

A Comprehensive Survey on Abnormal Crowd Behavior

Suraj Shukla

Department of Computer
Applications
Mangalamy Institute of
Management & Technology
Gr. Noida, India

Brijesh Kumar

Department of Computer
Applications
Mangalamy Institute of
Management & Technology
Gr. Noida, India

Himanshoo Tiwari

Department of Computer
Applications
Mangalamy Institute of
Management & Technology
Gr. Noida, India

Abstract— In the present scenario the population of the world are increases, the expansion of urban scale, the probability of stampede, parades or other sorts of people gatherings, they are provoked to multiple security issues and this crowding situation challenges the public safety. To ensure the public safety and security of people and their assets the smart surveillance system have been replaced the CCTV cameras. The smart surveillance system equipped with the smart visual sensors and use AI to analyze the captured videos and act accordingly on that. The main aim of Smart surveillance system is to monitor the activity of individuals in crowded scene where the chances of any crime related activity and disaster. This research examines the many auto-matic and real-time Surveillance methods used for abnormal event detection in security applications to recognise dynamic crowd behaviour. The critical feature of public place security and safety is that we cannot manually monitor the impulsive and complicated crowded surroundings. Manual examination of crowded settings is a time-consuming and error-prone task. The aberrant behaviour algorithms tried to increase efficiency and resistance to occlusion. This study provides an in-depth examination of existing convolution neural network (CNN)-based algorithms for crowd behaviour analysis. We present a catalogue that summarises key components of CNN for tackling crowd behaviour analysis. Details of the suggested architectures, crowd analysis requirements, and datasets are examined.

Keywords— *Crowd analysis, Crowd behavior analysis, abnormal behavior detection, CNN, Security surveillance*

I. INTRODUCTION

Automated crowd investigation has recently been investigated for a variety of purposes, including visual surveillance, crowd control, and public space planning. Crowd analysis is used in visual surveillance to detect odd and harmful events automatically. Crime is on the rise all around the world, thus CCTV cameras are installed everywhere for security and monitoring. Surveillance cameras are reasonable in addition to being ubiquitously present, but someone must constantly monitor the activities. Detecting human activity in a video stream is a fascinating task.

The study of crowd behaviour is becoming increasingly important as the human population grows and the human need to socialise grows. The global population

n of 7.7 billion people is growing at a rate of 1.07 percent per year, or 82 million people every year. With such a large population, it is fairly uncommon to see people congregating for various reasons.[22] With crowds becoming more widespread, the field of crowd behaviour analysis is gaining traction in the computer vision community. The study of crowd behaviour, both individual and collective, has been a hot topic in recent years.

Many applications, such as video surveillance, content-based video coding, and human-computer interaction, rely on moving object detection. The general method for moving object detection in the case of fixed cameras is background removal. The recognition of moving objects in video streams is the first relevant stage of information removal for numerous computer visualisation programmes, such as video surveillance, people tracking, traffic monitoring, and semantic annotation of videos. Video cameras are commonly used in surveillance applications to monitor public areas such as train stations, airports, and shopping malls. Tracking people becomes more difficult in large numbers. Outlier detection, also known as anomaly detection, is a versatile approach that may be used to a wide range of scenarios.

Large crowds can cause a number of safety issues, such as violence, stampedes, terrorist attacks, theft, and harassment, all of which can result in injuries, heat exhaustion, and death. Surveillance systems are widely used for security and monitoring in busy places, where the requirement for automation is well established. Computer vision is being used in a variety of studies to address these issues. Figure 1 depicts the general architecture of the crowd behaviour study. Density Estimation of Crowd or providing the overall count of the Crowd is a method for counting the number of people in a crowd. Crowd counting is a method of determining the number of individuals present in a public space. The dense crowd containing possible hazard in an otherwise sparsely inhabited area.[22]

CCTV cameras are frequently utilised by human agents to capture and monitor situations. Due to a lack of human resources, however, this is not practicable nor cost-effective. "Intelligent video surveillance systems" are intended to monitor and capture the flow of a scene, measure population density in a scene, and discover anomalies in a scene in this era of new technologies. This can also help to reduce physical work. Crowd abnormal behaviour detection is a system that groups unusual or suspicious crowd behaviour. Abnormal events such as terror in a crowd, as well as activities such as walking or jogging, differ from running automobiles in the garden in that they have a different moving flow from the ordinary moving flow of direction.

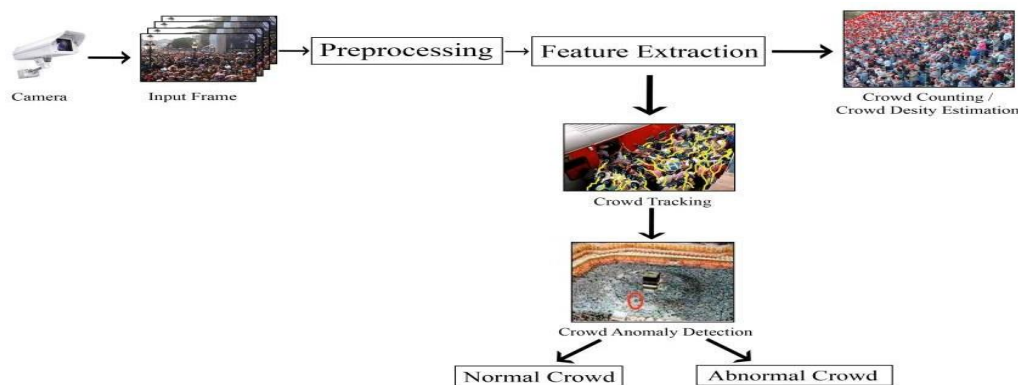


Fig. 1. Generic Architecture of Crowd Behavior Analysis [22]

II. LITRATURE REVIEW

Crowd analysis emerged progressively from computer vision principles such as object tracking, object recognition, and route analysis. Based on the model's approach, crowd behaviour techniques are divided into two types: traditional methods and deep learning methods. The standard strategy is to look for unique qualities that are unrelated to the problem. These newly created features may then be

utilised to execute various operations on the input feature sets in order to solve the problem utilising traditional approaches. [1].

A. **Traditional Approach**

Automation is critical in today's environment, as humans strive to automate things in order to interconnect with one another and create more man-machine connections. The most significant component of crowd analysis is automating it since it can offer us a good concept of crowd behaviour and the consequences of changed crowd behaviours. Crowd analysis is a fascinating topic in which academics are interested in observing crowd behaviour, particularly anomalous behaviour. [2]. Humans have evolved to be adept at utilizing the video surveillance tools at their disposal. The world is changing, and most individuals now own a smart camera-phone, which can be a powerful source of video surveillance.

Traditional closed-circuit tele-vision (CCTV) remains a good monitoring tool, but with the spread of smart-phones, video surveillance has skyrocketed. Although the quality of these films is debatable, the information content of these small smart surveillance gadgets (SSD) may be accessed. As a result, the current emphasis is on intelligent crowd analysis, which can be viewed from CCTV as well as a variety of SSD and may offer a complete and confident dynamic picture of crowd activity. The crowd is a gathering of people who are mostly unrelated and have congregated for the same or different reasons to be in the same place. It is critical to understand crowd behaviour in order to preserve a tranquil environment and avoid any unforeseen events. According to [2,] the crowd may be analysed using many qualities, which are as follows:

1. Crowd behavior understanding
2. Crowd counting
3. Crowd motion estimation
4. Crowd density estimation
5. Crowd Abnormality

1. Crowd behavior understanding

Saxena et al. presented our work on crowd behaviour detection using SRE to identify and extract crowd characteristics. The author of [12] suggests some future directions, such as defining the crowd motion computation parameters as automatically as feasible. The second step is to apply the method to more detailed and smooth situations (for example, throwing a stone from a crowd), as well as associated difficulties such as false alarms when the number of described events grows large. Candamo et al. provided a strategy for categorising these papers according to the expected human behaviour. The ones that follow are the behaviour groups identified in [13]: 1) single person or no interaction (behaviours demonstrated by a single individual that do not include any other persons or vehicles); 2) multiple-person interactions; 3) person-vehicle interactions; and 4) person-facility/location interactions. A brief introduction of the main person in the research who has no touch with anyone else. or vehicles);

2. Crowd counting

Subburaman et al. described a method for counting crowds in photos that uses head detection with gradient-oriented interest points. [14] Would like to eliminate false detections and introduce more ways for reasoning out occlusions in a cluttered scenario. Loy et al. approaches for crowd counting based on video images and gives a thorough evaluation of multiple methods using the same procedure [15].

3. Crowd motion analysis

Ullah et al. suggested a method for crowd motion segmentation and anomaly detection based on graph cuts utilising - expansion [16]. Ullah and colleagues suggested a new approach for detecting prevailing flows in crowd footage. The three-stage technique retrieves corner features from a video frame and then uses the enthalpy model to analyse the corner features based on their motion qualities.[17].

4. Crowd density estimation

Using LK optical flow and GBM, Li et al. offer a novel crowd density estimate technique that includes fore-ground detection and feature extraction. [18]. Rao et al. presented crowd density estimate based on motion cue grouping. The suggested method yields reliable estimations of crowd density.[19]

5. Crowd Abnormality estimation

Identification of abnormal conduct in crowds is a complex problem that necessitates a range of approaches in which crowd traits are exposed to different permutations and combinations to give us a clear idea of the existence of abnormality in crowds. Mehran et al. present a method for detecting anomalous behaviours in crowd settings based on the social force concept. [20] discuss the method's capacity to capture the dynamic of crowd behaviour based on individual interaction pressures without the requirement to track objects individually or conduct segmentation. Accordingly, Sjarif et al. provide a broad framework and pattern taxonomy for recognising anomalous behaviour in a crowded setting.[21].

B. Deep Learning based approach

Deep Learning is a subfield of Machine Learning that learns to represent information as a layered layering of perceptions, displaying amazing strength and adaptability. Deep Learning employs a disguised layer architecture to gradually learn categories. One of the primary goals of deep learning approaches is to extract information from high-dimensional information. Crowd behaviour evaluations based on Deep Learning are classified as audience counting, crowd monitoring, and crowd anomaly detection.

Crowd Counting

Crowd density estimation or crowd measurement techniques are used to determine the number of people in crowded locations. There is a large amount of literature on crowd counting difficulties, both classical and leveraging computer vision. The key hurdles include occlusion, non-uniform distribution, viewpoint distortion, clutter, size fluctuation, and intricate enlightenment.

Lebanoff et al. employed the Convolutional Neural Network (CNN) to count the number of individuals in highly dense crowd photos including up to 4500 people. They also presented the difference-to-sum ratio loss function, a unique loss function helpful for assessing error in a normalised manner. Training on more datasets and potentially employing a deeper pre-trained model like VGG-16 are potential enhancements. [3]. Santhini and co. Convolutional Neural Networks and deep learning models are introduced and utilised for crowd scene analysis, determining the quantity of individuals arriving in one location. group and also finds the crowd density map. People counting in extremely dense crowds are an important step for video surveillance and anomaly warning. [4]

Zhang et al. recommended a cross-scene counting approach that consists of mapping image frames to crowd counts and then adjusting the mapping to new target scenes [5]. The network is initially trained by switching between two related function objectives for crowd counts and density estimation. These objective functions may be optimised for a higher local maximum. Training samples that are identical to the target a situation are used to make the framework flexible to new circumstances. The network is being tested for crowd counting in single and multi-scene environments. Perspective maps, which are not freely available, are required for both teaching and testing situation.Liu et al. suggested a self-supervised technique that significantly boosts performance using unlabeled crowd images for training. [6]. The suggested method creates a rating of sub-images that is then used to train a network to estimate the number of persons in connection to another picture. A network is trained to compare photos and score them depending on the number of individuals in the photo-graphs. The current method for utilising self-supervised

learning is to train a self-supervised task, then fine-tune the resultant network on the testing phase with little data.

Crowd Tracking

People Tracking is an issue that demands the acquisition of skills in estimating position and item scale, past individual location, size, and present and preceding visual frames. The most major impediment of conventional systems for learning or tracking-by-detection is falsely positive matches, which result in erroneous track association. [32]. Lamba et al. employed 3DCNN and SVM to detect and forecast crowd behaviours based on spatio-temporal data. Crowd management necessitates an integrated framework capable of dealing with any form of crowd analysis, from panic situations to large-scale misbehaving groups.

Fernando et al. suggested a crowd tracking by prediction strategy for person localization based on a light-weight sequential Generative Adversarial Network architecture [7]. This is a robust lightweight technique that uses trajectory prediction to solve multi-person tracking challenges for data association. The proposed technique extends previous improvements in pedestrian trajectory estimation and introduces a unique system for trajectory-based data linkage.

Crowd Anomaly Detection

Abnormality detection in crowded circumstances is crucial in automatic video surveillance to avert casualties in high-traffic areas. In recent years, deep learning anomaly identification in a crowded scene has caught the interest of computer vision experts. To predict crowd behaviour, Varghese et al. recommended using a structure for deep learning and multiclass Support Vector Machine (SVM). Based on crowd emotions, we employ 3D Convolutional Neural Network (3DCNN) to extract spatio-temporal properties.[8] Using three datasets, the efficacy of the extracted crowd behaviours is examined, and it shows that our approach makes sense for real-time crowd behaviour prediction.

Houa et al. suggested an unsupervised anomaly detection technique based on a dictionary selection model [11]. A stacked auto encoder network utilised for feature representation is used to train an unsupervised feature space. For model optimisation, the forward-backward greedy strategy is used to improve the dictionary collection model and the sparse reconstruction model. Sun et al. suggested a method for detecting crowd aberrant behaviour such as stampede, conflict, panic, and tumble using label distribution learning. We assume that each behaviour sequence is connected with some behaviour labels, and the behaviour label distribution encompasses a series of behaviour labels, signifying the degree to which each behaviour label describes the behaviour sequence. [9] An algorithm for label distribution BFGS may be used to learn the distribution of behaviour labels. This method not only allows us to determine which behaviour occurred, but it also takes into consideration all behaviour labels for each behaviour sequence.

Sánchez et al. suggested a new hierarchical taxonomy that takes into consideration the several steps that confirm the crowd behaviour analysis challenge. Previous job categorizations grouped together extremely disparate activities, offering only a partial list of issues that might arise from crowd behaviour analysis. [10] We have emphasised the need of incorporating emotional factors while analysing crowd anomalies, because rapid shifts in crowd emotions are often a forerunner to anomalous occurrences.

III. COMPARATIVE ANALYSIS

This section presents a comparative examination of the state-of-the-art methodologies for crowd behaviour analysis. The merits and disadvantages of each technique of crowd counting, crowd monitoring, and crowd anomaly detection, as well as the method's strategy, are summarized.

TABLE 1: COMPARATIVE ANALYSIS OF DIFFERENT TECHNIQUES WITH CHALLENGES

| Author | Technique | Advantages | Challenges |
|--------|---------------|---|--|
| [13] | Traditional | Analyse the behaviour into categories such as 1) single person or no interaction 2) interactions between various people; 3) interactions between people and vehicles; and 4) interactions between people and facilities/locations | Techniques are frequently sensitive to low resolution, frame rate, severe lighting changes, negative weather effects, and frequent occlusions. |
| [14] | Traditional | technique for counting crowds in photos based on gradient orientation and head detection | Reduce false detections and include more ways for detecting occlusions in a cluttered situation. |
| [18] | Traditional | crowd density estimation approach including fore-ground detection and feature extraction. | There is a need to accelerate fore-ground detection approach and try to eliminate shadow noise in the image. |
| [4] | Traditional | Using SIFTS and HOG, determine the number of persons who arrived in one group and the crowd density map. | Implement GPU-based parallel processing architectures. GPU relies on millions of pictures that can be loaded and shown in fractions of seconds. |
| [5] | Deep Learning | To use a deep convolution neural network to address the cross-scene crowd counting problem. | Training data is used to fine-tune the pre-trained CNN model as it adapts to the unknown target scenario. |
| [7] | Deep Learning | The proposed technique extends previous improvements in pedestrian trajectory estimation and introduces a unique system for trajectory-based data linkage. | assures that the given technique is applicable in a wide range of applications such as auto-nomous driving, robotics, and egocentric vision. |
| [23] | Deep Learning | The advantages of the generative paradigm are that only normal samples are required throughout the training period. It is based on computing the difference from the typical pattern learnt when recognising what is aberrant. | Ignores the fact that abnormalities in the scene are location dependent. As per-video normalisation is utilised, the results presume that each test frame sequence has at least one normal and one aberrant frame. |
| [8] | Deep Learning | by employing a deep learning architecture and multiclass SVM. We use 3D Convolutional Neural Network (3DCNN) to extract spatio-temporal characteristics based on crowd sentiments. | Planning to forecast crowd behaviour class without training and using automated emotion-to-behavior mapping. |

IV. CONCLUSION

The paper discusses numerous crowd behaviour analysis approaches, which may be divided into three core domains: crowd counting, tracking, and crowd anomaly identification. Furthermore, each category technique is evaluated based on the feature extraction methods employed in the model, which include classic approach methods and deep learning method methods. The challenges and benefits of the approaches in each category are described, which will assist application developers in selecting the best way based on the needs.

REFERENCES

- [1] Tripathi, G., Singh, K., & Vishwakarma, D. K. (2019). Convolutional neural networks for crowd behaviour analysis: a survey. *The Visual Computer*, 35(5), 753-776.
- [2] Zhan, B., Monekosso, D. N., Remagnino, P., Velastin, S. A., & Xu, L. Q. (2008). Crowd analysis: a survey. *Machine Vision and Applications*, 19(5), 345-357.
- [3] Lebanoff, L., & Idrees, H. (2015). Counting in dense crowds using deep learning. University of Central California: Upland, CA, USA.
- [4] Santhini, C., & Gomathi, V. (2018, March). Crowd Scene Analysis Using Deep Learning Network. In 2018 International Conference on Current Trends towards Converging Technologies (ICCTCT) (pp. 1-5). IEEE.
- [5] Zhang, C., Li, H., Wang, X., & Yang, X. (2015). Cross-scene crowd counting via deep convolutional neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 833-841).
- [6] Liu, X., Van De Weijer, J., & Bagdanov, A. D. (2018). Leveraging unlabeled data for crowd counting by learning to rank. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 7661-7669).
- [7] Fernando, T., Denman, S., Sridharan, S., & Fookes, C. (2018, March). Tracking by prediction: A deep generative model for multi-person localisation and tracking. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1122-1132). IEEE.
- [8] Varghese, E. B., & Thampi, S. M. (2018, August). A deep learning approach to predict crowd behavior based on emotion. In International Conference on Smart Multimedia (pp. 296-307). Springer, Cham.
- [9] Sun, M., Zhang, D., Qian, L., & Shen, Y. (2015, June). Crowd abnormal behavior detection based on label distribution learning. In 2015 8th International Conference on Intelligent Computation Technology and Automation (ICICTA) (pp. 345-348). IEEE.
- [10] Sánchez, F. L., Hupont, I., Tabik, S., & Herrera, F. (2020). Revisiting crowd behaviour analysis through deep learning: Taxonomy, anomaly detection, crowd emotions, datasets, opportunities and prospects. *Information Fusion*, 64, 318-335.
- [11] Hou, D., Cong, Y., Sun, G., Liu, J., & Xu, X. (2019). Anomaly detection via adaptive greedy model. *Neurocomputing*, 330, 369-379.
- [12] Saxena, S., Brémond, F., Thonnat, M., & Ma, R. (2008, October). Crowd behavior recognition for video surveillance. In International Conference on Advanced Concepts for Intelligent Vision Systems (pp. 970-981). Springer, Berlin, Heidelberg.
- [13] Candamo, J., Shreve, M., Goldgof, D. B., Sapper, D. B., & Kasturi, R. (2009). Understanding transit scenes: A survey on human behavior-recognition algorithms. *IEEE transactions on intelligent transportation systems*, 11(1), 206-224.
- [14] Subburaman, V. B., Descamps, A., & Carincotte, C. (2012, September). Counting people in the crowd using a generic head detector. In 2012 IEEE ninth international conference on advanced video and signal-based surveillance (pp. 470-475). IEEE.
- [15] Loy, C. C., Chen, K., Gong, S., & Xiang, T. (2013). Crowd counting and profiling: Methodology and evaluation. In *Modeling, simulation and visual analysis of crowds* (pp. 347-382). Springer, New York, NY.
- [16] Ullah, H., & Conci, N. (2012, November). Crowd motion segmentation and anomaly detection via multi-label optimization. In ICPR workshop on pattern recognition and crowd analysis (Vol. 75).
- [17] Ullah, H., Ullah, M., & Conci, N. (2014, September). Dominant motion analysis in regular and irregular crowd scenes. In *International Workshop on Human Behavior Understanding* (pp. 62-72). Springer, Cham.
- [18] Li, W., Wu, X., Matsumoto, K., & Zhao, H. A. (2010, October). Crowd density estimation: An improved approach. In *IEEE 10th INTERNATIONAL CONFERENCE ON SIGNAL PROCESSING PROCEEDINGS* (pp. 1213-1216). IEEE.
- [19] Rao, A. S., Gubbi, J., Marusic, S., & Palaniswami, M. (2015). Estimation of crowd density by clustering motion cues. *The Visual Computer*, 31(11), 1533-1552.
- [20] Mehran, R., Oyama, A., & Shah, M. (2009, June). Abnormal crowd behavior detection using social force model. In 2009 IEEE conference on computer vision and pattern recognition (pp. 935-942). IEEE.

- [21] Sjarif, N. N. A., Shamsuddin, S. M., & Hashim, S. Z. (2012). Detection of abnormal behaviors in crowd scene: a review. *Int. J. Advance. Soft Comput. Appl*, 4(1), 1-33.
- [22] Vahora, S., Galiya, K., Sapariya, H., & Varshney, S. (2021). Comprehensive Analysis Of Crowd Behavior Techniques: A Thorough Exploration. *International Journal of Computing and Digital System*.
- [23] M. Ravanbakhsh, M. Nabi, H. Mousavi, E. Sangineto, N. Sebe, Plug-andplay CNN for crowd motion analysis: An application in abnormal event detection, in: 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), IEEE, 2018. doi:10.1109/wacv.2018.00188.