IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A Novel Deep Learning Architecture For Anomaly Detection From Public Surveillance Videos

Siva Prasad Patnayakuni
Senior Data Engineer, H-E-B, TX, USA

Abstract

Public surveillance cameras are meant for human safety and to ensure law and order correctly. In fact, public surveillance videos are very useful to police and investigation agencies. In this paper, we proposed a deep learning architecture for automatic anomaly detection in human actions from public surveillance videos. The proposed methodology exploits a concept known as motion influence map that effectively reflects human actions. This map has information pertaining to subjects associated with different interactions, size of objects, speed, movement and direction of objects. These characteristics play crucial in learning based approaches. The proposed framework has provision to detect local and global abnormal activities from videos. Different public datasets are used in the empirical study. We proposed an algorithm known as Intelligent Detection of Human Anomalies (IDHA). This algorithm takes dataset (videos) as input and perform learning based detection of human anomalies. Our experimental results revealed the significance of the proposed methodology. The proposed algorithm outperforms existing models.

Keywords *– Deep Learning, Anomaly Detection, Surveillance, Abnormal Human Activity Detection*

1. INTRODUCTION

Anomalous activity recognition from videos is one of the long-standing problems in computer

vision and machine learning with wide-ranging applications in surveillance. Millions of surveillance cameras are being deployed in public and private places requiring intelligent video monitoring. While Video Content Analysis (VCA) has a very large collection of applications in a surveillance environment, one such focused area of research is anomalous activity recognition. Anomalousactivity recognition deals with identifying the patterns and events that vary from the normal stream.Anomalies contain a huge range of activities that can go from abuse to fighting and road accidents toSnatching [1]. It is very important to have automatic detection technology using surveillance videos as it has plenty of computer vision applications in the real world. It is also evident in the review of existing methods found in literature.

Aggrandizing network based novel approach was proposed in [10] for human anomaly detection. Deep learning methods are combined to form a hybrid approach in [11] for detection of suspicious flows in videos. In [12], a methodology was proposed based on multi-view representation learning associated with deep learning. They also used auto encoders for anomaly detection. In [13], the authors exploited multiple timescales with the help of intermediate fused network for anomaly detection. In [15] proposed a methodology for bi-directional prediction mechanism for automatic detection of anomalies in public videos. Crowd behaviour detection in real time was the main purpose of the research in [16] where deep learning was used to detect such behaviour. In surveillance videos, the integrity attacks are automatically detection in [17] using deep learning and frame interpolation.From the review of literature, it is understood that fusion based approach along with deep learning with pre-processing has potential to leverage anomaly detection performance. Our contributions in this paper are as follows.

1. We proposed a deep learning architecture for automatic anomaly detection in human actions from public surveillance videos.
2. We proposed an algorithm known as Intelligent Detection of Human Anomalies (IDHA). This algorithm takes dataset (videos) as input and perform learning based detection of human anomalies.
3. We built an application to evaluate IDHA and compared our experimental results with existing methods.

The remainder of the paper is structured as follows. Section 2 reviews literature on different existing methods. Section 3 presents the proposed deep learning framework. Section 4 presents results of the present study. Section 5 concludes our work besides giving scope for future work.

2. RELATED WORK

This section reviews literature on different existing methods to detect anomalies from videos. A tool known as Anomaly3D was proposed in [1] based on 3D normality clusters while 3D CNN was used in [2] for anomaly recognition. Different approaches used for real time anomaly detection in crowd videos is explored in [3], [4], [9], [21], [23] and [30]. LSTM along with CNN features were explored in [5] for real-timeanomaly detection. In [6] different ensemble approaches are combined to aggregate and find crowd anomaly detection in videos. The notion of latent feature clustering is used to detect abnormal actions in videos in [7]. The concepts of motion learning and decoupled appearance are combined in [8] for anomaly detection in surveillance videos. Aggrandizing network based novel approach was proposed in [10] for human anomaly detection. Deep learning methods are combined to form a hybrid approach in [11] for detection of suspicious flows in videos. In [12], a methodology was proposed based on multi-view representation learning associated with deep learning. They also used auto encoders for anomaly detection. In [13], the authors exploited multiple timescales with the help of intermediate fused network for anomaly detection.

A deep learning based framework known as Skip-GANomaly is proposed in [14] for anomaly detection in videos using GAN based training approach. In [15] proposed a methodology for bi-directional prediction mechanism for automatic detection of anomalies in public videos. Crowd behaviour detection in real time was the main purpose of the research in [16] where deep learning was used to detect such behaviour. In surveillance videos, the integrity attacks are automatically detection in [17] using deep learning and frame interpolation. Visual anomaly detection approach was defined in [18] based on cognitive memory-augmented network. A multi-model approach was designed in [19] along with audio and visual cues for automatic detection of anomalies in videos. In presence of IoT integrated use case, in [20] there was image anomaly detection method defined. In [21]-[30] there are many deep learning based approaches for anomaly detection. From the review of literature, it is understood that fusion based approach along with deep learning with pre-processing has potential to leverage anomaly detection performance.

3. PROPOPSED ARCHITECTURE

We proposed a deep learning based architecture that has learning based pre-processing as well for efficient detection of human action anomalies in surveillance videos. The proposed architecture is shown in Figure 1. The given input video is subjected to motion information extraction. Since motion information is very important in crowded human-involved videos, motion information is extracted and represented in the form of vectors. It will help in identification of humans and performing segmentation. It will result in motion influence map that holds information pertaining to human actions. In such a map, the information can reflect different characteristics associated with motion such as speed, direction, object size and interactions among human objects. Such map is used in the proposed framework to ascertain the local and global abnormal activities as they occur. The framework also helps in not only detection but localization of abnormal human actions.

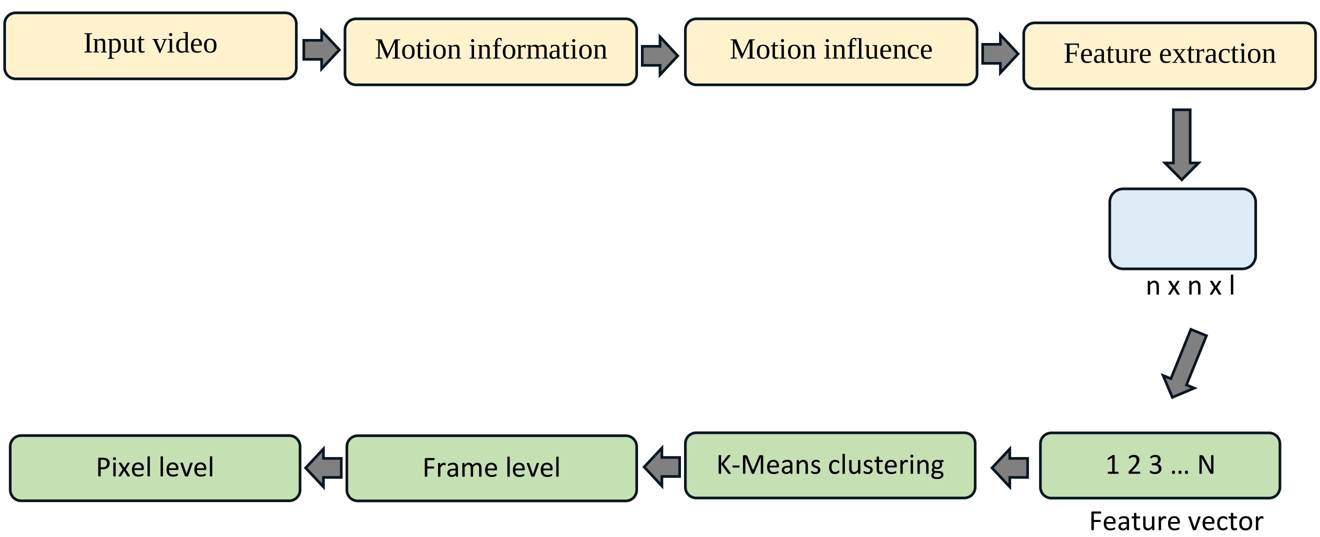

Figure 1: Proposed framework for automatic detection of human abnormal activities

After extracting motion information from the given video, a map is created to represent all characteristics of dynamic situations in the form of motion information. From such map, features are extraction and it results eventually in feature vector generation. The feature vectors are subjected to clustering process using K-Means clustering. This clustering phenomenon plays crucial role as it performs strong pre-processing to leverage classification performance. It will help in frame-level detection of anomalies and pixel level approach for localization. The proposed framework has its CNN based training that helps in classification of abnormal activities. Figure 2 shows different modules involved in the proposed framework.

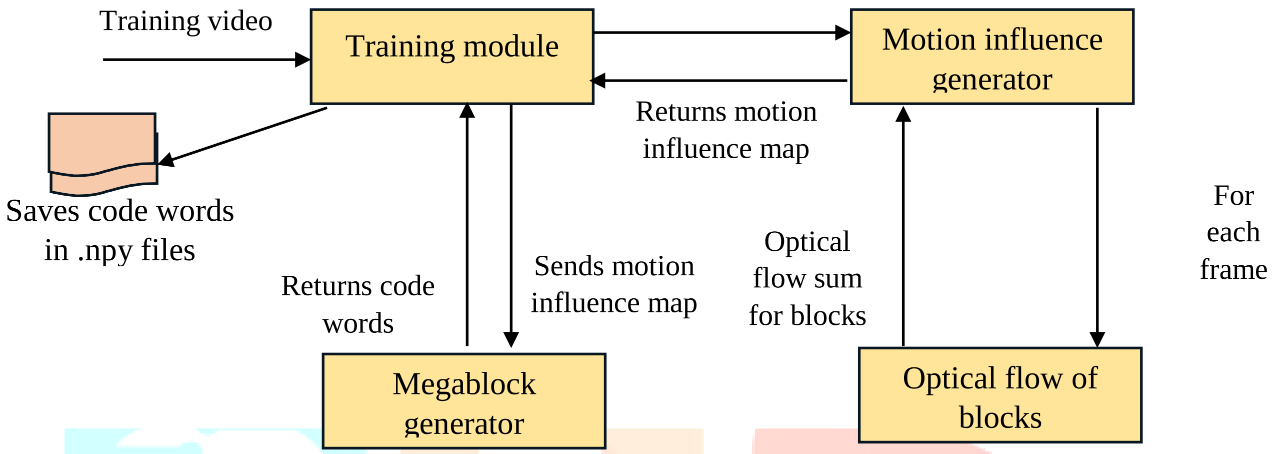

Figure 2: Illustrates and training process involved in the proposed framework

The given training video is given to training module. The training module invokes another module known as motion information generator that returns motion information map. In turn the motion information module, for each frame, computes optimal flows and returns back to motion information generator. The training module also invokes megablock generator which takes motion information and returns code words. The training process eventually results in understanding features and gain knowledge for discrimination of abnormal human activities.

Algorithm: Intelligent Detection of Human Anomalies (IDHA)

Input: Videos dataset D

Output: Abnormal human actions R

1. Begin
2. (T1, T2)←Split(D)
3. Initialize feature vector F
4. For each video t1 in T1
5.   mInfo←ExtractMotionInfo(t1)
6.   map←CreateInfluenceMap(mInfo)
7.   f←FeatureExtraction(map)
8.   Update F
9. End For
10. cluster←K-Means(F)
11. model←TrainCNNClassifier(clusters)
12. R←DetectAnomalies(T2, model)
13. Print R
14. End

Algorithm 1: Intelligent Detection of Human Anomalies (IDHA)

As presented in Algorithm 1, it takes videos dataset as input. It has provision for dividing videos into training and testing videos. There is an iterative process with each train video in terms of extracting motion information and generating a map followed by feature extraction. After completion of the process, the features extracted are subjected to clusters. This kind of pre-processing makes the training easier. The trained deep learning model has discriminating power which automatically detects test videos with identification and classification of human abnormal activities.

4. EXPERIMENTAL RESULTS

This section presents experimental results of the proposed framework which acts on crowded videos and detects human abnormal actions. The abnormal actions present in videos are automatically detected and localized. Dataset used for experiments is collected from [31].

Figure 3: Shows experimental results in terms of abnormal activity detection

As presented in Figure 3, it is evident that there are number of frames present in the results. Each frame is analysed and abnormalities are detected and localized. Abnormal crowd activity is automatically detected and tracked. The results revealed that the proposed methodology is able detect abnormalities in videos.

UNUSUAL HUMAN ACTIVITY DETECTION	Performance (%)			
	PRECISION	RECALL	F1-SCORE	ACCURACY
CNN	72.64	79.24	75.94	78.56
VGG-16	85.76	83.59	84.675	86.79
IDHA	83.19	89.34	86.15	93.37

Table 1: Shows performance comparison among different detection models

As presented in Table 1, the proposed algorithm IDHA's performance in abnormalities detection is compared with existing models.

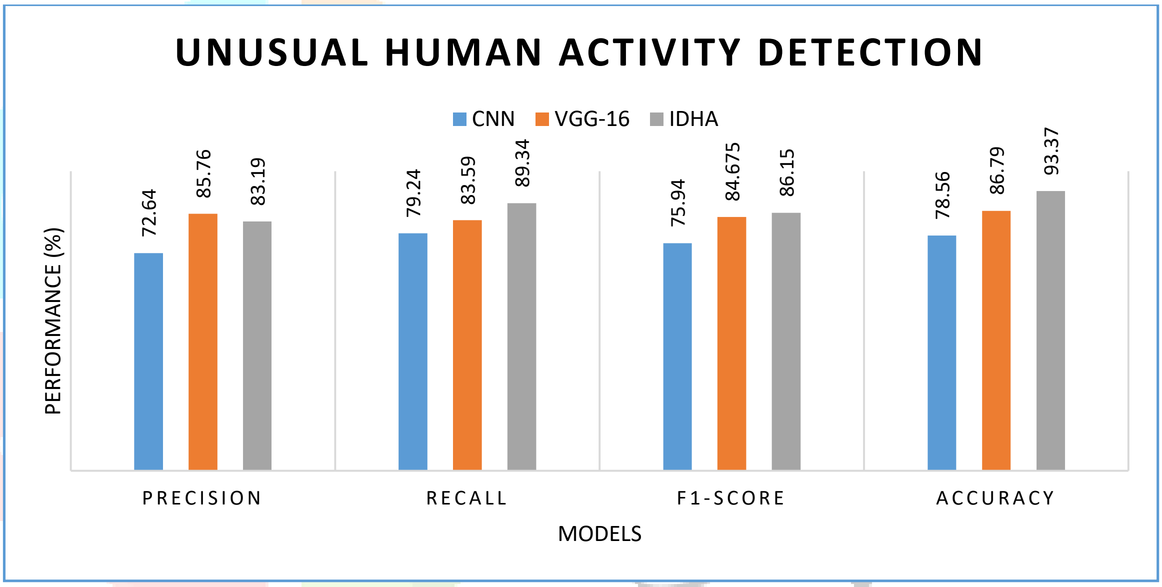

Figure 4: Performance comparison among different models

As presented in Figure 4, the performance of existing models and the proposed algorithm known as IDHA is provided. CNN model achieved 72.64% precision, 79.24% recall, 75.94% F1-Score and 78.5% accuracy. VGG-16 model achieved 85.76% precision, 83.59% recall, 84.67% F1-Score and 86.79% accuracy. The proposed IDHA model achieved 83.19% precision, 89.34% recall, 86.15% F1-Score and 93.37% accuracy. Therefore, it is understood from the results that the proposed model IDHA outperforms existing methods.

5. CONCLUSION AND FUTURE WORK

In this paper, we proposed a deep learning architecture for automatic anomaly detection in human actions from public surveillance videos. The proposed methodology exploits a concept known as motion influence map that effectively reflects human actions. This map has information pertaining to subjects associated with different interactions, size of objects, speed, movement and direction of objects. These characteristics play crucial in learning based approaches. The proposed framework has provision to detect local and global abnormal activities from videos. Different public datasets are used in the empirical study. We proposed an algorithm known as Intelligent Detection of Human Anomalies (IDHA). This algorithm takes dataset (videos) as input and perform learning based detection of human anomalies. Our experimental results revealed the significance of the proposed methodology. The proposed algorithm outperforms existing models. Out of all the models compared IDHA showed 93.37% accuracy which is highest among the models. In future, we intend to improve our framework with hybrid deep learning approaches.

References

[1] MujtabaAsad; Jie Yang; EnmeiTu; Liming Chen and Xiangjian He; (2021). Anomaly3D: Video anomaly detection based on 3D-normality clusters . Journal of Visual Communication and Image Representation. http://doi:10.1016/j.jvcir.2021.103047.

[2] RamnaMaqsood; Usama IjazBajwa; GulshanSaleem; Rana Hammad Raza and Muhammad Waqas Anwar; (2021). Anomaly recognition from surveillance videos using 3D convolution neural network . Multimedia Tools and Applications. http://doi:10.1007/s11042-021-10570-3.

[3] KhosroRezaee; Sara Mohammad Rezakhani; Mohammad R. Khosravi and Mohammad KazemMoghimi; (2021). A survey on deep learning-based real-time crowd anomaly detection for secure distributed video surveillance . Personal and Ubiquitous Computing. http://doi:10.1007/s00779-021-01586-5.

[4] Nayak, Rashmiranjan; Pati, Umesh Chandra and Das, Santos Kumar (2021). A comprehensive review on deep learning-based methods for video anomaly detection. Image and Vision Computing, 106, 104078–. http://doi:10.1016/j.imavis.2020.104078.

[5] Ullah, Waseem; Ullah, Amin; Haq, IjazUl; Muhammad, Khan; Sajjad, Muhammad and Baik, Sung Wook (2020). CNN features with bi-directional LSTM for real-time anomaly detection in surveillance networks. Multimedia Tools and Applications. http://doi:10.1007/s11042-020-09406-3.

[6] Singh, Kuldeep; Rajora, Shantanu; Tripathi, Gaurav; Vishwakarma, Dinesh Kumar and Walia, Gurjit Singh (2019). Crowd Anomaly Detection using Aggregation of Ensembles of Fine-Tuned ConvNets. Neurocomputing, S092523121931197X–. http://doi:10.1016/j.neucom.2019.08.059.

[7] MujtabaAsad; He Jiang; Jie Yang; EnmeiTu and Aftab Ahmad Malik; (2021). Multi-Stream 3D latent feature clustering for abnormality detection in videos . Applied Intelligence. http://doi:10.1007/s10489-021-02356-9.

[8] Bo Li, Sam Leroux and Pieter Simoens. (2021). Decoupled appearance and motion learning for efficient anomaly detection in surveillance video. Elsevier. pp.1-8. https://doi.org/10.1016/j.cviu.2021.103249.

[9] Ribeiro, Manassés; Lazzaretti, André Eugênio and Lopes, HeitorSilvério (2017). A study of deep convolutional auto-encoders for anomaly detection in videos. Pattern Recognition Letters, S0167865517302489–. http://doi:10.1016/j.patrec.2017.07.016.

[10] Gong, Maoguo; Zeng, Huimin; Xie, Yu; Li, Hao and Tang, Zedong (2019). Local distinguishability aggrandizing network for human anomaly detection. Neural Networks, S0893608019303417–. http://doi:10.1016/j.neunet.2019.11.002.

[11] Garg, Sahil; Kaur, Kuljeet; Kumar, Neeraj and Rodrigues, Joel J. (2019). Hybrid Deep Learning-based Anomaly Detection Scheme for Suspicious Flow Detection in SDN: A Social Multimedia Perspective. IEEE Transactions on Multimedia, 1–1. http://doi:10.1109/TMM.2019.2893549.

[12] Deepak, K.; Srivathsan, G.; Roshan, S. and Chandrakala, S. (2020). Deep Multi-view Representation Learning for Video Anomaly Detection Using Spatiotemporal Autoencoders. Circuits, Systems, and Signal Processing. http://doi:10.1007/s00034-020-01522-7.

[13] Wenqian Wang; Faliang Chang and HuadongMi; (2021). Intermediate fused network with multiple timescales for anomaly detection .Neurocomputing. http://doi:10.1016/j.neucom.2020.12.025.

[14] Akcay, Samet; Atapour-Abarghouei, Amir and Breckon, Toby P. (2019). International Joint Conference on Neural Networks (IJCNN) - Skip-GANomaly: Skip Connected and Adversarially Trained Encoder-Decoder Anomaly Detection. 1–8. http://doi:10.1109/ijcnn.2019.8851808.

[15] Chen, D., Wang, P., Yue, L., Zhang, Y., &Jia, T. (2020). Anomaly detection in surveillance video based on bidirectional prediction. Image and Vision Computing, 98, 103915. http://doi:10.1016/j.imavis.2020.103915.

[16] FaribaRezaei and Mehran Yazdi; (2021). Real-time crowd behavior recognition in surveillance videos based on deep learning methods . Journal of Real-Time Image Processing. http://doi:10.1007/s11554-021-01116-9.

[17] Pan and Jonathan (2019). IEEE International Conference on Internet of Things and Intelligence System (IoTaIS) - Physical Integrity Attack Detection of Surveillance Camera with Deep Learning based Video Frame Interpolation, 79–85. http://doi:10.1109/IoTaIS47347.2019.8980385.

[18] Tian Wang; Xing Xu; Fumin Shen and Yang Yang; (2021). A Cognitive Memory-Augmented Network for Visual Anomaly Detection . IEEE/CAA Journal of AutomaticaSinica. http://doi:10.1109/JAS.2021.1004045.

[19] Ata-Ur Rehman; Hafiz Sami Ullah; Haroon Farooq; Muhammad Salman Khan; Tayyeb Mahmood and Hafiz Owais Ahmed Khan; (2021). Multi-Modal Anomaly Detection by Using Audio and Visual Cues . IEEE Access. http://doi:10.1109/access.2021.3059519.

[20] Rui, Hou; MingMing, Pan; YunHao, Zhao and Yang, Yang (2019). Image Anomaly Detection for IoT Equipment based on Deep Learning. Journal of Visual Communication and Image Representation, 102599–. http://doi:10.1016/j.jvcir.2019.102599.

[21] Erhan, L.; Ndubuaku, M.; Di Mauro, M.; Song, W.; Chen, M.; Fortino, G.; Bagdasar, O. and Liotta, A. (2021). Smart anomaly detection in sensor systems: A multi-perspective review. Information Fusion, 67, 64–79. http://doi:10.1016/j.inffus.2020.10.001.

[22] Medhini G. Narasimhan and Sowmya Kamath S. (2017). Dynamic video anomaly detection and localization using sparse denoisingautoencoders. Springer, pp.1-23. http://DOI:10.1007/s11042-017-4940-2.

[23] YassineHimeur; KhalidaGhanem; Abdullah Alsalemi; FaycalBensaali and Abbes Amira; (2021). Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives . Applied Energy. http://doi:10.1016/j.apenergy.2021.116601.

[24] Wang, Siqi; Zhu, En; Yin, Jianping and Porikli, Fatih (2017). Video anomaly detection and localization by local motion based joint video representation and OCELM. Neurocomputing, S092523121731411X–. http://doi:10.1016/j.neucom.2016.08.156.

[25] Ullah, Amin; Muhammad, Khan; Haydarov, Killichbek; Haq, IjazUl; Lee, Miyoung and Baik, Sung Wook (2020). International Joint Conference on Neural Networks (IJCNN) - One-Shot Learning for Surveillance Anomaly Recognition using Siamese 3D CNN. 1–8. http://doi:10.1109/IJCNN48605.2020.9207595.

[26] Dongyue Chen; Lingyi Yue; Xingya Chang; Ming Xu and Tong Jia; (2021). NM-GAN: Noise-modulated generative adversarial network for video anomaly detection . Pattern Recognition. http://doi:10.1016/j.patcog.2021.107969.

[27] Protogerou, Aikaterini; Papadopoulos, Stavros; Drosou, Anastasios; Tzovaras, Dimitrios and Refanidis, Ioannis (2020). A graph neural network method for distributed anomaly detection in IoT. Evolving Systems. http://doi:10.1007/s12530-020-09347-0.

[28] Gohel, Hardik A.; Upadhyay, Himanshu; Lagos, Leonel; Cooper, Kevin and Sanzetenea, Andrew (2020). Predictive Maintenance Architecture Development for Nuclear Infrastructure using Machine Learning. Nuclear Engineering and Technology, S1738573319306783–. http://doi:10.1016/j.net.2019.12.029.

[29] Li, Nanjun; Chang, Faliang and Liu, Chunsheng (2020). Spatial-temporal Cascade Autoencoder for Video Anomaly Detection in Crowded Scenes. IEEE Transactions on Multimedia, 1–1. http://doi:10.1109/TMM.2020.2984093.

[30] AriyaluranHabeeb, RiyazAhamed; Nasaruddin, Fariza; Gani, Abdullah; Targio Hashem, Ibrahim Abaker; Ahmed, Ejaz and Imran, Muhammad (2018). Real-time big data processing for anomaly detection: A Survey. International Journal of Information Management, S0268401218301658–. http://doi:10.1016/j.ijinfomgt.2018.08.006.

[31] Anomaly detection and localization in crowded scenes. Retrieved from http://www.svcl.ucsd.edu/projects/anomaly/