body of work

- Several different attempts in surveillance systems to detect anomalous behaviour.

- Yihao Zhanget proposes anomaly detection in traffic video with the information provided in the HEVC compressed domain.

- In High Efficient Video Coding Tian Wanga  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).

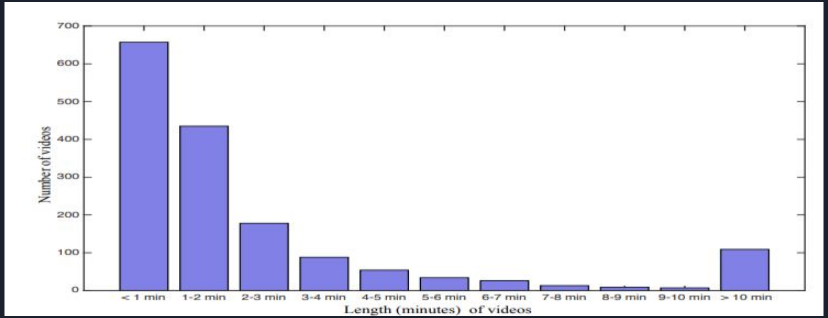
# Dataset-1

- The dataset used for this project is University of Central Florida(UCF) anomaly detection dataset.
- Consists of long untrimmed surveillance videos of Abuse, Arrest, Arson, Assault, Accident, Burglary, Explosion, Fighting, Robbery, Shooting, Stealing, Shoplifting, and Vandalism.
- A total of 1900 videos in which 950 are normal and anomaly videos.
- We have worked on two approaches for which  are considering a sample of 130 videos, 65 videos  from both normal and anomaly for each approach respectively. Also, 10 videos for testing part.

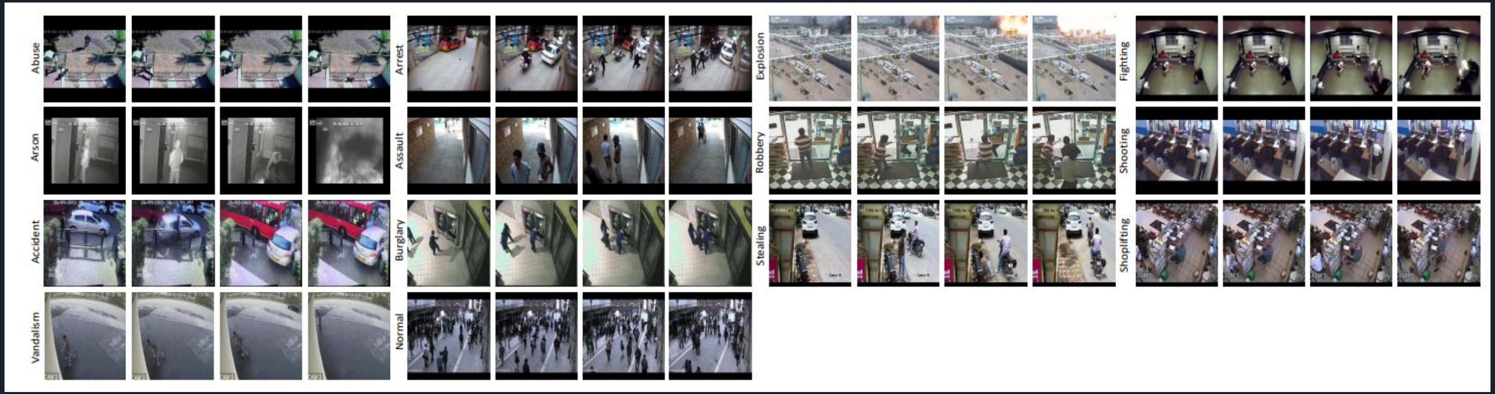
| | # of videos | Average # of frames | Dataset length | Example anomalies |
|---|---|---|---|---|
| UCSD Ped1 [27] | 70 | 201 | 5 min | Bikers, small carts, walking across walkways |
| UCSD Ped2 [27] | 28 | 163 | 5 min | Bikers, small carts, walking across walkways |
| Subway Entrance [3] | 1 | 121,749 | 1.5 hours | Wrong direction, No payment |
| Subwa Exit [3] | 1 | 64,901 | 1.5 hours | Wrong direction, No payment |
| Avenue [28] | 37 | 839 | 30 min | Run, throw, new object |
| UMN [2] | 5 | 1290 | 5 min | Run |
| BOSS [1] | 12 | 4052 | 27 min | Harass, disease, panic |
| Abnormal Crowd [31] | 31 | 1408 | 24 min | Panic, fight, congestion, obstacle, neutral |
| **Ours** | **1900** | **7247** | **128 hours** | **Abuse, arrest, arson, assault, accident, burglary, fighting, robbery** |

https://arxiv.org/abs/1801.04264

# Dataset-2




https://arxiv.org/abs/1801.04264

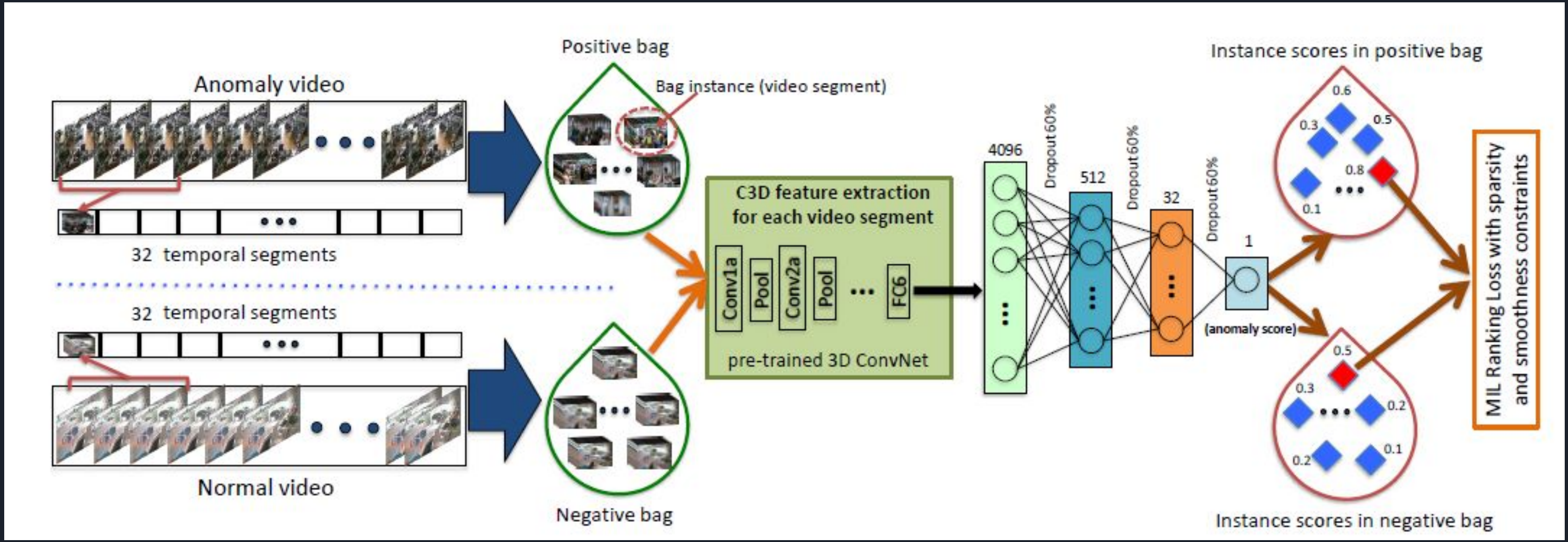



https://arxiv.org/abs/1801.04264

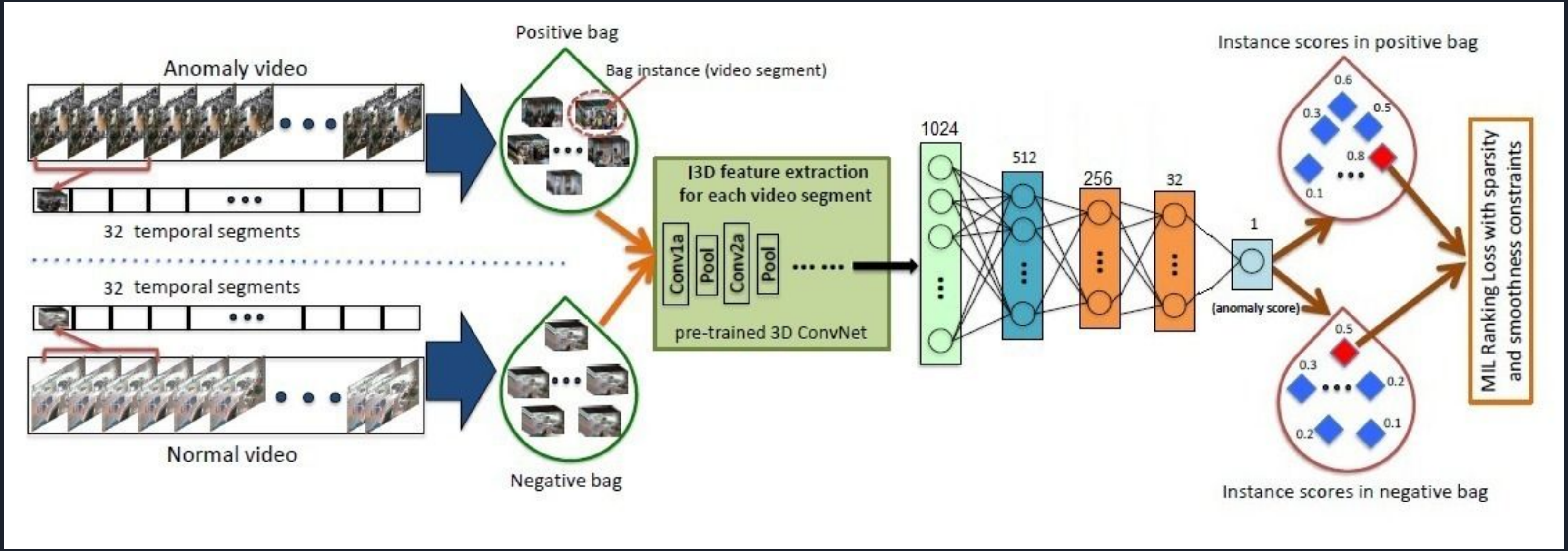
| # of videos | Anomaly |
|---|---|
| 50 (48) | Abuse |
| 50 (45) | Arrest |
| 50 (41) | Arson |
| 50 (47) | Assault |
| 100 (87) | Burglary |
| 50 (29) | Explosion |
| 50 (45) | Fighting |
| 150 (127) | Road Accidents |
| 150 (145) | Robbery |
| 50 (27) | Shooting |
| 50 (29) | Shoplifting |
| 100 (95) | Stealing |
| 50 (45) | Vandalism |
| 950 (800) | **Normal events** |

https://arxiv.org/abs/1801.04264

# Our Approach(C3d)

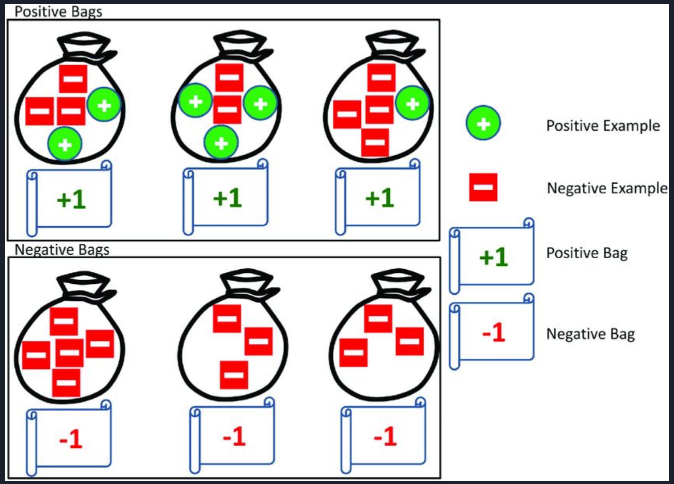


# Our Approach(I3d)



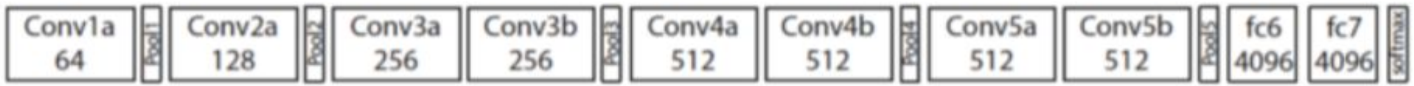
# Multiple Instance learning

- We formulate anomaly detection as a regression problem in the ranking framework by utilizing normal and anomalous data.
- In MIL, precise temporal locations of anomalous events in videos are unknown. Video-level labels indicating the presence of an anomaly.
- Single video is a bag if the instance of video contains the anomaly we label it as a positive bag(anomalus video) else we consider it negative video(normal video).




https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.researchgate.net%2Ffigure%2FAn-illustration-of-the-concept-of-multiple-instance-learning-In-MIL-training-examples_fig1_315925709&psig=AOvVaw0cKoj8zHcr2o5xsVh5dJ6g&ust=1648551839569000&source=images&cd=vfe&ved=0CAsQjRxqFwoTCJDWvajU6PYCFQAAAAAdAAAAABAD

# C3d Architecture




C3D Architecture [1]

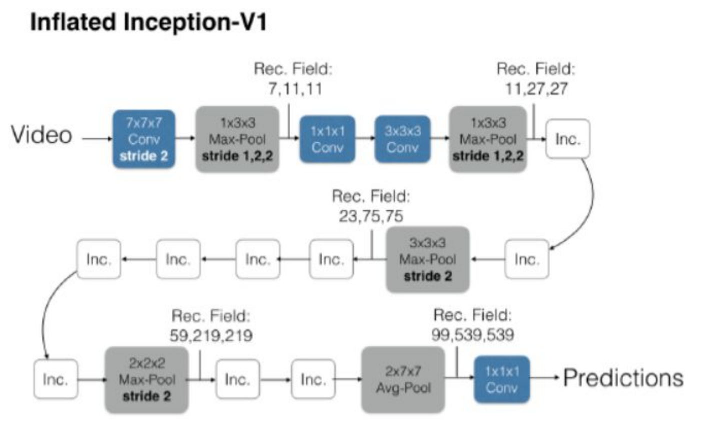
https://arxiv.org/abs/1801.04264

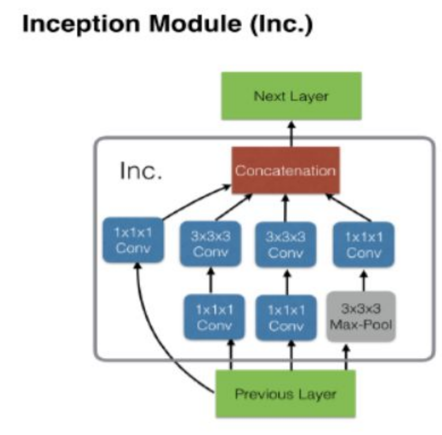
- The C3D model is given an input video segment of 16 frames (after downsampling to a fixed size which depends on dataset used) and the outputs a 4096-element vector.

- The fully connected layers have a size of 4096 dimensions which will be used in the DNN model for calculating the anomaly score

# I3D Architecture

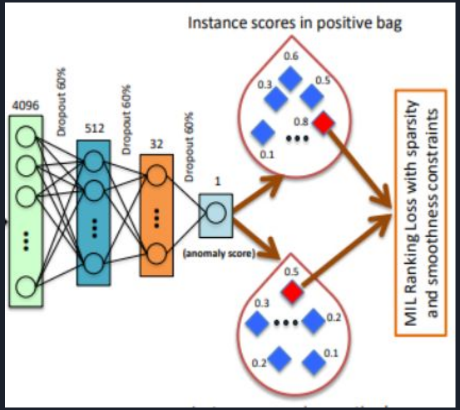
- The architecture of inflated 3D CNN model goes something like this – input is a video, 3D input as in 2-dimensional frame with time as the third dimension.
- Repeating the weights of the 2D filters N times along the time dimension, and resizing them by dividing by N.
- Inflated because of the reason that we are having these modules dilated into the middle of the model.
- Train the two networks separately and average their predictions at test time.

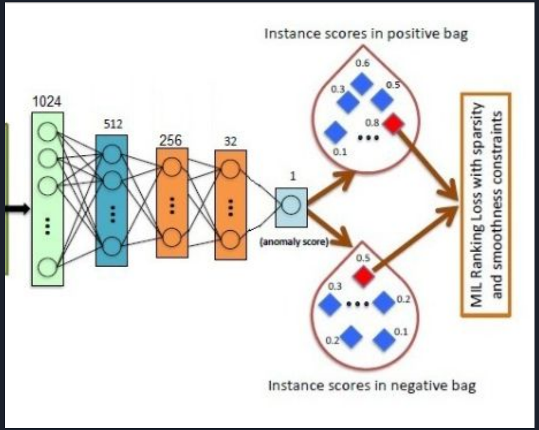



https://medium.com/nerd-for-tech/review-quo-vadis-action-recognition-a-new-model-and-the-kinetics-dataset-video-classification-a7535aa8bf48

# DNN Model




- Fully connected layers have a size of 4096 and 1024 dimensions for each approach respectively  using it as a DNN model for anomaly score

- Feature of 16 frames clip are represented in the form of (4096D and 1024D) were fed into a 3-layer feed forward neural network. This approach will use forward propagation and backward propagation using hinge loss formulation, sparsity and smoothness.

# Loss Function

- The straightforward approach would be to use a ranking loss which encourages high scores for anomalous video segments as compared to normal segments, such as:

  f(Va) > f(Vn),

  where Va and Vn represent anomalous and normal video segments, f(Va) and f(Vn) represent the corresponding predicted anomaly scores ranging from 0 to 1

$$l(\mathcal{B}_a, \mathcal{B}_n) = \max(0, 1 - \max_{i \in \mathcal{B}_a} f(\mathcal{V}_a^i) + \max_{i \in \mathcal{B}_n} f(\mathcal{V}_n^i)).$$

https://arxiv.org/abs/1801.04264

# Loss Function with sparsity and smoothness

- First, in real-world scenarios, anomaly often occurs only for a short time. In this case, the scores of the instances (segments) in the anomalous bag should be sparse, indicating only a few segments may contain the anomaly.
- Second, since the video is a sequence of segments, the anomaly score should vary smoothly between video segments

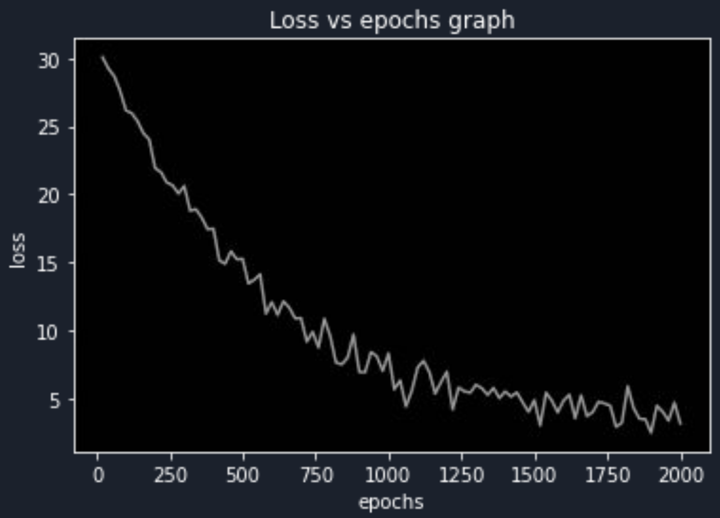
$$l(\mathcal{B}_a, \mathcal{B}_n) = \max(0, 1 - \max_{i \in \mathcal{B}_a} f(\mathcal{V}_a^i) + \max_{i \in \mathcal{B}_n} f(\mathcal{V}_n^i)) + \lambda_1 \overbrace{\sum_i^{(n-1)} (f(\mathcal{V}_a^i) - f(\mathcal{V}_a^{i+1}))^2}^{①} + \lambda_2 \overbrace{\sum_i^{n} f(\mathcal{V}_a^i)}^{②},$$

https://arxiv.org/abs/1801.04264

- By incorporating the sparsity and smoothness constraints on the instance scores, the loss function becomes where 1 indicates the temporal smoothness term and 2 represents the sparsity term.

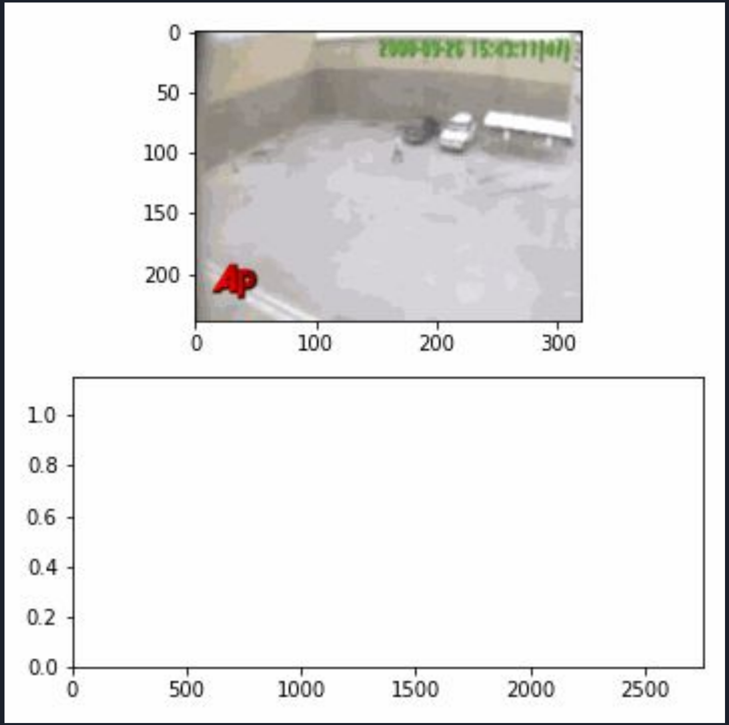
# Results for 130 videos(C3d)

- We have trained our model for 2000 iterations, batch size is 60, learning rate is 0.01 and we have got the sum of  hinge-loss, sparsity loss and smoothness loss which is 5.38.

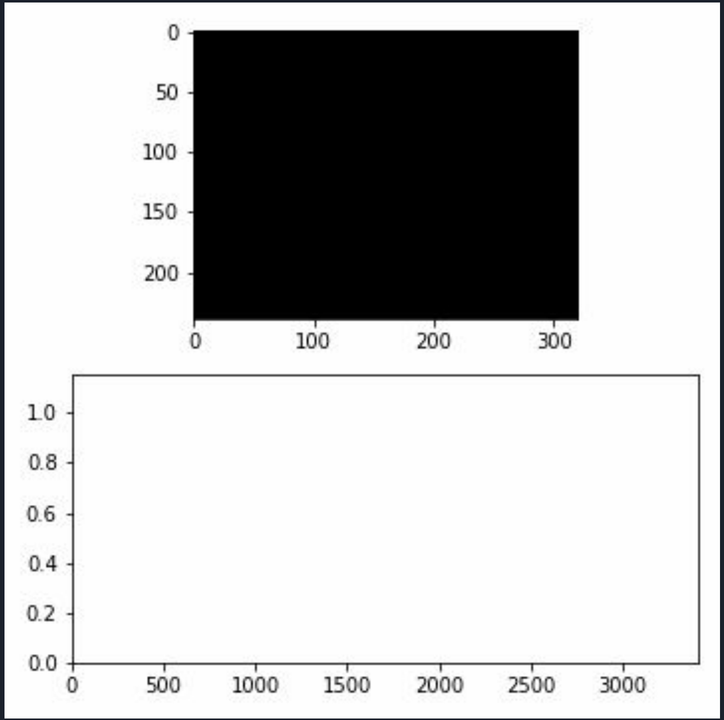


# True Positive and False Negative Results

Explosion Anomaly

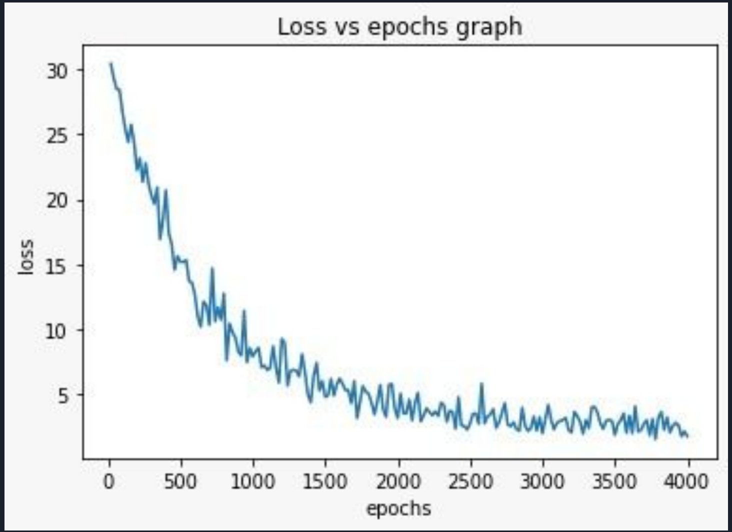



Abuse Anomaly



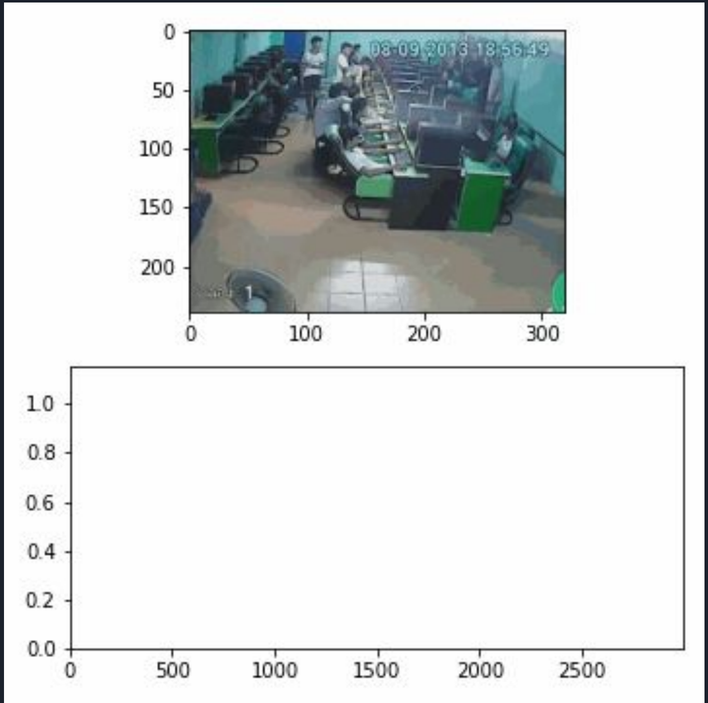
# Results for C3d(260 video sample size)

- We have trained our model for **4000** iterations, batch size is **32**, learning rate is **0.01** and we have got the sum of hinge-loss, sparsity loss and smoothness loss which is **1.7413**.

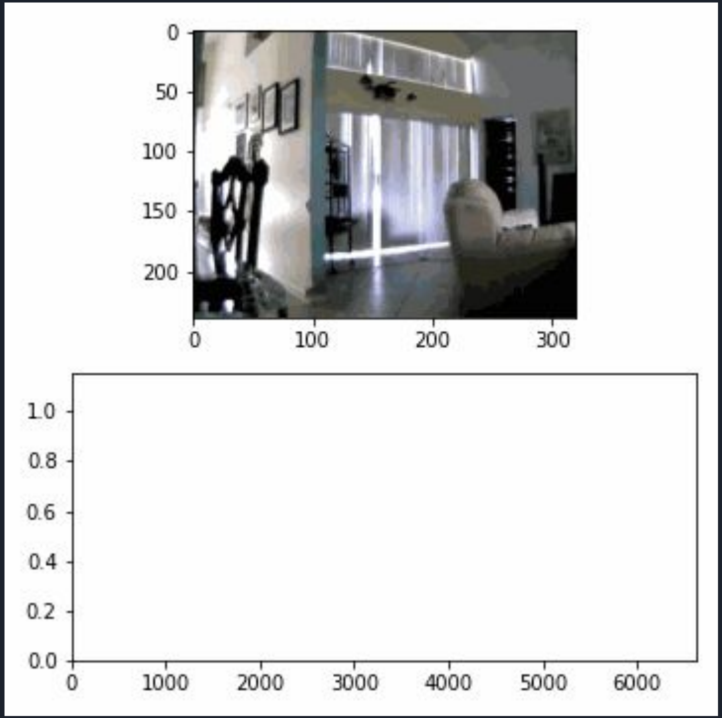


# True Positive and False Negative Results

Fighting Anomaly

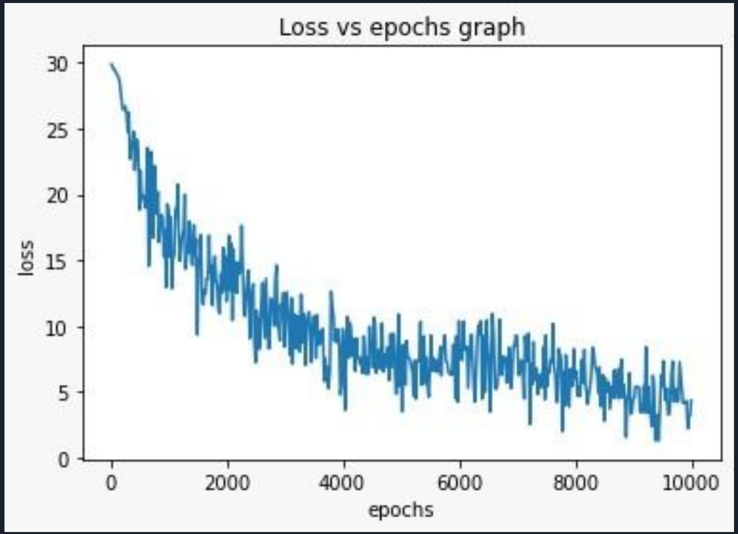



Burglary Anomaly



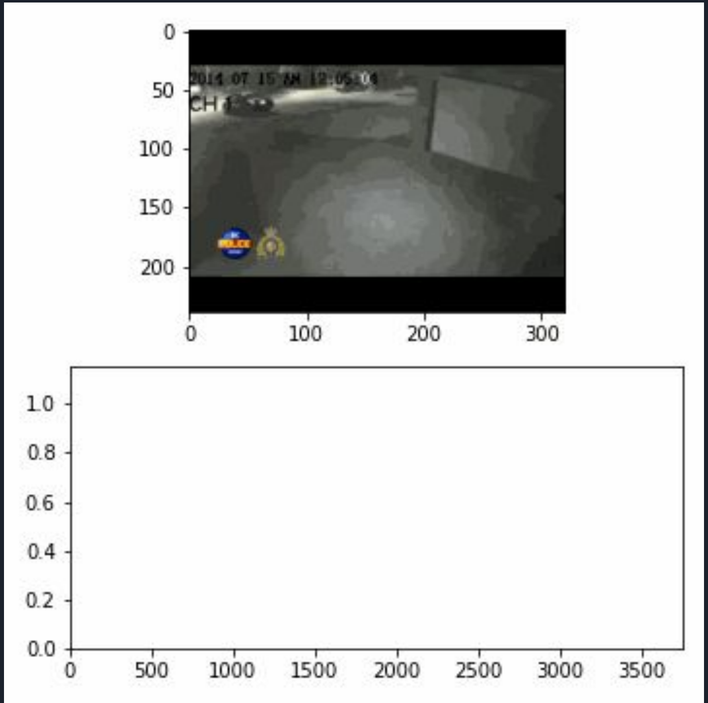
# Results for I3d(130 video sample)

- We have trained our I3d model for **10000** iterations, batch size is **32**, learning rate is **0.01** and we have got the sum of  hinge-loss, sparsity loss and smoothness loss which is **2.23**.

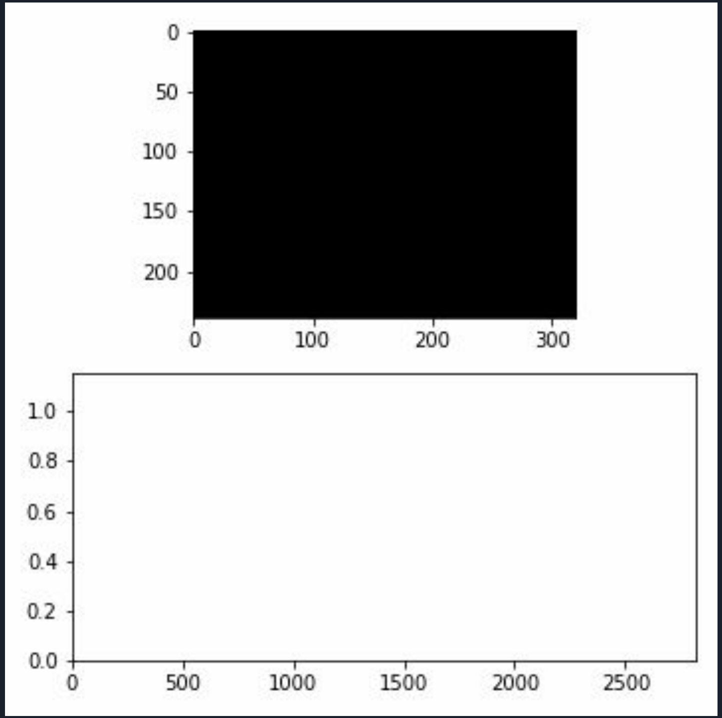


# True Positive and False Negative Results

Arson Anomaly




Explosion Anomaly



# Individual Roles:

| Feature extraction using c3d and i3d for anomaly videos | Feature extraction using c3d amd i3d for normal videos | Training on videos | Testing manually on anomalus videos | Documentation |
|---|---|---|---|---|
| Dinesh Nariani, Henil Shah | Devanshu Magiawala, Henil Shah | Dinesh Nariani | Devanshu Magiawala | All |

# Future Work

- Defining a testing mechanism for proper testing of this model.

- In the future works one can try on increasing the sample size and trying different features extractor to get best results.

# References

**C3d Model Feature extraction understanding:**

B. M. Nair, “Deep Dive into Convolutional 3D features for action and activity recognition (C3D),” Medium, 23-Jul-2018. [Online]. Available: https://medium.com/@nair.binum/quick-overview-of-convolutional-3d-features-for-action-and-activity-recognition-c3d-138f96d58d8f. [Accessed: 28-Mar-2022].

**Dataset:**

“Anomaly-detection-dataset,” Dropbox. [Online]. Available: https://www.dropbox.com/sh/75v5ehq4cdg5g5g/AABvnJSwZI7zXb8_myBA0CLHa?dl=0. [Accessed: 28-Mar-2022].

**Research Link and Literature Review:**

W. Sultani, C. Chen, and M. Shah, “Real-world anomaly detection in surveillance videos,” arXiv [cs.CV], pp. 6479–6488, 2018.

**MIL Link:**

P. Maia, “An introduction to multiple Instance Learning,” NILG.AI, 18-May-2021. [Online]. Available: https://nilg.ai/blog/202105/an-introduction-to-multiple-instance-learning/. [Accessed: 28-Mar-2022].