Industrial Engineering Journal
ISSN: 0970-2555
Volume: 52, Issue 1, No. 5, May 2023

A DEEP LEARNING INTELLIGENT VIDEO SURVEILLANCE

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***Abstract*—Detecting abnormal activity plays a very important role in monitoring applications. Detect anomalous activity in people without system intervention. You can implement automatic video capture. Human fall detection, sudden jumps, with important applications in safety and protection fields. A proposed system usage for detecting human activity or roadside behavior using a probabilistic neural network (PNN) method for classifying the activity or behavior between training datasets and test videos. . A split between classes of normal activity was also learned using multi-PNN. Human activity detection has become a trend in smart surveillance and poses multiple challenges such as: B. At the same time, effective detection of huge video data streams with low computational complexity. Current activity detection techniques use convolutional neural network (CNN) models with computationally complex classifiers, making it difficult to respond quickly to abnormal activity. Therefore, in this paper, we propose a framework for activity detection. First, we use an effective CNN model to detect anomalous activities involving people in surveillance streams. Detected people are tracked across the video stream using an ultra-fast object tracker called Minimum Output Sum of Squared Error (MOSSE). Then, for each tracked person, a pyramidal convolutional feature is extracted from two consecutive frames using an efficient LiteFlowNet CNN. Finally, a new deep-skip connected gate recurrent unit is trained to learn different temporal variations of a series of frames for activity detection and detection. We conclude with results showing the efficiency of the proposed method.**

Keywords— CNN, video cameras, classifiers, surveillance systems, PNN, MOSSE.

I. INTRODUCTION

In recent years, video surveillance applications have attracted more and more researchers. As a result, different types of modeling and several techniques for analyzing and detecting human activity have been proposed. In particular, much research is concerned with detecting and capturing human activity in general, and anomalous activity in particular. An important application is the home care of the elderly and disabled in care centers and hospitals. Human activity detection is a recent field of interest in providing techniques and methods that enable the detection and classification of human activity, currently being extended to detect normal or abnormal activity. increase. The motivation behind the latter is to provide immediate intervention to save people's lives or to provide services they cannot provide on their own. The field is new and interesting, attracting the attention of researchers trying to find solutions to the problems that arise in studying such kinds of activities. However, the suggestions made so far are those used for recognition of normal human activity with minor modifications. These proposals are still very limited due to the very limited amount of work and research in this area. Additionally, they are not efficient and suffer from several limitations and technical issues. To this end, this paper reviews existing research to provide researchers with a general overview of what exists in the field and to provide tools to help identify approaches to propose new approaches. Suggest a review and analysis. The manuscript is structured as follows. The second section provides a definition of anomalous activity, its different types, and some examples of anomalous activity by groups or individuals. The third section then discusses the motivations that led to the emergence of this research axis and the development of techniques that enable the analysis and detection of human activity in general and anomalous activity in particular. The fourth section is devoted to approaches proposed in the literature for detecting anomalous activity. For each proposal, this section lists the purpose for which it was created, its various phases, and the means used to validate it. We then discuss some aspects that influence or affect the validity and reliability of human activity classifications. The sixth section presents his three modes of automatic learning: supervised, unsupervised and semi-supervised. It then lists the limitations encountered that must be taken into account to improve the detection and identification system for anomalous activity. Finally, we conclude with a conclusion summarizing our study.

II. RELATED WORK

This paper is a lot of work on detecting anomalous behavior we adopted a supervised learning approach. Diverse posts made with Behavioral Development Detector for intelligent building surveillance applications. Of automatic loaders, human surveillance, vehicles or Human activity and behavior are detected and detected for the purpose of monitoring and alerting to detect human behavior.

Types of anomalies to detect objects or actions as follows:

Industrial Engineering Journal
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Volume: 52, Issue 1, No. 5, May 2023

a). Detection of abnormal human behavior by video

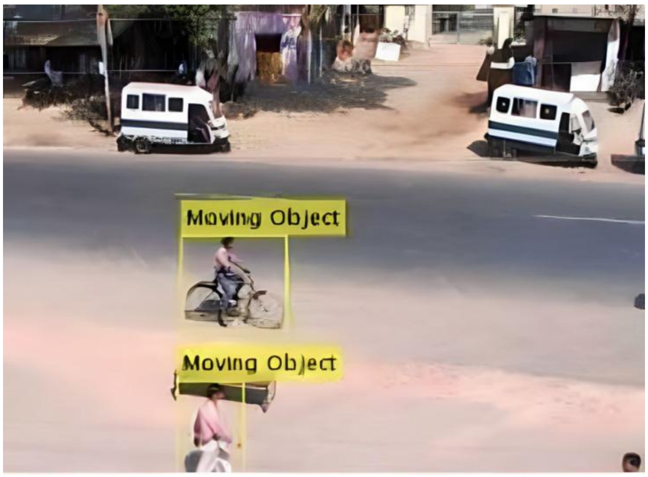

Fig 1. Moving Object

This technique only focuses on updating abnormal people Activity detection. Hidden Markov Models (HMM) and Dynamic Bayesian Network Models (DBNM) can be used Detect suspicious behavior as shown in Figure 1.

b). Motion detection, tracking and classification automatic video_surveillance

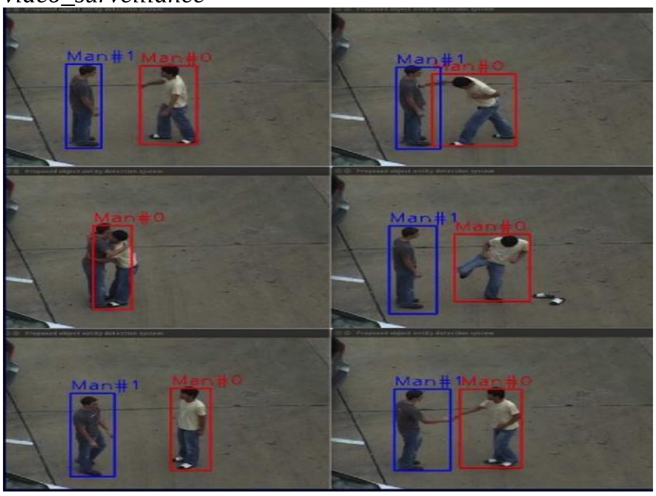

Fig 2. Tracking of Moving Object

III. Proposed System

In the proposed work, Motion detection is performed by using OpenCV and Pandas library. Captured videos are treated as a stack of pictures called frames. Different frames are compared to the static frame which has no movements. We compared two images by comparing the intensity value of each pixel. In this project we have used STAE (Spatial Temporal Auto Encoder) deep learning model to predict abnormal behaviour and this model get trained on normal peoples walking videos frames and then test video will be input to this model which will analyse STAE pattern and then return the event and this event will be compared with test frame using Euclidean distance and if this distance crossed normal behaviour threshold then application will display alert message.

The system will provide an easy way to monitor the traffic and give the appropriate result, parking lots for security purposes also, visible security cameras will help you detect thieves from breaking into cars. and will help in the security field on various platforms like parking lots, home security, it will make it easy to monitor the various abnormal activities and suspicious events.

Advantages

1. More Security.
2. Easy to monitor.

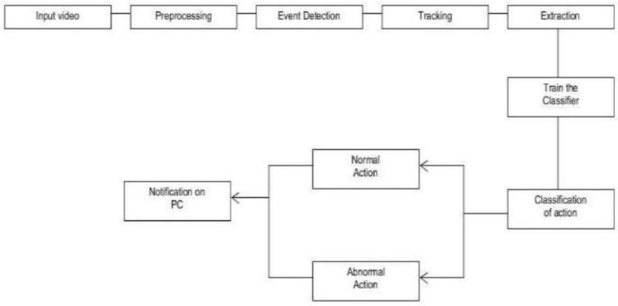

Fig 3. Proposed system diagram for detection of Event

IV. Architecture Diagram

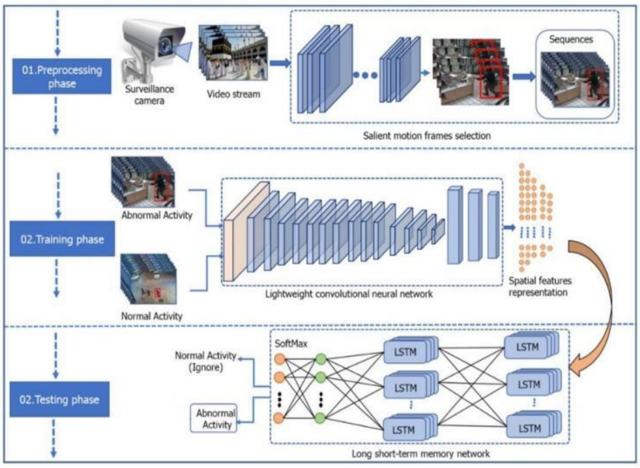

Fig 4. Architecture diagram for Detection of Event

a) Preprocessing phase

OpenCV is an open source Python library that includes: Various functions for image and video manipulation. And you can record videos from OpenCV cameras. cv2.VideoCapture() method is defined to capture the video capture camera objects. Create and use an infinite loop read()

Industrial Engineering Journal
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method to read the frame created above object. Show the frame using the Cv2.imshow() method on video. The loop breaks when the user clicks on specific key.

Motion detection is carried out in the proposed study utilising the OpenCV and Pandas libraries. Videos that are captured are handled as a frame stack of photos. Various frames are contrasted with a static frame that is still. By contrasting the intensity values of each pixel in two photographs, we could compare them. To make a change easier to see, we first convert a colour image to grayscale, and then we transform a grayscale image to GuassianBlur. The difference between the current frame and the static backdrop is then determined. If we discover that the difference between them is larger than 30, it will seem white. Then contour of the moving object.

b) Training Phase

Finding the crucial aspects of the data is the process of feature extraction. It condenses an initial collection of unprocessed data into smaller, easier-to-process units. Using the imread () approach, we will begin by reading coloured pictures in this case. The form of the image is discovered using the shape function. Let's say the picture is 375*500 in form. Hence, there will be 187500 characteristics. Using the reshape function in NumPy, where we supply the image's dimensions, you may alter the image's shape if you so choose. The picture in this instance has a dimension (375, 500, and 3). The RGB value and the number of channels are represented by these three. We will now generate the features using the earlier technique. In this instance, there will be a total of 375*500*3 = 562500 features. The dimensions of this colourful image's 3D matrix are (375*500*3), where 375 represents the image's height, 500 its breadth, and 3 its number of channels. We'll take a for loop to obtain the image's average pixel values. We'll now create a new matrix with the same height and width but just one channel. We'll make use of the Numpy module to turn the matrix into a 1D array. CT is discovered.

c) Testing Phase

Detecting, locating, and tracking each person throughout the video stream is a crucial stage in the detection of surveillance activities. Using object detectors that have been trained on broad categories of data is not practical for this purpose. In order to do this, we updated the data in a lightweight CNN model for human identification and gave it the ability to operate in a dynamic surveillance environment. It is superior than cutting-edge techniques, and experimentation has proven its efficacy. Our system can attain LSTM-level accuracy because to this design, which also makes it more effective than the LSTM.

V. Sequence Diagram

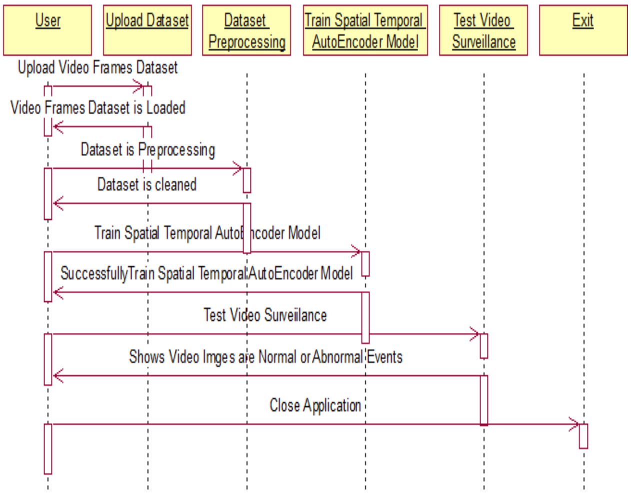

Fig 4. Sequence diagram for Event Detection

VI. Support Vector Machine (SVM)

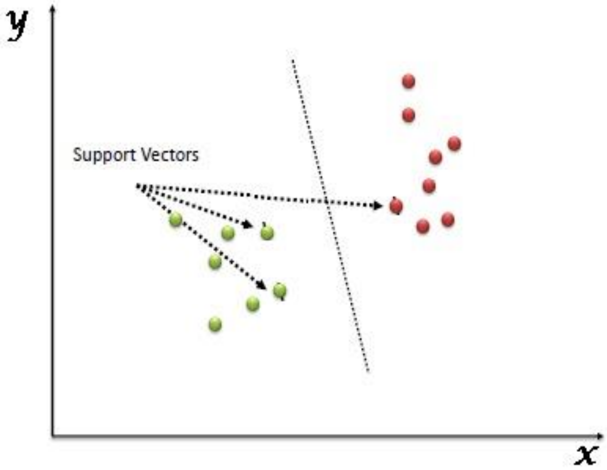

Fig 5. Support Vector Machine Diagram

- To extract periodic, scale, and translation invariant characteristics, utilize the R transform.
- As a non-linear method, several algorithms are utilised to get around the similarities across various classes of activities.
- Because of the SVM algorithm's applicability for time-dependent sequential data, it is employed in this study to train and recognise activities.

VII. Experimental Results

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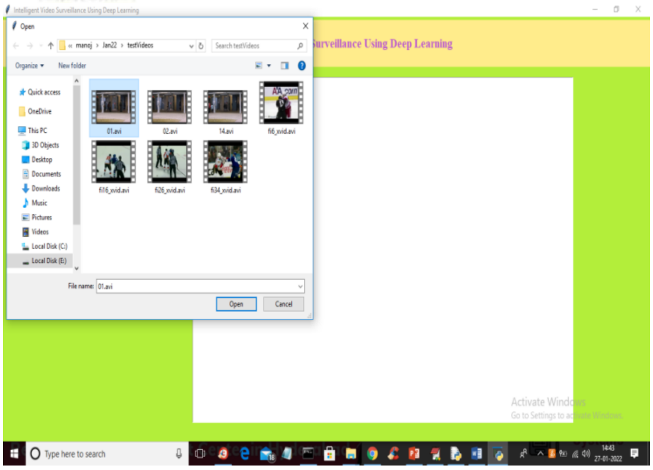

Fig 5. Input for Detection of abnormal or normal event

- We will use the file as input for detection of abnormal or normal event.
- Then choose one video stream for detection activity

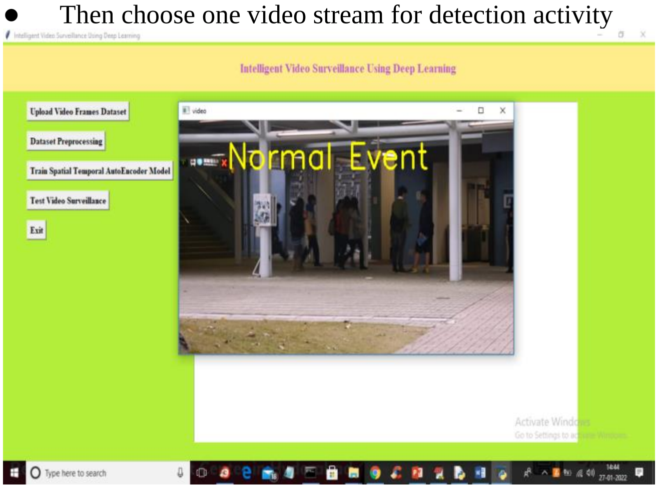

Fig 6. Output shows as a Normal Event

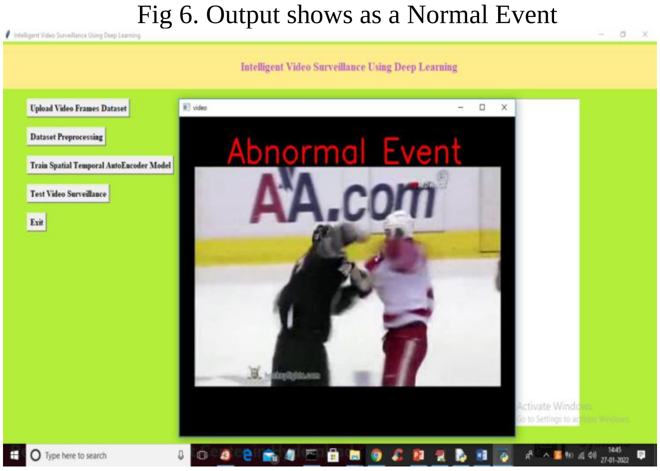

Fig 7. Output shows as a Abnormal event

- The system will begin processing the video after it has been opened in order to look for any unusual behaviour, and the outcome will be shown through the video.
- Every time an aberrant action takes place, the system will notice it and classify it as abnormal.
- If there is no abnormal event detected then it will label as 'Normal'.

VIII. Table

Threat	Vulnerability	Asset	Impact	Control Recommendations
System Failure Overheating in serve	Air conditioning system is old.	Server	All service will be unavailable for at least 2-3 hours.	Setup new air conditioner.
Malicious Human DDOS Attack.	Firewall is not configured properly.	Server.	Resources will be unavailable or not work properly	Monitor & configure the firewall.
Accidental or purposely attack of human.	CCTV doesn't have secured shield or cover.	CCTV	CCTV will get damaged.	Setup shield or proper covering the CCTV.
Accuracy.	Low performance of algorithm or training dataset	Server	It will show result with low accuracy.	Monitor & reset working of functions.

Fig 8. Overview of video Surveillance System

IX. Conclusion

The study examines sophisticated video surveillance analytic methods. Wide range of applications are covered in peer-reviewed studies. Tables were used to list the methodologies, tools, and dataset that were found. Before moving on to crowd analysis, the survey starts with a broad review of video surveillance. Crowd analysis is challenging since, in real-world situations, crowds are big and moving around a lot. It is challenging to distinguish between each entity and their behaviour. There was discussion of techniques for assessing crowd behaviour. Future directions to offer an effective solution were mentioned based on the problems with the present solutions.

References

[1] Review of human activity recognition methods. Frontiers in Robotics and AI, 2015, vol. 2, p. 28. VRIGKAS, Michalis, NIKOU, Christopher's, ET KAKADIARIS, Iohannis A. A

[2]ADAM, Amit, RIVLIN, Ehud, SHIMSHONI, Ilan, et al. Robust real-time unusual event detection using multiple fixed-location monitors.

[3] POPULAR, Oluwatoyin P. ET WANG, Kejun. Video-based abnormal human behavior recognition—A review.

IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 2012, vol. 42, no 6, p. 865-878.
[4] BENABBAS, Yassin, IHADDADENE, Nacim, ET DJERABA, Chaabane. Motion pattern extraction and event detection for automatic visual surveillance. EURASIP Journal on Image and Video Processing, 2010, vol. 2011, no 1, p. 163682.
[5] HUNG, Ya-Xuan, CHIANG, Chih-Yen, HSU, and Steen J., et al. Abnormality detection for improving elder's daily life independence. In: International Conference on Smart Homes and Health Telematics. Springer Berlin Heidelberg, 2010. p. 186-194.
[6] SHIN, Jae Hyuk, LEE, Boreom, ET PARK, Kwang Suk. Detection of abnormal living patterns for the elderly living alone using support vector data description. IEEE Transactions on Information Technology in Biomedicine, 2011, vol. 15, no 3, p. 438-448.
[7] PALANIAPPAN, Adithyan, BHARGAVI, R., ET VAIDEHI, V. Abnormal human activity recognition using SVM based approach. In: Recent Trends in Information Technology (ICRTIT), 2012 International Conference on. IEEE, 2012. p. 97-102.
[8] A. Datta, M. Shah and N. Lobo, “Person-on-person violence detection in video data”, Proceedings of the 16th International Conference on Pattern Recognition, vol. 1, pp. 433-438, 2002.
[9] Paolo Rota, Nicola Conci, Nicu Sebe, and James M Rehg, "Real-life violent social interaction detection", International Conference on Image Processing, pp. 3456– 3460, 2002.
[10] M. Drulea, and S. Nedevschi, “Total Variation Regularization of Local-Global Optical Flow”, IEEE Int. Con. Intelligent Transportation Systems, pp. 318-323, 2011.
[11] E. ESEN, M. ARABACI, and M. SOYAL,”Fight Detection in Surveillance Videos”, Int. Workshop on Content-Based Multimedia Indexing, pp. 131-135, Jun 2013.
[12] Varun Chandola, Arindam Banerjee, and Vipin Kumar, "Anomaly detection: A survey," ACM computing surveys (CSUR), vol. 41, no. 3, pp. 15, 2009.
[13] Yael Pritch, Alex Rav-Acha, and Shmuel Peleg, "Nonchronological video synopsis and indexing," IEEE transactions on pattern analysis and machine intelligence,vol. 30, no. 11, pp. 1971–1984, 2008.
[14] Chris Stauffer and W Eric L Grimson, “Adaptive background mixture models for real-time tracking,” in Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on. IEEE, 1999, vol. 2, pp.246–252.
[15]Olivier Barnich and Marc Van Droogenbroeck, "Vibe: A universal background subtraction algorithm for video sequences," IEEE Transactions on Image processing, vol. 20, no. 6, pp. 1709–1724, 2011.
[16] Pierre-Luc St-Charles, Guillaume-Alexandre Bilodeau, and Robert Bergevin, “Subsense: A universal change detection method with local adaptive sensitivity,” IEEE Transactions on Image Processing, vol. 24, no. 1, pp. 359–373, 2015.
[17] Yi Wang, Pierre-Marc Jodoin, Fatih Porikli, Janusz Konrad, Yannick Benezeth, and Prakash Ishwar, “Cdnet 2014: an expanded change detection benchmark dataset,”in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2014, pp. 387–394.
[18] Timo Ojala, Matti Pietikainen, and Topi Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Transactions on pattern analysis and machine intelligence, vol. 24, no. 7, pp. 971–987, 2002.
[19] Kaiming He, Georgia Gkioxari, Piotr Doll´ar, and Ross Girshick, "Mask r-CNN," in Computer Vision (ICCV), 2017 IEEE International Conference on. IEEE, 2017, pp. 2980–2988.
[20] Marc Braham and Marc Van Droogenbroeck, “Deep background subtraction with scene-specific convolutional neural networks,” in Systems, Signals and Image Processing (IWSSIP), 2016 International Conference on. IEEE, 2016, pp. 1–4