Unnatural/Abnormal Behaviour Detection Using Machine Learning

ARUNABH ASHISH[1], MARTAND JOSHI[2], LAKSHYA MEENA[3], PROF. S.H. PATIL[4]
[1, 2, 3] *Department of computer Engineering, Bharati Vidyapeeth Deemed to be University, College of Engineering,Pune, India*
[4] *Professor, Department of Computer Engineering, Bharati Vidyapeeth Deemed to be University,College of Engineering, Pune, India*

***Abstract—* The contents of this study primarily focus on various data mining approaches that are useful in predicting unnatural/abnormal behaviors. This paper presents a novel method of utilizing observed history for detecting abnormal behaviors in surveillance applications. An unsupervised algorithm is proposed to detect abnormal behaviors and re-train itself in real-time. Motion vectors of objects are estimated using the optical flow method. This method has been evaluated under both indoor and outdoor surveillance scenarios. It demonstrates promising results that this detection procedure is able to discover abnormal behaviors and adapt to changes in the behavioral patterns incrementally.**

In this study, we have selected a video clip and used Online-Convert to convert it into multiple frames of 10 frames per second. This dataset is used as the training dataset whereas the video clip is used for the testing phase. We have used various classifier methods in order to improve accuracy, which is then summarized further. Support Vector Machine, k-nearest neighbour, and Logistic Regression are the methods in question. The models used have performed equally or even better than other models. This research offers a development in which fundamental prefixes such as movement, gesture, speed, neighbour density andothers are used to determine any kind of abnormal behaviour. Our aim ahead is to improve the system and implement it in public sectors using various equipment and models.

***Indexed Terms—* Machine Learning, OpenCV, sklearn, skimage, computer vision SVM, Logistic Regression, k- nearest neighbor**

I. INTRODUCTION

In recent years, with the frequent occurrences of abnormal group events such as fights, stampedes, riots, and demonstrations, video surveillance equipment has been widely used in public places such as railway stations, streets, campuses, and banks. Abnormal behavior detection using traditional video surveillance is mainly realized by manual methods. However, a long-term continuous observation often leads to staff fatigue, making them prone to missed inspections. The emergence of machine learning can be exploited to realize the automatic detection of abnormal human behaviors. Compared with traditional manual methods, this method can save manpower and reduce missed detections.

The above research is mainly based on the detection of abnormal human behavior in outdoor scenes. In campus scenes, students spend most of their time in indoor venues such as classrooms. The effect obtained when the above studies are applied to the detection of abnormal behavior by indoor personnel is not ideal. Moreover, although the detection method based on deep learning is convenient for feature extraction, its detection time cannot meet the needs of realistic applications. Abnormal behavior detection requires high efficiency in terms of detection time.

II. TECHNOLOGY CLASSIFIERS

- PANDAS: - Pandas is a data manipulation and analysis software package for the Python programming language. It provides data structures and functions for manipulating numerical tables and time series in particular. It’s free software distributed under the BSD three - clause license.

- Matplotlib: - Matplotlib is a cross-platform, data visualization and graphical plotting library for Python and its numerical extension NumPy. As such, it offers a viable open-source alternative to MATLAB. A Python matplotlib script is structured so that a few lines of code are all that is required in most instances to generate a visual data plot.
- SKIMAGE: - Scikit-Image is an image processing Python package that works with NumPy arrays which is a collection of algorithms for image processing. Let's discuss how to deal with images into set of information and it's some application in the real world.
- OpenCV is a cross-platform library using which we can develop real-time computer vision applications. It mainly focuses on image processing, video capture and analysis including features like face detection and object detection.
- SKLEARN: - Scikit-learn (previously scikits.learn and also known as sklearn) is a Python machine learning package. It includes support-vector machines, random forests, gradient boosting, k-means, and DBSCAN, among other classification, regression, and clustering techniques, and is designed to work with Python numerical and scientific libraries NumPy and SciPy. Scikit-learn is a NumFOCUS-supported project.
- NUMPY: - NumPy, which stands for Numerical Python, is a library consisting of multidimensional array objects and a collection of routines for processing those arrays. Using NumPy, mathematical and logical operations on arrays can be performed. This tutorial explains the basics of NumPy such as its architecture and environment. It also discusses the various array functions, types of indexing, etc.

III. PROPOSED METHODOLOGY

The proposed system consists of planning and executing the system which secured the answers for the existing system
required. The task additionally includes an extensive assessment of the system, and is to give proficient security to Urban by building up an Unsupervised Abnormal Crowd Behavior Detection system. We developed a system which can characterize normal and abnormal behaviors in crowds utilizing a constant video observation system to analyze and monitor crowded urban environments.

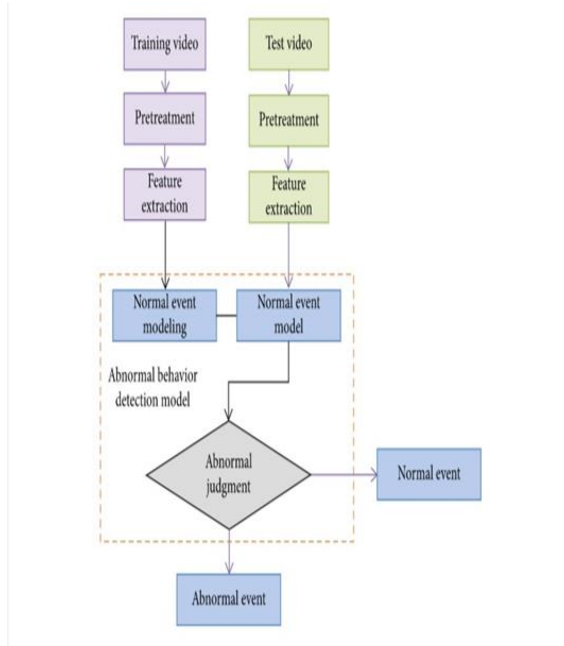

Figure 1. Proposed System

People pay more and more attention to anomaly detection, and there are more and more methods. In the literature, a method for estimating sudden changes and unusual motion changes was proposed. First, generate a motion heat map to use as the foreground of the video. Then, use optical flow to detect features and track them. Calculate a set of statistical measures and determine thresholds based on these measures to make decisions. In the literature, the social force model is used to detect and locate anomalies. The algorithm first uses the optical flow method to extract the particle trajectory. Then, use the social force model to calculate the force flow for each pixel. Finally, based on a fixed threshold likelihood estimation, normal and Unusual are marked. In the literature, the force field model is used to describe the clustering behavior with attributes such as direction, location, and group size. The group attribute that appears suddenly is marked as an unusual event. An Unusual event detection for occluded scenes is proposed. The algorithm first uses the average displacement method to segment the video into regions and then uses the shape matching method to match the model with the video segment. The literature uses the principle of thermal imaging to detect pedestrian posture in a mass.

After background subtraction and head detection, a number of weak classifiers combined with the human body model are used to detect unusual poses. Model-based anomaly detection methods have received widespread attention due to their high success rate. However, most of these methods require learning and training and the model is complex

Fig 2:

IV. MODELS USED

- K-nearest neighbors (KNN): The KNN method is a supervised machine learning technique that may be used to handle classification and regression issues [6].It's simple to set up and comprehend, but it has the disadvantage of being substantially slower as the amount of data in use rises.
- Support Vector Machine: SVM stands for Support Vector Machine and is one of the most widely used Supervised Learning algorithms for Classification and Regression issues. However, it is mostly utilized in Machine Learning for Classification difficulties. The SVM algorithm's purpose is to find the optimum line or decision boundary for categorizing n-dimensional space into classes so that additional data points may bereadily placed in the proper category in the future. A hyperplane is the name for the optimal choice boundary.
- Logistic regression hyperparameter tuning: - Hyperparameters in machine learning algorithms allow you to adjust the algorithm's behavior to your individual dataset. Hyperparameters are not the same as parameters, which are the internal coefficients or weights discovered by the learning procedure for a mode.

V. FEATURE EXTRACTION

For each input frame of the taken scenario, a set of the interested point is extracted. Usually, we take a mask to define these points of interest. This mask is got from motion map of the frame. Our approach implements Harris corner detector for extracting interest points. After getting points of interest in one frame, we start finding these points on next frame using optical flow pattern. For tracking purpose, we applied Kanade-Lucas-Tomasi feature tracker. After matching features points between individual frames, we get a set of vectors.

$$O = \{O_1, \dots O_N\} | O_i = (x_i, y_i, d_i, \theta_i)\} \quad (1)$$

Where x_i *and* y_i are coordinates of feature$i$,$d_i$is the distance between matched feature points of two consecutive frame.$\theta_i$is the motion direction between two matched points of consecutive frames.

$$d_i = \sqrt{(q_{x_i} - p_{x_i})^2 + (q_{y_i} - p_{y_i})^2} \quad (2)$$

$$\theta_i = \operatorname{atan}\left(\frac{q_{y_i} - p_{y_i}}{q_{x_i} - p_{x_i}}\right) \quad (3)$$

Here p(x_i,y_i) and q(x_i,y_i) are location of interest points moving from two consecutive frame.

In normal frames of the video, individuals are moving in all direction where as in the abnormal frame of the video individuals are running or walking in one direction. After getting feature vector we convert all feature vectors in the form of Histogram representation. Histogram representation of each frame is trained by SVM method in order to get support vectors.

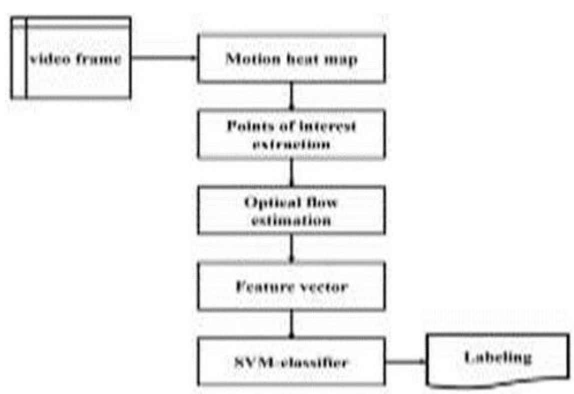

Fig 3:

These support vectors are analyzed by SVM classifier to detect abnormal event of the video. The complete flow diagram of the proposed approach is shown in figure

VI. SVM CLASSIFIER

Support Vector Machine is classification method, which was initially based on the theory of statistical learning. Later by supporting of kernel method it can deal with the nonlinear problem also. The problem of SVM can be represented as:

$$\min_{\omega, \varepsilon, \rho} \frac{1}{2}\|\omega\|^2 + \frac{1}{\nu n}\sum_{i=1}^{n} \varepsilon_i - \rho \qquad (4)$$

Subject to $(\omega, \Phi, (x_i) \geq \rho - \varepsilon_i, \varepsilon_i \geq 0)$

Where ω width of margin and $x_i \in X, i \in [1 \dots n]$ are n training samples of X. ε_i is the stack variable for penalizing the outliers.

The hyper parameter $\nu \in (0,1]$ is the weight for the controlled slack variable. is a map of non-empty set of data X .

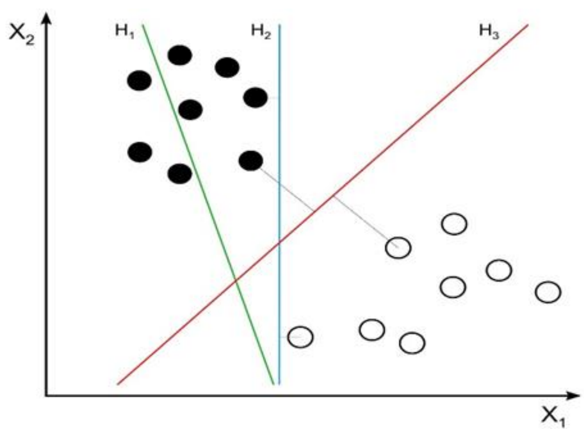

Fig 4
ABNORMAL DETECTION BY OPTICAL FLOW WITH SV CLASSIFIER

By adopting the optical flow feature descriptor and the SVM classification method, the abnormal detection in video stream is summarized in following steps:

I. Image frames conversion
II. Extraction of Motion Heat Map which represents the active area of motion.
III. Extracting the point of interest
IV. Tracking the feature points in each frame
V. compute the optical flow of each frame $[I_1, \dots, I_m]$ $[I_1, I_2 \dots, I_m] \rightarrow [O_1, O_2 \dots, O_m]$
VI. Compute the histogram of each frame $[O_1, O_2 \dots, O_m] \rightarrow [H_1, H_2 \dots, H_m]$
VII. Training data are learned by SVM classifiers to get support vector $[H_1, H_2 \dots, H_m] \rightarrow [S_1, S_2 \dots, S_m]$
VIII. Each frame is classified by SVM classifier with the help of analyzing support vectors.

VII. RESULT AND ANALYSIS

The experiment performance of the proposed approach is evaluated using the dataset is taken from University of Minnesota (UMN). First, the dataset is converted into frames. Then these frames are exposed to proposed approach. We compared our result to ground truth and different state of arts method. Our proposed approach is clearly outperforming SFM and other state of art technique like chaotic invariants, sparse recons., Local statistics, MDT and GLCM. We have presented this comparison result in form of table1. The UMN dataset scenario is shown in figure 5 - figure 8. Figure 5 and 7 represents normal activity whereas figure 6 and figure 8 represents abnormal activity.

Fig 5: Hit and Run Scenario

Fig 6: Abnormal Hit and Run Scenario

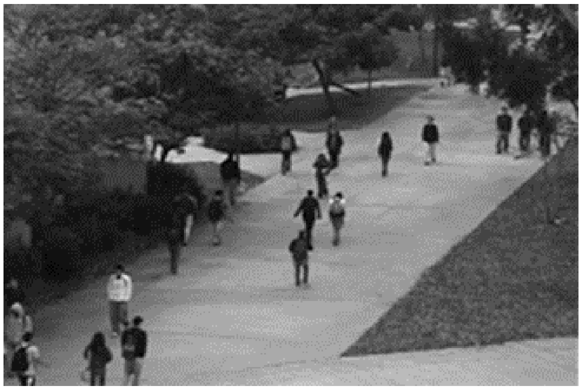
Fig 7: Park Scenario


Fig 8: Park Scenario

Below is a descriptive comparison of the three models used, with the help of ROC (Receiver Operating Characteristics) Curves and Tabular data.

ROC Curves:-

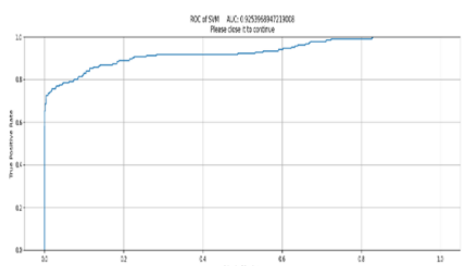
Fig 9: SVM ROC Curve

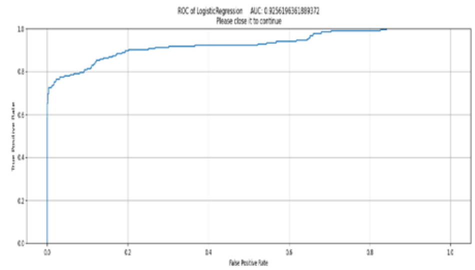
Fig 10: Logistic Regression ROC Curve

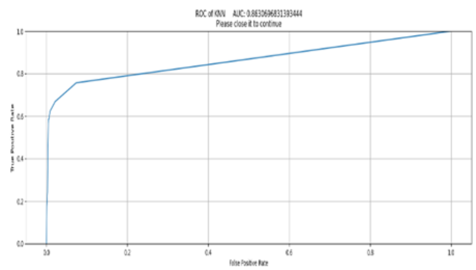
Fig 11: KNN ROC Curve

Table:-

Sr. No.	Model Name	Training Accuracy	Testing Accuracy	Area Under Curve of ROC
1.	SVM	0.9759433	0.9675396	0.9254143
2.	Logistic Regression	0.9754716	0.9645887	0.9256196
3.	KNN	0.9844339	0.9671707	0.8630696

VIII. CONCLUSION

Crowd Unusual behaviour detection technology is one of the research hotspots in the field of vision, and it is an important part of the field of intelligent surveillance. It is widely used in the smart security of airports, shopping malls, schools, and communities. With the continuous deepening of research on crowd unusual behaviour detection algorithms, significant progress has been made.. First, the optical flow information between the RGB image and the video frame is used as the input of the network. After that, the motion trajectory map is extracted based on the single frame original image.

We have presented a technique which is based on optical flow approach and SVM classification system to detect abnormal video events. The dataset used in our experiment is UMN dataset. Optical flow techniques tracks low-level information like points of interest. The displacement and angle between points of interest are estimated. These parameters give the feature vector. For each individual feature, we have a feature vector. These feature vectors are converted into histogram representation. For each frame in a video, histogram representation is estimated. These histogram representations are converted to support vectors. Support vectors are analyzed by SVM classifiers to give results. ROC results are shown in the form of graphs which is comparable result against state of art methods in terms of area under curve and performance.

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