

# Abnormal Human Activity Detection using Unsupervised Machine Learning Techniques

Mounika Chalapati, A. Raghuvira Pratap



**Abstract:** Nowadays there is a significant study effort due to the popularity of CCTV to enhance analysis methods for surveillance videos and video-based images in conjunction with machine learning techniques for the purpose of independent assessment of such information sources. Although recognition of human intervention in computer vision is extremely attained subject, abnormal behavior detection is lately attracting more research attention. In this paper, we are interested in the studying the two main steps that compose abnormal human activity detection system which are the behavior representation and modelling. And we use different techniques, related to feature extraction and description for behavior representation as well as unsupervised classification methods for behavior modelling. In addition, available datasets and metrics for performance evaluation will be presented. Finally, this paper will be aimed to detect abnormal behaved object in crowd, such as fast motion in a crowd of walking people

**Keywords:** Abnormal Human Activity, Classification, Crowd, Feature Extraction, Unsupervised.

## I. INTRODUCTION

Abnormal detection of human activity using unsupervised classification methods is most important in the classification of behaviours. A core component is the perception of meaning and human activities. In these ongoing years, utilizations of video reconnaissance have pulled in more and more analysts. Thusly, different kinds of displaying just as a few procedures of examination and detection of human activities are recommended. Especially, numerous inquiries about are engaged with the acknowledgment and detection of human activities when all is said in done and particularly irregular activities. One significant application is supervision of older and handicapped individuals at home in care focuses, or medical clinics.

Detection of human activities is an ongoing field which is intrigued to give procedures and strategies permitting the recognition and order of human activities, and stretched out now to perceive typical or irregular activities. The inspiration

driving the last is to give a prompt mediation to save lives of people or to guarantee them a few administrations they can't do without anyone else. The irregular human exercises can be assembled into a pile of three basic assignments in video reconnaissance analysis; at the lower layer is the identification and grouping of intriguing items, the middle layer executes following of the recognized moving articles starting with one casing of video then onto the next, lastly, the elevated level analysis of the followed item to perceive human conduct

## II. RELATED WORK

Thomas Gatt et.al., [1] introduced a method titled as detecting human abnormal behavior through a video generated model. In this study, right now, robotized camera-based framework that can detect unpredictable human conduct is proposed. The principle point of this investigation is to decide if a set of human body key points extricated from a conventional camera can be utilized to distinguish unusual human conduct, for example, falling.

Congcong Liu et.al., [2] proposed a method titled as abnormal human activity detection using bayes classifier and convolutional neural network. In this, human movement acknowledgment technique was presented in observation video. bayes classifier and Convolutional Neural Network are utilized in the framework to recognize four practices, including moving, and thumping. The KTH dataset is utilized as bayes Classifier and convolutionary Neural Network input. Charvi Jain et.al., [3] proposed a method titled as abnormal behavior detection at traffic junctions using lucas kanade and Harris Horner detector. In this, constant item's conduct discovery is executed utilizing Lucas Kanade and Harris Corner based methodology. This work can be utilized to build up a reconnaissance arrangement of static camera and mechanical robotization visual frameworks. Shih-Chung Hsu et.al., [4] proposed a method titled as a video-based abnormal human behavior detection for psychiatric patient monitoring. This paper proposes a strange human conduct recognition framework for observing mental patient. An ordinary conduct can be portrayed by the spatial and fleeting highlights of human exercises.

Dishani Lahiri et.al., [5] introduced a method titled as abnormal human action recognition using average energy images. In this paper, A novel Average Energy Image based element descriptor is intended for strange human action acknowledgment by coordinating HOG and PCA with AEI.

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# Abnormal Human Activity Detection using Unsupervised Machine Learning Techniques

Vivek Ashokan et.al., [6] introduced a method titled as comparative evaluation of classifiers for abnormal event detection in ATM's. This paper expects to look at the adequacy of every one of these strategies for strange occasion recognition in ATMs. Highlight Extraction is finished by HOG method for every one of the three classifiers. Fam Boon Lung et.al., [7] propose a method titled as spatio-temporal descriptor for abnormal human activity detection.

In this paper, they propose such a Spatio-Temporal Descriptor (STD) in view of spatio-transient highlights of a picture arrangement. K Nandini et.al., [8] introduced a method titled as anomaly detection for safety monitoring. In packed scene unusual occasion discovery is a significant issue. So, they used irregular detectors in this device to identify the incidents. Incoming occurrences remove irregular patterns.

Han-Yang Wang et.al., [9] introduced a method titled as deep learning-based human activity analysis for aerial images. So as to adapt to the issue of viewpoint projection for ethereal pictures, we alter the CNN design of a best in class object identification technique and assemble an elevated picture informational index with an automaton for new model preparing.

Mairo Leier et.al., [10] introduced a method titled as Fall detection and activity recognition system for usage in smart work-wear. The point of this paper is to propose a human action acknowledgment and fall recognition arrangement that gives additional wellbeing to individuals working in testing conditions.

## III. METHODOLOGY

The process for the abnormal human activity detection in a video using unsupervised machine learning methods as shown in below figure.

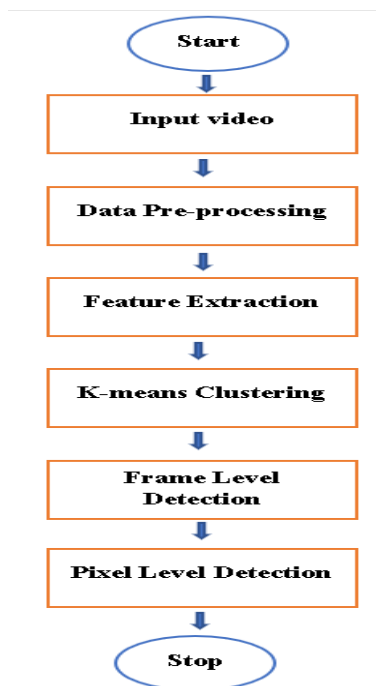


Fig 1. Structure of Proposed Methodology

The proposed methodology consists of following phases for developing abnormal human activity system respectively.

- Data set Collection
- Data Pre-processing
- Feature Extraction
- K-means Clustering
- Frame Level Detection
- Pixel Level Detection

### A. Data set Collection

In this paper, we take video file as our input video for detecting abnormal human activities respectively. The video file extension was .avi (audio video Interleave) which consists of both video and audio.

### B. Data Pre-processing

The video file is given as a contribution to the framework, which is exposed to pre-handling. A video is treated as succession of pictures called outlines and these edges are handled consecutively. An RGB outline is first changed over to gray scale. A gray scaled picture comprises of just the force data of the picture as opposed to the clear hues. RGB vector is 3 dimensional while gray scaled vector is one dimensional.

### C. Feature Extraction

In this paper, we extracted features of the implementation phase map module in motion. Extraction work on the movement impact map, a square where uncommon action happens alongside its neighboring squares, has unique vector development impact. In this way, as an activity is caught by different successive edges, over the latest  $t$  number of casings, we remove a component vector from a cuboid distinguished by  $n/n$  squares. Extricating Features Following the ongoing ' $t$ ' number of casings partitioned into uber hinders, a 8  $t$ -dimensional linked capacity vector is separated over all edges for each super square.

### D. K-means Clustering

For extracted features, we apply k-means clustering algorithm. We cluster for each mega block utilizing the spatio-fleeting highlights, and set the focuses as codewords. That is, we have  $K$  codewords for the  $(I, j)$  super square,  $\{w(i, j) k\} k=1$ . Here, we recall that we just use video clasps of typical exercises in our preparation arrange. Henceforth, a super square's codewords model the examples of regular exercises that may happen in the area concerned.

### E. Frame Level Detection

In this, the lower the estimation of a thing, the more outlandish an abnormal movement is to happen in the individual square, the edge level identification of uncommon exercises in a base separation lattice. Then again, if a higher worth happens in the negligible separation lattice, we can expect that there are surprising occasions in  $t$  back to back edges. Furthermore, we locate the most elevated an incentive in the base separation lattice as the agent estimation of the casing.

In the event that the base separation framework's most noteworthy worth is more prominent than the limit, at that point we distinguish the present casing as uncommon.

**F. Pixel Level Detection**

Discovery of unpredictable exercises Pixel level Once an edge is recognized as unordinary, we look at the estimation of each uber square's base separation network with the edge esteem. In the event that the worth is more noteworthy than the edge, we mark the square as irregular.

**IV. IMPLEMENTATION**

The process of implementation includes the actual materialization of the ideas expressed in the document of analysis and created during the design phase. In this, we use python programming language, and the requirements are Python OpenCV 3 and NumPy, Pandas respectively. Implementation should be a flawless mapping of the design document in an acceptable programming language to achieve the desired end product. And we've also had a brief discussion on the relevant modules and methods present in this paper. Our implementation code was divided into five modules they are,

- Optical flow of blocks
- Motion influence generator
- Mega block generator
- Training
- Testing

A method for depicting motion characteristics is defined in this section for detecting and localizing unusual activities within a crowded scene. Here we should note that we found two uncommon forms of activity:

**A. Optical flow of blocks**

Optical flow Using FarneBack algorithm, optical flow for each frame in the video is calculated for each pixel in a frame after the pre-processing step. Optical flow is the pattern of apparent motion in a visual scene of objects, surfaces, and edges caused by the relative motion between an observer and the scene. Dividing a frame into blocks After computing the optical flows within a frame for each pixel, we divide the frame into uniform blocks M by N without loss of generality, where the blocks can be indexed by {B1, B2, . . . , BMN}. Calculating each block's optical flow After dividing the frames into blocks, we calculate each block's optical flow by calculating the average optical flow of all the block's pixels.

**B. Motion influence generator**

Motion Influence Map different factors can influence a pedestrian's direction of movement within a crowd, for example, deterrents along the path, close by people on foot, and moving trucks. We call that quality of cooperation as the impact of movement. We accept that two components decide the squares leveled out to which a moving item will influence.:

- The direction of motion
- The speed of motion.

The speedier an article moves; the more adjoining obstructs that are under the item's control. Neighboring squares have a more noteworthy impact than obstructs from a far distance.

**Algorithm for creating motion influence map:**

INPUT: B ← motion vector set, S ← block size, K ← a set of blocks in a frame  
 OUTPUT: H ← motion influence map H j (j K) is set to zero at the beginning of each frame  
 for all I K do Td = bi × S;  
 Step1: Fi/2 = bi + 2; -Fi/2 = bi - 2;  
 Step2:  
 for all j K do if i = j then Calculate the Euclidean distance D (i, j) between bi and bj  
 Step3:  
 if D (i, j) < Td then Calculate the angle ij between bi and bj.  
 Step4:  
 if - Fi 2 < ij < Fi 2 then H j (bi) = H j (bi) + exp- D(i,j)bi  
 end if  
 end if  
 end for  
 end for

**C. Mega block generator**

The development of Mega blocks frames is divided into non-overlapping mega blocks, every one of which is a blend of different squares of control on movement. A Mega block's Motion Influence value is the summation of the values of motion influence of all the smaller blocks which constitute a larger block.

**D. Training**

We only use video clips of normal activities during our training stage. Hence, a mega-block's code words model examples of regular exercises that may happen in the separate zone.

**E. Testing**

Now that we've produced the code words for normal activity, it's time to test the created model with a test data set containing unusual activity.

**V. RESULTS AND DISCUSSION**

In this, we show experimental results of abnormal human activity detection in a video using unsupervised classification algorithms respectively.



**Fig 2. Input video as image**



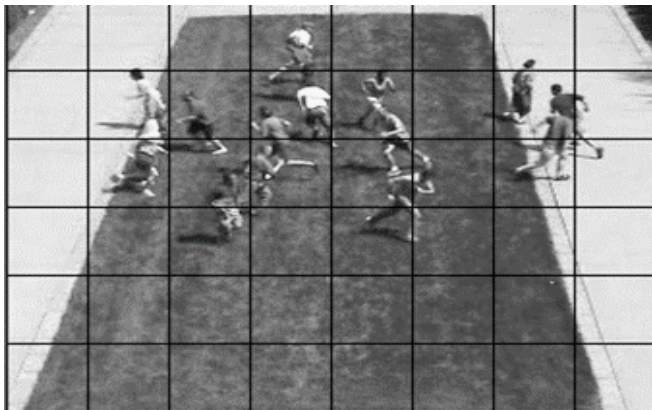
# Abnormal Human Activity Detection using Unsupervised Machine Learning Techniques

```
ster\Unusual-Human-Activity-Detection-master\Dataset\videos\scenel\train1.avi
240 320
0
1
2
3
4
5
6
7
8
9
10
11
|
```

**Fig 3. Trained image as frame numbers**

```
Motion Inf Map 474
(6.0, 8.0, 474)
5.836865823887345e-05
3.3702958216479853e-07
[[[[ 0.00000000e+00 0.00000000e+00 6.62814174e-43 ... 0.00000000e+00
0.00000000e+00 0.00000000e+00]
[ 0.00000000e+00 0.00000000e+00 1.25904358e-36 ... 0.00000000e+00
0.00000000e+00 0.00000000e+00]
[ 0.00000000e+00 0.00000000e+00 0.00000000e+00 ... 0.00000000e+00
0.00000000e+00 0.00000000e+00]
[ 7.23691134e-24 2.80284741e-23 5.68606538e-21 ... 1.93163036e-32
7.11888482e-30 2.80259693e-45]
[ 0.00000000e+00 0.00000000e+00 0.00000000e+00 ... 0.00000000e+00
0.00000000e+00 0.00000000e+00]]]
```

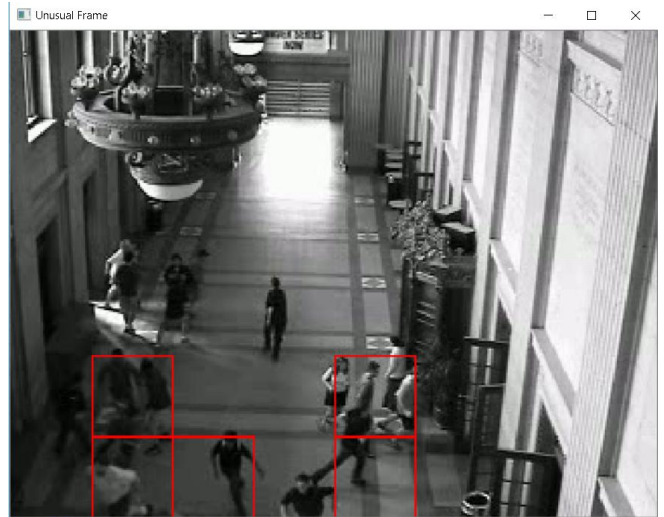
**Fig 4. Trained image as motion inf map**



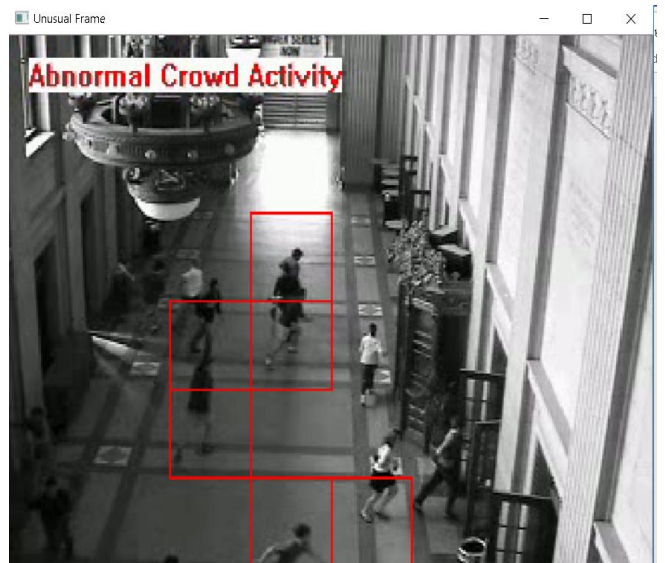
**Fig 5. Image divided into blocks**



**Fig 6. Unusual Frame 1**



**Fig 7. Unusual Frame 2**



**Fig 8. Abnormal Crowd Activity**

**Table 1. Performance analysis of unusual human activity detection in video**

	<i>Formula</i>	<i>Percentage</i>
<b>Accuracy</b>	$(TP + TN)/total$	92.25
<b>Precision</b>	$TP/Prediction: Yes$	81.39
<b>Recall</b>	$TP/Actual: Yes$	86.35
<b>F-Score</b>	$(2 * precision * recall) / (precision + recall)$	0.85123

## VI. CONCLUSION

In this paper, A novel unsupervised learning strategy was developed to detect inappropriate human behavior through recordings. The approach proposed was tested thoroughly on a complex video dataset. The findings presented showed the usefulness of the proposed classification models, which were able to distinguish correctly between normal and abnormal sequences. Firstly, we take input video as our input data and then we apply pre-processing for that video, after the completion of pre-processing we extracted features in a video. K-means clustering was performed on given features then we complete frame level and pixel level detection. For most of the cases, we could succeed. And also, we get good accuracy from training and testing modules.

## REFERENCES

1. Liu C, Ying J, Han F, Ruan M. Abnormal Human Activity Recognition using Bayes Classifier and Convolutional Neural Network. In2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP) 2018 Jul 13 (pp. 33-37). IEEE.
2. Gatt T, Seychell D, Dingli A. Detecting human abnormal behavior through a video generated model. In2019 11th International Symposium on Image and Signal Processing and Analysis (ISPA) 2019 Sep 23 (pp. 264-270). IEEE.
3. Jain C, Gautam D. Abnormal behavior detection at traffic junctions using Lucas Kanade and Harris Corner detector. In2018 4th International Conference on Recent Advances in Information Technology (RAIT) 2018 Mar 15 (pp. 1-5). IEEE.
4. Hsu SC, Chuang CH, Huang CL, Teng R, Lin MJ. A video-based abnormal human behavior detection for psychiatric patient monitoring. In2018 International Workshop on Advanced Image Technology (IWAIT) 2018 Jan 7 (pp. 1-4). IEEE.
5. Lahiri D, Dhiman C, Vishwakarma DK. Abnormal human action recognition using average energy images. In2017 Conference on Information and Communication Technology (CICT) 2017 Nov 3 (pp. 1-5). IEEE.
6. Ashokan V, Murthy OR. Comparative evaluation of classifiers for abnormal event detection in ATMs. In2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICT) 2017 Jul 6 (pp. 1330-1333). IEEE.
7. Lung FB, Jaward MH, Parkkinen J. Spatio-temporal descriptor for abnormal human activity detection. In2015 14th IAPR International Conference on Machine Vision Applications (MVA) 2015 May 18 (pp. 471-474). IEEE.
8. Nandhini K, Pavithra M, Revathi K, Rajiv A. Anomaly detection for safety monitoring. In2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN) 2017 Mar 16 (pp. 1-6). IEEE.
9. Wang HY, Chang YC, Hsieh YY, Chen HT, Chuang JH. Deep learning-based human activity analysis for aerial images. In2017 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS) 2017 Nov 6 (pp. 713-718). IEEE.
10. Leier M, Jervan G, Allik A, Pilt K, Karai D, Fridolin I. Fall detection and activity recognition system for usage in smart work-wear. In2018 16th Biennial Baltic Electronics Conference (BEC) 2018 Oct 8 (pp. 1-4). IEEE.



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