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Towards detection of abnormal event and reporting for pedestrian video surveillance

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***Abstract*---**An Anomaly can be defined as an observation that does follow the normal activities with respect to others. Anomaly is polysemy that varies in a different context. For video sequences, an anomaly can be defined in terms of motion or state of motion that obtrude concerning to state and time. This work is based on Pedestrian Video Surveillance, having a normal event as a pedestrian and abnormal event as cars, skaters, bikers, wheelchairs, etc. i.e., non-pedestrian. A comprehensive study has been carried out of many existing systems for the Anomaly detection system. Based on many existing techniques we select a method called optical flow for the feature presentation of the detection of motion and Histogram of optical flow (HOOF) for the action contour of optical flow for every time instant irrespective of scale and direction of motion. As HOOF represents the motion of an object in a region, so there may be cases that the information related to the motion is not well represented. We used these two techniques along with the labelling of the frame inorderto overcome the problem of HOOF for the classifier. And gives the improved results. For training the model, the UCSD dataset is used which is very versatile having ample scenarios of normal and abnormal activities. For classification, three classifiers are used namely k-NN,LR and SVMwhich train the model to classify the event into a normal and abnormal event. The results of these classifiers are compared and give the best result out of it for all the video sequences.

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***Keywords*---**abnormal event, reporting, pedestrian video surveillance.

Introduction

In the ongoing scenario, it is important to use a surveillance system to keep an eye on the crowd in concern with security. The present work is to detect the anomaly in terms of skaters, bicycles, and cars, i.e., non-pedestrian, which is not allowed in the pedestrian walkway, is captured by the camera mounted at a certain elevation. The proposed framework analyses the video, compare them with existing video frames and then find motion that deviates from the previous frame. The deviation is computed with the help of optical flow.This helps in getting the compositional context of the events.The term pedestrian refers to the person who is in the action of walking or running on the street. In some sections, a person in a wheelchair is also considered a pedestrian. Surveillance played the most vital role in today's scenario because of its proficiency to monitor an individual's activities, behavior, and details to provide a safe place for people. This surveillance system is used in many applications like crime detection, the application of banks, tracking of pedestrians, malls, educational institutes, private detectors, and so on. The above-mentioned application uses the surveillance system to detect anomalies [1] that is recognize unusual activities from the group of data or objects.According to [2] the discussion shows an abnormal event in the video footage results in the form of the image depicted in fig 1 below. This paper analyses the video footage and apply data mining technique for the detection of discussed anomaly. There are various types of technique developed for detecting motion of a person in the crowded place or a particular place. Generally, data mining technique is categorized into unsupervised, semi-supervised and supervised techniques for detection of anomalies. Unsupervised learning does not use labelled data for examining the video for detection of anomaly behavior, but it effectively detects suspicious activity [3] in the surveillance system by using learning methods and activation functions. Semi supervised method classifies the anomaly with the help of learning model and training process. While Supervised learning uses labelled data for both normal and abnormal events for the training process which effectively determine the suspicious activity [4] in the given data. According to the discussion, there are many methods are available for anomaly detection like support vector machine, Hidden Markova model, classifier of correlation, subspace analyzer, fuzzy logic, Bayesian networks, autoencoders, association rule, local outliner factor, tensor board examination, optical flow, isolation forest, k nearest neighbor and neural network are used to detect the anomalous behavior.

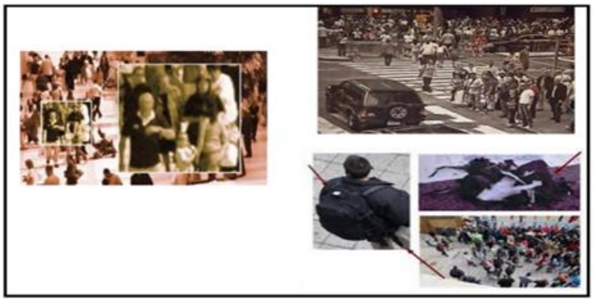

Figure 1. Sample image of captured Video footage

Framework And Methodology

Initial Design

In this work computation of optical flow as a feature extraction and selection of the motion is executed. But by using raw optical flow bring up challenges [5]like it does not give desired result if there is noise in background, any change in the scale, direction of movement and this project takes event in motion therefore the pixel of the person or an object change in time.

To overcome the issues, Histogram of oriented optical flow (HOOF) is used. When we take optical flow for the walking man with the stationary background it shows somehow same optical flow. Also, usage of optical flow for the far away person does not give much of an effect while working for zoomed in person gives the promising result. Similarly, when an object is travelling from left to right, the result of optical flow is on the vertical axis as if the person is moving from right to left. In [19], The histogram is independent of the direction of motion when Binning is placed in such a way that the angle made between the horizontal line and optical vector is the primary angle. In this way we get the same histogram when any object is moving from left to right or right to left and going far from camera or coming close to camera. Generally, bin B is the custom choice of the designer but the higher the bin the more promising result is computed. We can compute histogram of whole frame in-spite to precompute the person with the help of magnitude-based bin.In this work labelling of frame to overcome the issue of HOOF i.e.,HOOF represent optical flow values of object involve in the action of motion. Therefore, the dynamic nature of an object, there may be instance of HOOF may not have complete information of this dynamic nature. So, by providing labelling there will be support for the classifier along with the HOOF feature vector to classify between binary choice. In other word labelling ensures the nature of anomalies in the given feature vector or frame. By computing the labels of the frame, this system can be thought of Supervised approach for Detection of Anomalies in the Pedestrian Video Surveillance. In [5], authors used HOOF for activity recognition using 30 bins and gives 94.4% average recognition rate. We used this HOOF algorithm but with 9 bins and classify them with three classifiers having highest accuracy for detecting anomaly is 96.7% as a test result. We used Logistic Regression and k-NN method for classification as there is no existing system that uses LR as a classifier.

Algorithm

In this section we describe the algorithm of the proposed work. The input of the algorithm is the video sequence frame and output will be window showing video and red box around flickering the anomaly.

Algorithm: Anomaly detection in Video
Input: Frames of Video Sequence
Output: Window showing Anomaly and ROC Graph

```
begin
        For I ← 1 to do
                Convert Video Clips to respective frames
                Rescale the frames and convert into greyscale
                Label the frames into class of normal and abnormal
        End For

        For I ← 1 do
                Calculate optical flow of each frame
                For J←1 do for each flow
                        Compute HOOF for the flow vector
                End For
        End For

        For I ← 1 to do
                Apply SVM, LR and k-NN classifier on HOOF flow vector along with labels
                created
        End For

        Accumulate results
end
```

Architecture

The Architecture of framework is shown below, with each component described thoroughly in subsequent section. Anomaly detections perform on the pedestrian video surveillance. Therefore, UCSD dataset is chosen for detecting anomalies. The system first fed with this video clips and then Frame processing. Afterwards the frame will be used for the foreground detection to detect the object. Basically,[6] this process segregates the foreground from the background of the images based on the changes going on in the foreground. In this case we are detecting bikers or cars or anomaly in the given video clip. There will be some changes by using which we can detect anomaly depending on their speed. However, in a walking area a person could not walk at the same speed as the biker or a car. Therefore, optical flow will used to detect such objects

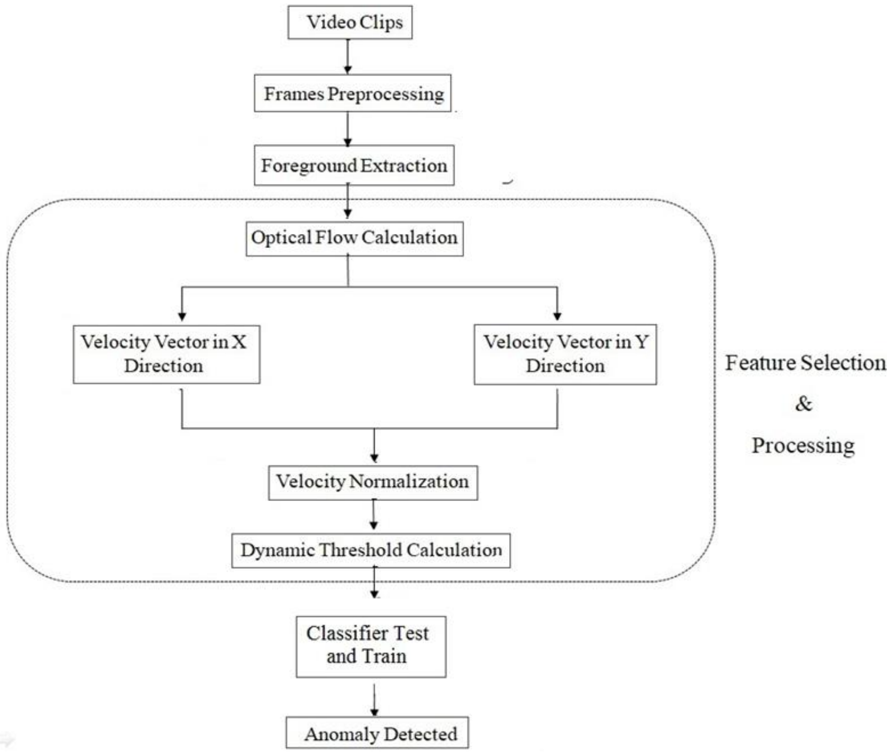

Figure 2. System Architecture

Pre-processing and Foreground Extraction

The main goal of pre-processing is to give suitable input to the system so that it can model the real time application. In this step we mainly focus on rescaling. The input comes in this step is the video to be processed on. In this step, we split these videos into the consecutive frames. And then resize it to 320*180. By rescaling we reduce the size of frames and also preserves the aspect ratio. After this the frames are converted into grayscale. After receiving the grayscale frame from above step, we need to focus on labelling the data. So, this step focusses on creating a binary mask the label the motion of pixels in all the frames. The label named with "static" and "dynamic". A Background model is created by using the technique of gaussian mixture model [7] and then gets updated on next frames.

Let [20] Ft designate the frame sequence of the video, Ft ($\vec{p}$) gives the information at location pixel $\vec{p}$ and Bt ($\vec{p}$) designate the binary mask value for the sequence frame. For computing the label of motion following background subtraction is used:

$$\mathrm{B}G_t = \begin{cases} 1, & if\ |F_t(\vec{p}) - \mathrm{BG_t}(\vec{p})| \geq \tau \\ 0, & if\ |F_t(\vec{p}) - \mathrm{BG_t}(\vec{p})| < \tau \end{cases}$$

Where BGt ($\vec{p}$) is the background of the current sequential frame and τ denotes threshold. Following equation shows the manner by which the background value is updated with incoming frames:

$$BG_t(\vec{p}) = \alpha F_t(\vec{p}) + (1-\alpha)BG_{t-1}(\vec{p})$$

Where α is the speed control coefficient which is responsible for controlling the frequency of the updating the frames with incoming sequences.

Optical Flow Calculation

It apparently gives useful information about the spatial distance and location for an object and also the rate of change in movement. As in this work,[8] abnormal activities can be depicted by the rate of change of movement, their brightness changes, with the help of direction of movement and also movement change of amplitude.Each pixel has a velocity vector in the graphic. This indicates how fast the pixel was traveling through the screen, and it also compute the direction in which it was traveling in the picture plane. An [21] irregular behavior can be detected by using the path and momentum of the motion, which is why we should use the optical flow to characterize the situation. The following description is the optical movement of two sets of images. On the basis of this experiment, we are reluctant to get the optical flow with larger speed change as in anomalies like bikers, skaters, car etc. are the high-speed moving vehicle with respect to the pedestrian.

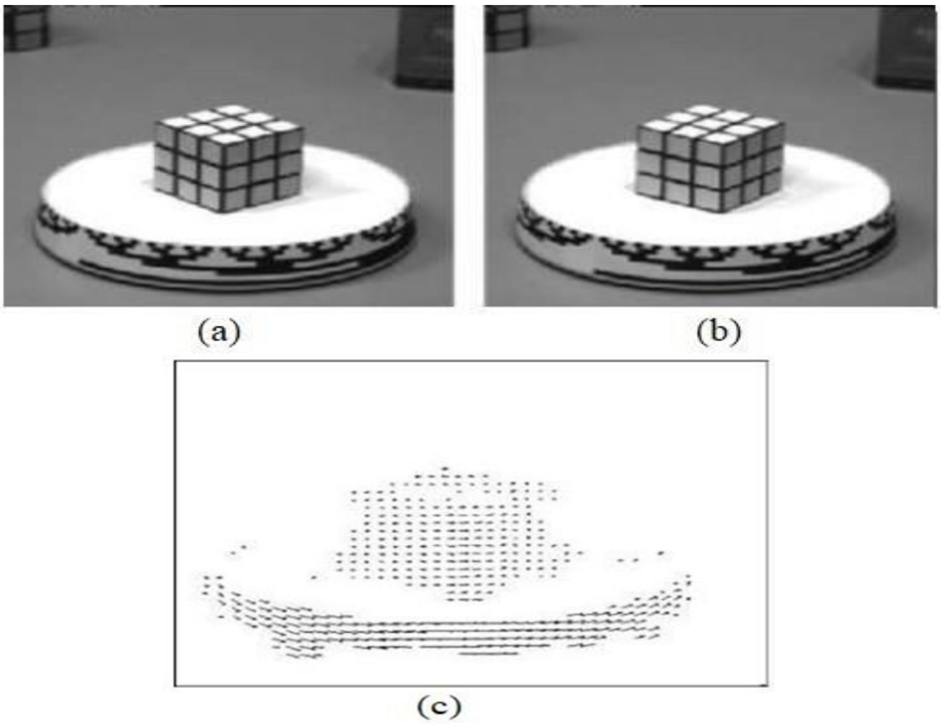

Figure 3. (a)and(b)have the frame sequences. (c) It depicts the optical flow for the Frame

Computation method: The following is the optical flow computation approach suggested in [9]. Considering each image intensity as constant for each corresponding pixel for every two sequences of picture. Let the brightness of image at point (x, y) at the time square t denoted as B (x, y,t).

$$B_0(x, y, t) \approx B_1$$

By Implementing Taylor's Series, we have following derivation

$$B_x = a + B_y + B_t = 0$$

In this case, neighbouring pixel have almost same velocity as others and also the brightness of neighbours moves smoothly everywhere. There may be disturbance in the flow when one object may occlude another one. In [10], Global energy function of optical flow formulated for the 2D image sequence describe below:

$$E = \iint \left[\left(B_x a + B_y b + B_t\right)^2 + \alpha\left(\left||\nabla a|\right|^2 + \left||\nabla b|\right|^2\right)\right] dxdy$$

Where Bx, By and Bz represents the details of each image intensity along with x, y and t dimension respectively. Also, for this solution needs to be more iterative as itrefers on the neighbouring pixel for the neighbour gets new data. Using avariance equationfor getting the following equation:

$$B_x\left(B_x a + B_y b + B_t\right) - \alpha^2 \Delta a = 0$$
$$B_y\left(B_x a + B_y b + B_t\right) - \alpha^2 \Delta b = 0$$

Where Δ=δ^2/(δx^2)+δ^2/(δy^2) is a Laplace operator.Therefore, the iterative solution can be given as:

$$\begin{cases} a^{k+1} = a^{-k} - \dfrac{B_x\left(B_x a^{-k} + B_y b^{-k} + B_t\right)}{\alpha^2 + B_x^2 + B_y^2} \\[2em] b^{k+1} = b^{-k} - \dfrac{B_y\left(B_x a^{-k} + B_y b^{-k} + B_t\right)}{\alpha^2 + B_x^2 + B_y^2} \end{cases}$$

Where k represents the iteration of the algorithm. As [26] with the help of changing coordinate of the moving feature of two consecutive frame we have a result of velocity vector which is called as motion vector of 2D plane which gives the velocity of X coordinate and Y coordinate.

Histogram of oriented optical flow calculation

HOOF is measured at the top of a dense grid of overlapping block and spatial properties of optical flow features at a different angle and converted into a high dimensional vector of features. Below Figure shows the cells of 2 X 2 descriptor of HOOF. In [11], The horizontal optical vector and vertical optical vector vote for the orientation bins in the horizon of 0o to -360o. Now on the basis of optical flow orientation, which is centered between the pixels, compute a weighted vote for a histogram channel which is edge oriented and the vote is stockpile by the edge over the orientation bins(B) in the spatial location.

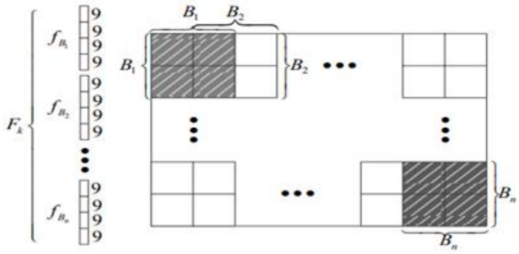

Figure 4. HOOF Computation in k^{th} Frame

Computation Method: In [12],Process the image into blocks such that afterwards each block is splitted into cells. A cube contains $b_h \times b_w$ cells, where $b_h \times b_w$ are the number of cells in x and y direction. In this work, adjustment of the resolution of every frame to 240 X 320. After whichevery frame is splitted into blocks of size 2 X 2 cells and for every cell having size 8 X 8 values.

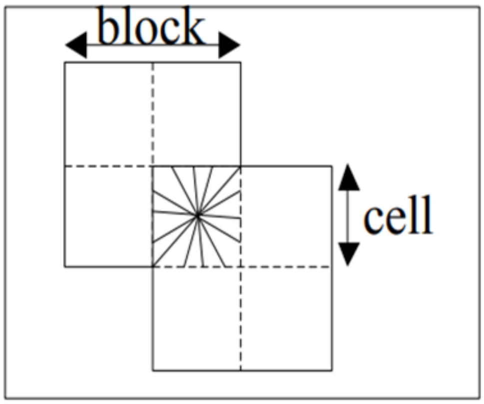

Figure 5. Division of block into cell

HOOF algorithm is represented below with the assumption of having only one block and within this block there is only one cell represented.

Algorithm: HOOF

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1. Deriving the optical flow for each two sequences of frame in a video.
2. Then for every optical flow vector is binned in respect to its angle i.e., the horizontal axis and using its immensity it can be given importance.
3. Thus for each of the optical flow vector $v=[a,b]^T$ within a direction, $\theta=\tan^{-1}(\frac{b}{a})$ in the range

$$-\frac{\pi}{2}+\pi\frac{k-1}{B} \leq \theta < \frac{-\pi}{2}+\pi\frac{k}{B}$$

Following diagram is the example of HOOF with 4 bins and the orientation bar graph:

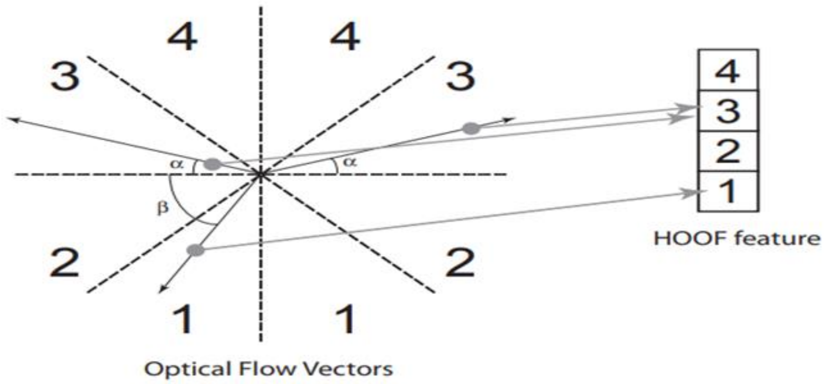

Figure 6: Formation of histogram with four bins

Classification technique

Classification is the procedure to classify the set of data into category, the data can be in the form of structural and non-structural dataset. It starts with the prediction of data to their given category. Category usually refers to the class, label or target. There are many classifiers available with different property. In this work three classifiers are used which is described below.

Support Vector Machine

It is One of the classifiers used in experiment i.e., [13] Support vector machines (SVM) gives a new way to design classification techniquesthat comes in the basis of theory of statistical learning. The SVM models gains the knowledge to separate the last regions between classes belonging to two classes by directing the input designupon a high variance space and demanding a separating hyperplane for thisparticular space.Later, SVM has also been extended to a non-linear design capability with the introduction of different kernel methods. The concept behind every non-linear multi class isdescribed below:

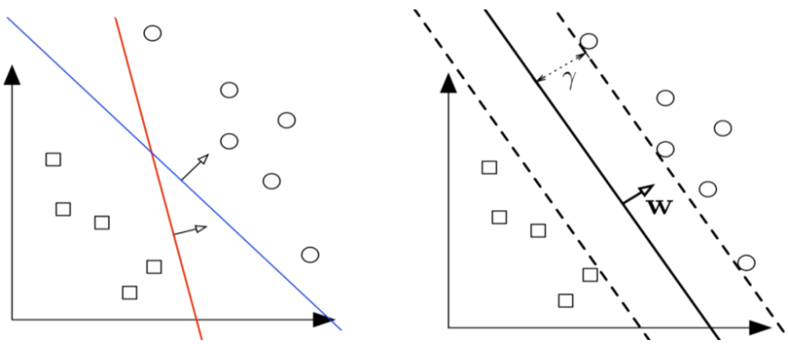

Figure 7. Greatest-margin hyper plane for every pair of classes and SVM for inclined andnon-distributed design.

K-Nearest Neighbours

K-nearest neighbour is the most popular algorithm in the machine learning where k represents that how many neighbours we are going to consider in terms of distance. It is supervised learning algorithm. k-NN also called as instant based learning and lazy learning because when it gets the training set it stores them rather process them instead it just stored the examples. In [14], When we need to classify something then it does something means when it gets the test instant it uses the stored instances in the memory in order to find possible answer. This algorithm is used for both classification and regression. k-NN believe that the similar data is present in the near vicinity in other word similar things are close to each other

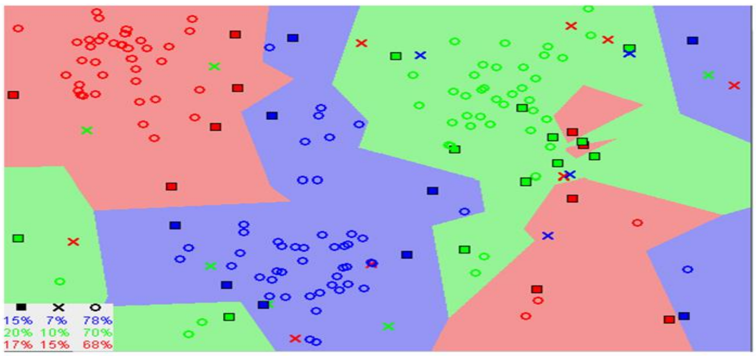

Figure 8. Similarity Of Datapoint Occurs in Vicinity

The distance in this algorithm is measured by two methods, Euclidean distance and Manhattan distance. In Euclidean distance, the distance between the test data and the k near points are calculated, whichever is the smallest is used as a prediction in classification and in regression problem we simply take averages of the distance.

Logistic Regression Classifier

The concept of Logistic regression comes from the linear regression. Linear regression works well for the regression problem but when it comes with the classification it fails. Therefore, to solve this problem we use Logistic regression for every classification technique. In LR we have hypothesis technique i.e., h(x) shown below:

$$h(x) = \sum_{i=0}^{N} \beta_i X_i$$

In [15], Where N is the figure of predictor or variables, and learning involves the value of βi. Now in case of classification the equation will provide the real worth and it is not suitable for classification technique. For this we can use logistic function or in other word it is called as sigmoid function.

Results and Discussion

To demonstrate the use of the anomaly detection system, the following three classification algorithms were performed.

Description of Database

The [16], UCSD Anomaly Detection Dataset has been acquired by a stationary video camera placed at an elevation, keep a look over the pedestrian street. This Walkway is only design for the Pedestrian therefore, commonly taking place of anomalies include skaters, cars, bikers, cycle, small carts. All abnormalities have been naturally Existing, i.e., they were not at all staged as a reason of combining the data as much as possible. The data was divided in two phases i.e., namely Test and Train each corresponding to a different scene. Each Test and Train folder contain 34 and 36 folders having frames of the video.

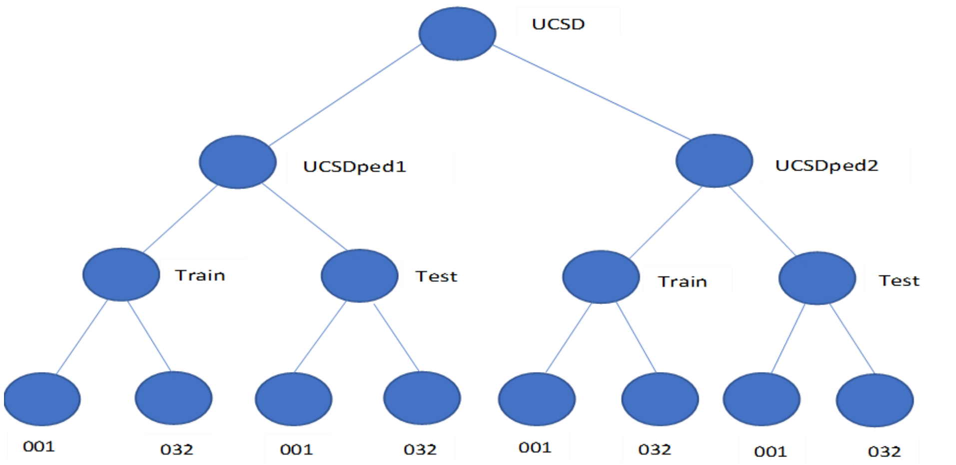

Figure 9. Structure of Dataset

Performance Analysis

The effectiveness of the proposed algorithm could be analysed at two levels, namely frame level and pixel level. In [17], If a frame has at least one abnormality, then that should be detected. Pixel level analysis deals with the localization accuracy i.e., the detected events weredifferentiated with every ground factobservation. The Perfection levels of these three different classifiers as k-NN, Logistic Regression and SVM are compared in terms of their performance level and their corresponding accuracy levels are plotted. In [22], Naves Bayes being for the branch of a Bayesian network follow the directed acrylic graph method to predict the Variance.

AUC-ROC are[23] curve that has an efficiency metric for each classification technique at different threshold settings. ROC is having a possibility curve, and AUC is the degree or indicator of separability. This says how often the models are carefully to distinguish between different classes. The higher of the AUC, the better will be the formula that is to estimate 0s as 0s and 1s as 1s.

True Positive test result [24] are one which detects every condition whenever the condition is present.
True Negative test result [25] are one whichthat does not detect the condition when every condition is absent.
False Positive: The number of errors caused by peoples.
False Negative: the number of errors caused by missing the peoples or the test result which are wrongly indicated.

Confusion matrix is a success metric for the challenge of machine learning classification, where results may be two or more classes. It is a table of four separate combinations of expected and real values.

N=200	Predicted No	Predicted Yes
Actual No	3	3
Actual Yes	10	184

Table 1. Confusion matrix for SVM classifier

As per the formula for the error rate and accuracy, here we showed the results about individual counting via face detection using this confusion matrix:

Err = 6/200= 0.033
Accuracy = 1-err
= 1-0.033
= 0.967
Accuracy (in percentage) = 96.7%

N=200	Predicted No	Predicted Yes
Actual No	4	3
Actual Yes	15	178

Table 2. Confusion matrix for k-NN classifier

Err = 7/200= 0.036
Accuracy =1-err
= 1-0.036
= 0.964
Accuracy (in percentage) = 96.4%

N=200	Predicted No	Predicted Yes
Actual No	3	4
Actual Yes	7	186

Table 3. Confusion matrix for Logistic Regression classifier

Err = 7/200= 0.036
Accuracy =1-err
= 1-0.036
= 0.964
Accuracy (in percentage) = 96.4%

The Figures below shows the ROC curve and the performance of the classification which can be described based on threshold variation. Figures show the [18], ROC curves of the performance comparison in terms of accuracy level between k-NN, SVM and Logistic Regression classifiers for UCSD Dataset based on both motion and appearance information. Figures below also show the ROC curves of the performance comparison in terms of accuracy.

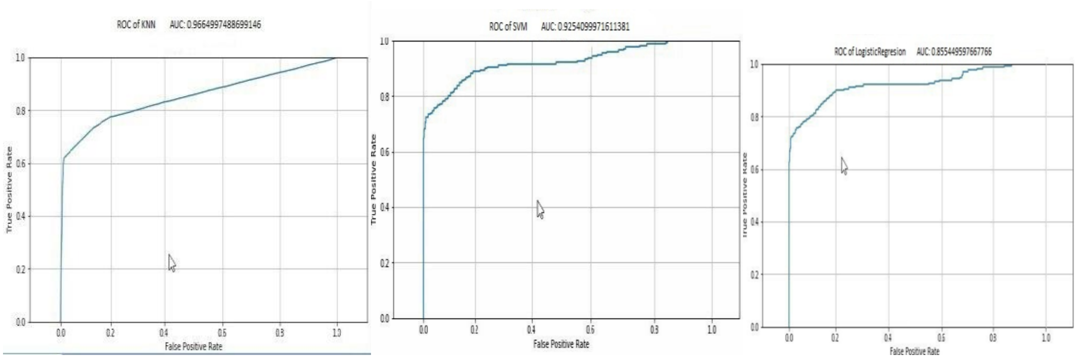

Figure 10. ROC curves of the performance graph in terms of accuracy level of ALL Classifier for UCSD Dataset based on both motion and appearance information

Performance of the classifier is shown below in table and comparison of three classifiers shown in the figure:

SNO	Classifiers	Train Accuracy	Test Accuracy
1	SVM	97.5	96.7
2	Logistic Regression	97.5	96.4
3	KNN	98.5	96.6

Table 4. Performance Metrics comparison of KNN, SVM and Logistic Regression classifiers (All the measurements represented in terms of %)

Conclusion

Uponrepeated simulations,on Anomaly detection in Video Sequence and Pedestrian Video Surveillance. Several methods to develop the anomaly detection system depending upon the nature of the anomaly which differs in the context are well-described.It implements the algorithm described that overcome the issue showing anomaly detection with the highest train accuracy of 98.5% and test accuracy of 96.7%. Also, Confusion matrix is described for every classifier showing false positive and true positive. Output window is screenshotted of every classifier along with their originals showing anomalies in red box also intermediate result has been shown of feature abstraction. The rare presence of anomalies makes the designing of this type of system difficult.Also, classifier scheme-based works have been elaborated. A comprehended study has been carried out by the State-Of-Art to know the challenges of anomaly detection in the motion, in order to distinguish between the existing system and the proposed framework, there are three aspects. First, the definition of an anomaly, a featured technique used for the extraction and estimation method.Many existing works have been apprehended to understand and evaluate the existing work of anomaly detection.This includes the pixel-based abstraction technique rather than object-based. As for the high density of the objects, it will be more suitable to detect them using a pixel-level abstraction technique. A dataset having video sequences containing the anomalies have been tasted to identify the possible outcomes.

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