Intelligent Video Surveillance Techniques to Detect Suspicious Human Activities: A Critical Review

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Abstract- Smart video surveillance systems have grown tremendously for providing security to sensitive places. These intelligent systems are integrated with advanced Artificial intelligence and Deep Neural Network algorithms to automatically detect suspicious and non-suspicious activities of humans. In this scenario, one of the most challenging tasks is seeing and recognizing suspicious activity in real-time. This study results from a comparative analysis of fragments extracted from a survey of 42 publications accessible at IEEE, Springer, and Elsevier online repositories, carried out to comprehend suspicious activity detection strategies, which resulted in an exhaustive comparison of several proposed methodologies. Many technologies, mainly based on intelligent approaches such as Neural Systems, Support Vector Machines, Saliency map features, and so on, have evolved as the basis for intelligence in such systems. The review's results are given in the form of techniques and approaches used to solve research challenges, .and the study concludes with a road map for future research

***Keywords*— Intelligence Video Surveillance, Object Detection, Object Classification, Artificial Intelligence, Deep Neural Network, Suspicious Activity Detection**

INTRODUCTION1

Among the several sense-organs, vision delivers the most information to most animals, including humans. It is used as a primary source to acknowledge and assess the circumstances [1]. The visual information is essential for appraising general and specific situations [2,3]. Despite substantial advances in image processing and computer vision application technologies, fully comprehending and interpreting a scenario as a human remains challenging [3]. Video surveillances possess top order in the list of applications for scenarios [4, 5, 6].

Video surveillance is defined as a system that uses several cameras to provide a continuous view of different places within the same region. The surveillance system is generally used to detect odd or deviant (suspect) behavior [7, 8, 9, 10]. Abnormal or suspicious activity is based on different situations and scenarios. In an environment like an office, academic and secure places like airports and banks, suspicious activity can be defined as running, colliding, falling, jumping, fighting, and slipping [8]. Figure 1 depicts a running scenario by two objects (humans), which occurred at some point in a video stream. The object has been tracked and marked by the system with red bounding box to highlight the suspicious activity [11]. If the scenario is an indoor place like a shop, the abnormal activity become 'Shoplifting', 'Robbery' or 'Break-In [12]. Similarly, kicking, pushing, punching, etc. could be marked as suspicious activities which must be detected during its occurrence in a video surveillance system.

The role of activity detection and identification is delegated to personnel in typical video surveillance systems, i.e., staff may be hired for constant monitoring at any point of time if any anomalous (suspicious) behavior occurring [13]. Furthermore, lack of financial resources may restrict an organization from hiring of any external firm to monitor the CCTV footage. As a result, CCTV footage is analyzed once a crime happens in their case. To illustrate, imagine a world where robots are able to identify suspicious activity and alert the proper authorities in real time, therefore reducing mob unrest and violence, acting as a go-between for monitoring in both public and private locations, and so on. Many research investigations have been conducted in this area to automate surveillance systems that automatically identify suspicious or anomalous human activity.

Figure 1. Object tracking (suspicious activity) [11].

The study results from a comparative analysis of excerpts from a literature review of 42 publications accessible at various online repositories, which was conducted to understand automatic suspicious activity detection systems better. The research begins with a thorough examination of several object detection, identification, and classification strategies in video streams. The literature survey reveals the current state and developments in video analysis. Finally, the

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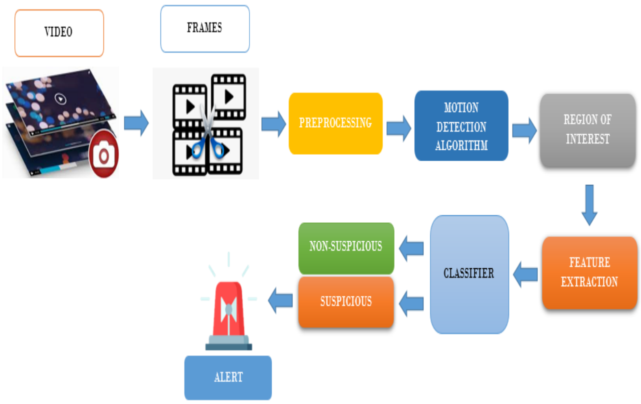
critical concerns that need to be addressed soon are expressed openly.



Figire 2 Model for Detecting Suspicious Behavior in Video Sequences.

BASIC SOLUTION APPROACHES FOR SUSPICIOUS ACTIVITY DETECTION

The fundamental approach for detecting suspicious behavior in video sequences is shown in Figure 2. Researchers applied the following methods to find suspicious behavior in movies [9-11, 14, 15]. This part will go through the fundamentals of detecting questionable conduct.

Preprocessing

Preprocessing enhances the quality of frames acquired from the captured video since they may have a lot of noise or variance, be in poor light, or be the result of sensor issues during video collecting. Figure 3 depicts how a morphological strategy reduces noise in a frame [11]. Morphological methods may be applied in MATLAB utilizing the open function to increase the quality of blob recognition of moving objects in video. To eliminate certain forms of noise, filters such as the Gaussian and average filters and the Wiener filter to increase the quality of blur frames can be utilized.

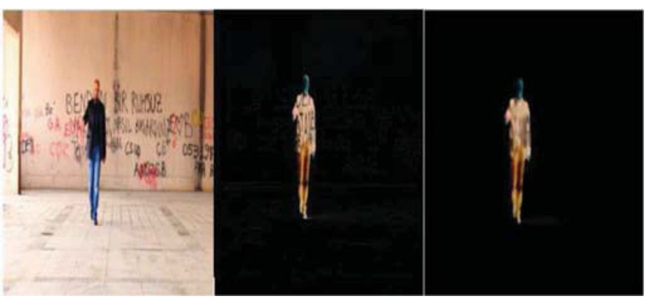


Figure 3. Morphological operations [11]

Figure 4. Background subtraction [11].
(A (Circumstantial frame), B (forefront frame), C-E(morphological functions), F (the result “background subtraction”))

Motion Detection Algorithms

The motion detection approach is utilized after preprocessing to pinpoint the motion region or region of interest in this series. Several motion detection algorithms are used. The first is background subtraction. As shown in Figure 4, the most used approach for foreground identification [11, 16-19]. Another prominent method for background removal is temporal differencing [20]. Statistical techniques [21], Optical Flow [8], and YOLO (You Only Look Once) [13] are the next three.

Feature Detection and Extraction

Approaches for detecting essential features or regions of interest in a picture, such as edges, corners, roughness, and blobs, are feature detection, image perception, and pattern recognition. Extraction of feature is just a dimensionality reduction strategy where massive data is furnished to fewer characteristics known as feature vectors. As a result, there is a requirement to translate enormous amounts of data into a collection of features. It is

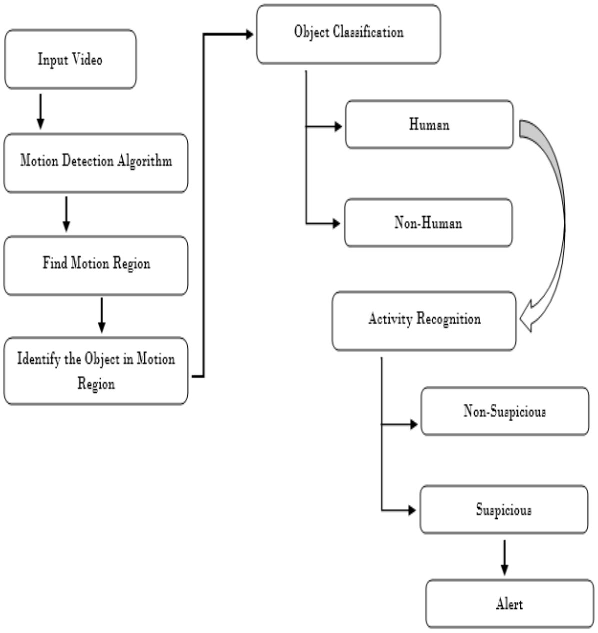


Figure. 5 Human Activity Recognition in Surveillance System [20].

You must now select the proper feature to address a critical issue. Some feature extraction algorithms, such as the LBPH (Local Binary Pattern Histogram) [13] classifier, are used in scenarios requiring dynamic classification, such as an object (i.e., person) can be detected and recognized immediately when added to a classifier model; another is the HOG (histogram of oriented gradients) [22] classifier, which uses frame features to train the classifier to classify the input test frames to either standard or structure showing some.

Classification

Classification is counted as the process of pattern categorization. It helps to sort the input data into many groups. This is frequently used to give class labels to newly tested data using the learned model. Usually, distinguishing between usual and unusual events is a two-class problem. In the previous literature [22], researchers employed support vector machines to recognize normal and abnormal circumstances since SVM is well suited for two-class scenarios. A variety of classifiers were also used, including YOLO (You Only Look Once) [13], RNN [10], Random Forest [14], shape-based and motion-based classification [11].

BASIC MODEL FOR RECOGNITION OF ABNORMAL HUMAN BEHAVIOR

In this part, equipment, such as surveillance cameras, is utilized to capture and evaluate a video sequence. The gathered footage must be divided into frame-by-frame series. When the frames have been obtained, the object detection operation will begin. Figure 5 displays the whole activity recognition mechanism in video surveillance sequentially.

Video-Input

The video connected to the system is captured using an input device such as a security camera [20]. Multiple security cameras can be mounted, each covering a specific range for video collection.

Motion Detection Algorithms

The identification of moving objects is a crucial aspect in wide-scene analysis. The motion region of the given frame is extracted for object recognition using the motion detection method [8, 11, 13, 17-19, 23, 24], and the object is then removed from the moving backdrop.

Object Identification in Motion Region

After localizing the motion region in the video frame, the Object detection Algorithm [17] will be applied to identify the object. For this purpose, different algorithms such as background subtraction. [11, 16-19], Optical Flow [8], YOLO (You Only Look Once) [13] are identified in the literature as depicted in Figure 6.

Object Classification

The next stage in detecting activity is to identify the object as human or non-human based on the various approaches and nature of the research.

Human Activity Detection

Analysis of the video sequence is carried out after the detection of a human being in the footage to assess whether or not the behavior is suspicious. There are many instances of anomalous conduct: patient misbehavior in the hospital, weird human behavior in ATM videos, academic misbehavior, financial misbehavior, and misbehavior in shop-ping malls, to name a few.

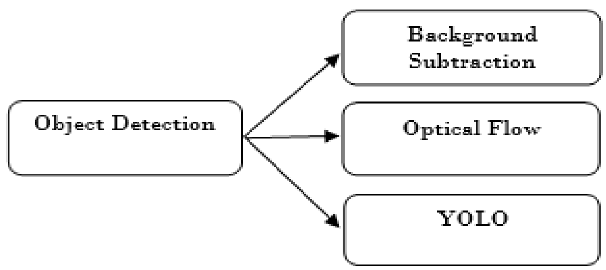


Figure. 6 Object Detection Methods [20].

Alert system

When unusual behavior is detected, the system will immediately issue an alert or an alarm to notify security personnel of the activity and the need for rapid action.
Suspicious Activity Detection

Intelligent home prediction [25–27], detection of health emergencies [28], and detection of abnormal actions in the crowd [29–31] are examples of existing research on activity prediction. Further, the detection is performed in an academic environment [10], Shopping environment [12,13], War field environment [15]. In this regard, the following section provides a detail view of previous studies for anomaly activity detection.

[11] presents a method to assist intelligent monitoring in recognizing anomalous activities that indicate a security issue. The algorithms mentioned in this section were designed to identify two types of human activities: walking and running. There were no constraints on the number of persons or the direction of the motions in the scene. On the other hand, the video was shot using an interior fixed camera. The background removal method detects moving items in the location that match humans. Object categorization was accomplished using "shape-based classification" and "motion-based classification" methods. Likewise, data from networked security cameras were used in an innovative deep learning method [9] created to forecast odd occurrences. In an IoT environment, the technology was able to notify such circumstances. According to previous research, the predicted activity rate was determined to be 98.88 percent, which is a fantastic result.

Similarly, research was conducted in [15] for an intelligent combat field monitoring system that employs an IoT environment. The study comprises a raspberry pi processor interfaced with a night vision camera capable of perceiving the surroundings, making intelligent decisions, directing the environment, and acting on it. The Internet of Things is utilized to notify concerned authorities about an enemy's state. The devised approach, which employs an optical flow motion-based moving object identification method, was implemented in real-time.

Likewise, crowd behavior analysis and identification are becoming a prominent topic [32]. A residual deep learning architecture-based investigation was done to count the crowds, identify aggressive behavior, and classify the density levels of the people in the crowd [30]. The experiment used a 100-image dataset to test the performance of the suggested multitask architecture. Residual deep learning architectures have been proven to attain state-of-the-art performance in both picture identification and object detection tasks [26] therefore the work yields encouraging findings. Another study [33] was conducted for crowd behavior detection, which used the simplified Histogram of Oriented Tracklist (sHOT) model for anomaly identification in crowded settings. Other studies by [34-40] also add to crowd behavior analysis. In addition, an intelligent video surveillance system is implemented for shop security [13]. The technology detects and recognizes suspicious activities in real-time, notifying and updating the appropriate authorities at the same time. The system could provide security at the entry, counter, and object placement areas by conducting all object and person categorization and detection utilizing YOLO (You Only Look Once).

By following the research works, a study to ensure security in an academic environment was also highlighted [10]. In this regard, a Deep Learning technique was utilized to identify suspicious or normal behavior in an academic setting, and it sends an alarm message to the appropriate authorities if a suspicious action is predicted. The system employs CNN for the objective of extracting high-level characteristics from pictures to minimize the complexity of the input. In addition, the system was also equipped with RNN algorithm that was used for the classification purpose. The overall accuracy achieved by the system was 87.15%. Moreover, the literature is also presented in table I.

GAPS IDENTIFIED

This evaluation procedure might determine the areas of improvement or gaps in research work after a thorough assessment of IVS publications, and it is expressed as follows:
Improve its accuracy in the following scenarios:

- In the presence of clutter in the test scenario, complex backdrop, surroundings, and situations become a difficulty in practically all techniques.
- Feature changes over time pose a risk to shape and feature-based recognition algorithms.
- Misplaced tracks and object confusion because of unavoidable resemblance.
- Occluded objects, shadows, non-rigid targets, variable lighting conditions, target splitting and merging

ii. If two objects with the same color profile are engaged in the same occlusion event, color-based categorization and tracking may fail.
iii. A shortage of professional and difficult-to-test high-quality data sets
iv. Criteria such as standard measurement, hit-and-miss weighting, and ground truth generation are contested.
v. Targets that are too close to the camera cannot be verified using the vision-based cell model approach. Detection errors occur when the bounding box of a moving object gets too tight due to sunlight. When used outdoors, it failed to detect two fast-moving objects.

Along with the deficiencies that resulted from the research, uncertain market needs are a hurdle to overcome to make this research output useful to society, industry, and domicile.

CONCLUSION AND FUTURE WORK

Suspicious Behavior Detection comprised actions such as loitering people, unattended bags, intrusion detection, moving object detection, and so on. A variety of methods were utilized to detect the target. The use of deep neural network-based solution techniques improves the accuracy of the investigations. The importance of Intelligent Video Surveillance applications, particularly in Human Fall

Detection, is demonstrated in this study because it directly relates to societal well-being, as is the care of unattended elderly persons at home in the lives of most of the working population, as demonstrated in this study. Suspicious activity detection has also been suggested as a possible application for a single system. Several apps could be created to offer security applications for the benefit of society. Moving object detection, intrusion detection, lingering persons, unexplained items, and more applications may be devised and executed using a simple approach. The thorough evaluation might eventually result in significant and comparable discoveries in the areas of image recognition and intelligent video surveillance, as well as gaps and scope of work for future research.

Ref No	Key issue	Solution Approach	Object Detection	Object Classification	Parameters	Results
[11]	Suspicious activities	For each frame, compute the centroid's absolute x coordinate and compare it to the threshold value in x to determine the centroid's displacement in x.	Background Subtraction Method	Shape-based classification and motion-based classification	walking and running	Promising results
[41]	Distinguish the suspicious activities for surveillance environments	CNN model named "L4-Branched-ActionNet" and Entropy & ant colony system (ACS)	CNN	SVM and KNN	Not defined	Attained an accuracy of 0.9796
[42]	classify human activities as normal or suspicious	YOLOv3	YOLOv3	YOLOv3	jogging, walking, fighting, and chasing	average precision accuracy of 82.30%, and average F1 score of 88.10%
[7]	Assessing the risk	AI and deep learning algorithms	AI and deep learning algorithms	AI and deep learning algorithms	observable behavioral indicators (parameters)	Promising results
[8]	Suspicious behavior detection	A temporal salien mbining the moving reactivity attributes of motion magnitude and gradient acquired from optical flow.	Optical flow	Optical Flow	Running, colliding, falling, jumping, fighting, and lipping.	An average accuracy of 95%,
[9]	Occurrence of abnormal events	differential development of random forest trees with kernel densities (RFKD),	random-forest differential evolution	Multi-classifier	Not defined	98.88% Accuracy
[10]	Suspicious or regular activity in an academic environment	Deep learning CNN and Recurrent Neural Network (RNN).	Convolutional Neural Network	Recurrent Neural Network	Undefined	87.15% accuracy
[14]	Suspicious moving an object of an abnormal behavior	Strategy to detect anomalous activity based on object attributes that are independent of object size, shape, and speed	Foreground subtraction	Features based descriptor	size, shape, and speed	Effective results
[12]	Suspicious activity for Surveillance	Pre-trained Image-Net weights	pre-trained Image-Net weights	Pre-trained Image-Net weights	'Shoplifting,' 'Robbery' or 'Break-In'	89% as compared to other algorithms
[13]	Recognition in real-time	Neural Networks	Once you're done scanning, YOLO (You Only Look Once) will do the rest for you.	The LBPH classifier is also used in conjunction with YOLO.	Situations when dynamic categorization needs to be implemented.	Promising results
[22]	Violent activities of a person	Frames are categorized into two categories. First, having violence and second, containing normal activity through SVM classifier with HOG features derived	Histogram of oriented gradients (HOG) features of the frames to train the SVM Classifier	SVM Classifier	Kicking, pushing, punching, etc.	Accuracy of 89%
[15]	Motion based moving & object detection in real time.	Calculating the motion of image intensities	Optical flow algorithm for movement detection	Optical Flow	Undefined	Promising results

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