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Recent Advancements in Deep Learning for Crowd Anomaly Detection: A Comprehensive Survey

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Abstract: Recent necessary events on our globe have drawn tons of attention to the necessity of autonomous crowd activity analysis. In computer vision and cognitive science, crowd behaviour analysis has piqued people's curiosity. Consider a watchman observing an oversized set of CCTV camera footage from police investigation cameras. The guard cannot possibly concentrate on all or any of the cameras for long periods of time. The COVID-19 breakout sessions and public events, for example, necessitate an automated system to manage, count, secure, and track a crowd that occupies the same space. Due to significant occlusion, complicated actions, and posture changes, assessing crowd situations is difficult. An algorithm that monitored each video and flagged probably strange activity mechanically would alter the guard to perform his duties with inflated accuracy and at large scale. This is often the motivation behind video anomaly detection. The basic idea is to learn a model of normal activity given training video of normal activity and then to use this model to detect anomalies, which are activities that are different from any seen in the training video. The training video cannot be expected to also contain anomalies simply because one cannot possibly know or capture all possible future anomalous events. Deep learning is a subset of machine learning that employs artificial neural networks to learn tasks from data. It has been used for various applications such as image classification, object detection, and natural language processing. In recent years, deep learning has also been applied to crowd anomaly detection Crowd anomaly detection is a difficult but important problem. Recently, deep learning has shown great promise in solving this problem. Deep learning anomaly detection technologies overruled the traditional machine learning systems. In this survey, we will briefly exhaustively overview of deep learning-based video anomaly detection systems that have been released since 2019.

Keywords: *Crowd behaviour analysis, Autonomous system, Crowd anomaly, Surveillance videos, Deep learning*

1. Introduction

In recent years, the world has made exceptional evolution in various fields. Connected technologies such as smart grids, internet of vehicles, long term evolution and 5G communications. Cisco [1] reports that by 2022, the number of IP-connected devices is expected to triple that of the world's population, generating 4.8 ZB of his IP traffic per year. The phenomenon of crowds is one of the most intriguing and complex topics in the world of computer sciences. Crowds are often characterized as behaving in a highly coordinated and synchronized manner, exhibiting collective intelligence that far exceeds the individual intelligence of any single person in the crowd.

However, crowds can also produce behaviors that are anomalous or abnormal. Research communities and there have been many algorithms proposed to detect anomalies in large data sets.

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Anomaly detection [2] is the task of identifying patterns that are absent in the given data aligns with the anticipated conduct. These deviant tendencies are frequently referenced as anomalies, outliers, contradictory observations, exceptions, deviations, surprises, Specificities or impurities in various application domains. Of these, anomalies and outliers are the two mostly used terms associated with anomaly detection, sometimes interchangeable. The ability to discover or detect anomalous behavior can provide very useful insights across industries. By reporting an unusual case or taking a planned response when it occurs, organizations can save time, money and customers [3]. Anomaly detection has many uses for applications such as fraud detection in credit cards, insurance or healthcare cyber security attack detection, security system error detection, Military surveillance of enemy activity. The importance of anomaly detection stems from the fact that there are anomalies in the data. Transform it into a variety of important actionable information. This survey aims to provide a structured and comprehensive overview to detect anomalies activities.

2. Taxonomy for Crowd Behaviour Analysis

Crowd analysis is often grouped into two main segments: crowd statistics and crowd behaviour analysis. The tracking technique is a new branch that this study explores. The recently proposed taxonomy for crowd analysis is shown in (Fig. 2.1).

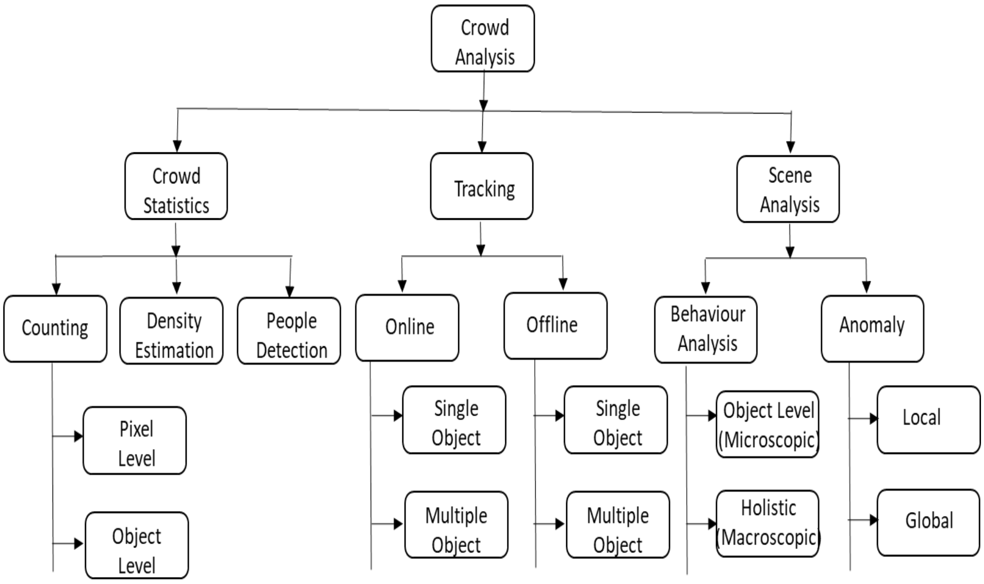

Fig. 2.1. Taxonomy for crowd analysis [8, 9]

Crowd statistics: Examining trends and patterns in statistical data analysis, which includes crowd density estimation, crowd counting and people detection. Crowd density may be determined by dividing the total population by one meter. While crowd counting is a technique for calculating the total number of individuals in a location. People detection will help out to identify persons in our video. With the help of this function, we can modify our choices for video alerts and choose whether you want to view video and warnings for all motion, only individuals, or to suppress them altogether. These projections are useful for managing the flow of people in a given space and preventing stampedes, overcrowding, and accidents.

Tracking: Finding the position of items are shifting across time is called object tracking. One or more items can be monitored concurrently, and an item may be monitored online or offline. Tracking anomalies picked up by object detection may be done using changes in characteristics over time.

Scene Analysis: Automatic video analysis, can recognize and examine spatial and temporal occurrences. Video scene analysis is a hotly debated research area due to its utility in tracking moving vehicles, recognizing people, monitoring crowds, and locating abnormalities in real time. The CCTVs placed throughout busy public spaces make it easier to analyses motion, comprehend behaviour, spot anomalies, and determine if a crowd is organized or unorganized. In the further taxonomy classification of crowd behavior investigation for anomaly, the authors [9] are provide a hierarchical relationship between relevant sub-areas in order to link them together. The suggested classification is founded on two overlapping factors. There are basically two primary approaches for the crowd behaviour analysis problem, based on the relationship in between the people and the crowd. In this way two techniques, macroscopic and microscopic make difference, and this distinction will be further examined. Microscopic approach is processed with bottom up approach. These pieces treat the crowd compilation of people. Subjects in the video are examined, and then the information learned about them is applied to derive information about the crowd as a whole [10, 11].

Macroscopic approach is processed with top down approach. These are comprehensive methods in which the crowd is handled as one entity with no the necessity to track and segment every person separately [12, 13]. On the other hand, the various linked sub-tasks are arranged in a pipeline, regardless of the technique that is used. According to (Fig. 4), there are four key phases in this channel, with the next stages heavily reliant on the preceding ones.

Microscopic methods typically work better in circumstances where people can be properly tracked. Specifically, when occlusions are not severe, density is low, and pedestrians are easily visible. However, tracking quality drastically declines as population density rises. Given that general populations are being researched rather than specific people, macroscopic techniques are more appropriate in this situation. According to various authors we can divided the crowd behaviours analysis in various stages, which is mentioned in Fig 2.2.

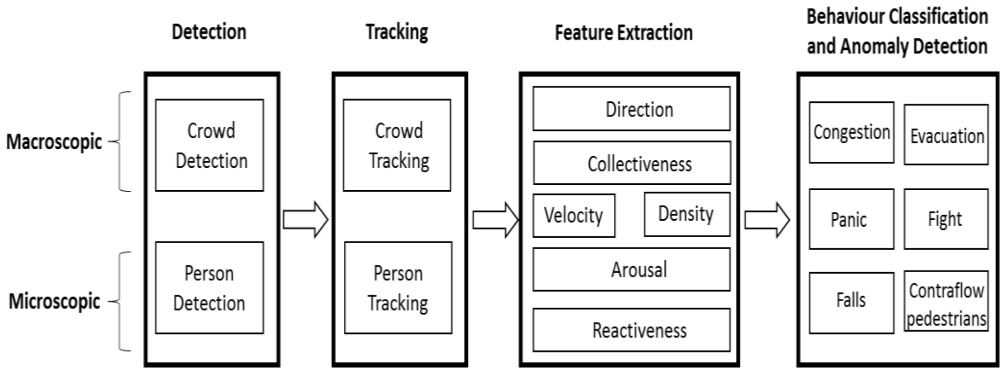

Fig. 2.2. Stage of crowd behaviour analysis [9]

2.1 Stage of Crowd Behaviour Analysis

1. Detection stage. Its objective is to determine the sites of people (in microscopic approach) and crowds (in macroscopic approach) in every picture. It's a well-researched sub-task, and there are already numerous excellent performance and accuracy detection models available.

2. Tracking stage. It seeks to identify certain people and crowd directions in a set of related frames in a unique way. Quite often, the major crowd movement fluxes are also identified.

3. Feature extraction stage. It calculates several metrics that characterize the crowd's dynamics, topological organization, and emotional state. These measures can be monitored longitudinally and computed at the individual level when the numerous subjects are examined individually (microscopic approach) or regarding crowd level, it refers to the situation where a large group of pedestrians is perceived as a unified entity (macroscopic approach). Crowd density, speed, and arousal monitoring are a few examples.

4. Crowd behaviour classification and anomaly detection stage. Its goal is to pinpoint the locations of people (in microscopic approach) and crowds (in macroscopic approach) in every instance picture. It's a well-researched Subtask, and there are already multiple excellent performance and accuracy detection models available.

5. Final stage. This final stage seeks to identify specific behaviours and/or anomalous events in video sequences based on the attributes that were retrieved. Depending on the supervised or unsupervised learning paradigm used, there are two basic ways at this step. The works that approach the task under the guidance and control of a supervisor are classified as behavior-related. These studies specify a collection of behaviours (such as conversing, strolling beside one another, welcoming one another, fighting, grabbing, etc.) then train models for classifying them. Anomaly behaviour detection, however, seeks out previously unidentified aberrant tendencies in the crowd. In the third stage crowd feature a related emotional aspect

consist a feature extraction step which is often carried out with the detection and monitoring of people (or crowds) included in the scene. Despite the enormous variety of data that may be gleaned analyzing a video sequence, we discovered the following elements to be crucial for comprehending crowd behaviour as Velocity, Direction, Density, Collectiveness, Valence, Arousal [14-17].

2.2 Anomalous in Crowd Behaviour Analysis

Summarizing characteristics extraction is necessary to provide meaningful facts regarding crowd behaviour. As earlier mentioned, that there are two primary strategies used during in this strategy: crowd anomaly detection, which uses unsupervised learning, and crowd behaviour classification, which uses supervised learning over the collected features. Observing crowd attributes over time provides the possibility to the discovery of anomalous behaviours in crowds, since rapid changes in these qualities are diagnostic of abnormal patterns. As an illustration, quick changes in crowd speed values are typically a sign of alertness; undesirable congestion can be classified with less velocity and more density; and severe valence and arousal values can result in violent interactions within the groups of individuals. When investigating from an anomaly detection point of view, additional option organization comes from the root of the anomaly by itself. Precisely we discussed earlier, the nature of anomalies can be varied, and hence the way to solve a challenge may be slightly different.

In our review study, we discovered five distinct kinds of anomalies as Anomalous movement, Anomalous appearance, Anomalous action, Anomalous affect, and Anomalous position. Anomalous position. This anomaly's cause is a result of an object's unusual placement in the scene. This kind of abnormality happens, for instance, when a stranger enters a zone that is banned or when a pedestrian is seen in a risky region. Given that it often only comprises a pedestrian detection stage and computation of bounding box overlapping, it is regarded as the simplest type of anomaly to detect.

Anomalous movement. In this instance, an unusual direction of one person or group inside the spot is what creates the abnormal pattern. There are two main types of irregularity: speed, which occurs when an individual moves quicker or more slowly than their surroundings; and direction, which occurs since there are developed streamed but a person's movement deviates from them.

Anomalous appearance. Anomalous appearance is an anomaly that occurs when an unidentified entity approaches the scene. A classic example of this anomaly is the existence of a person who is not recognized as part of the scene.

Anomalous action. Anomalous action is an event that, while not violating the laws of nature, is unexpected. In order to be considered anomalous, an event must be a departure from what would be expected. It is the abnormality whose identification is most challenging. It requires recognizing unusual behaviour patterns and comprehending the typical patterns of the people there.

Anomalous affect. It is the affect that our emotions are not always rational or logical and that they can be influenced by something other than what we are experiencing. The presence of anomalous or intense emotions in the population causes this phenomenon. Due to the absence of properly annotated datasets, it is the most understudied topic, but it also represents a promising area for future research because emotional issues frequently occur before abnormal circumstances like violence.

2.3 The Origin of Anomaly Detection in Crowd Behaviors Analysis

The two regions of the crowd behaviour analysis process that have received the least attention thus far are crowd emotions and crowd anomaly detection. Crowd emotional elements have been overlooked in this survey as there are lots research are going on this field. Whether the Crowd anomalous detection is one of the trickiest and most challenging jobs that have been covered thus far, mostly because of the absence of the efficacy, which typically includes anomaly detection strategies. Monitoring public security frequently entails spotting unusual activity in crowd-surveillance footage. The concept of anomaly detection in crowded situations describes the process of identifying inconsistencies, discrepancies, or distortions that deviate from expected behaviour in image or video series of data. In [18] defines anomaly detection as the process of finding patterns that stand out significantly from the standard. On the basis of [19], anomaly detection is the process of identifying crowd activities with anomalous activities. The anomalous behaviours in crowded places often manifest as crowd disturbance. The objective of anomaly detection is to locate and classify abnormalities in provided datasets [20]. Detecting anomalies may be categorized into three distinct groups: semi-supervised, unsupervised, and supervised. For supervised anomaly detection, the dataset that comprises both data and labels may be employed. The labels specify the event's kind, indicating whether it is "normal" or "abnormal." The unsupervised anomaly detection technique uses unlabeled datasets. The unsupervised technique assumes that the majority of the dataset's occurrences are normal and treats the rest as anomalies. Semi-supervised anomaly detection approaches are employed when the dataset hasn't been totally labelled or unlabeled, indicating that some data are labelled and others aren't. In order to detect novel trends in the new data, anomaly detection techniques often evaluate the patterns in the current normal data, show them, and finally simulate them [21]. Anomaly detection is used in a variety of fields, including surveillance systems [22–25], intrusion detection [26–28], fraud detection [29, 30], and health monitoring [31–33].

Despite being challenging, these methods have a substantial advantage especially compared to approaches of classification. As the range of human activities and interactions is extensive, it is highly challenging to accurately describe these behaviours in a database, which is the main issue with supervised learning in behaviour understanding. As a result, when encountering behaviors that are not present in the training database, systems will not operate as intended. Contrarily, anomaly detection approaches will handle these circumstances without any difficulty because they will flag the suspicious actions as anomalies, triggering and alarm that can then be investigated further. There is a limited number of reviews in the literature that specifically address anomaly detection. The existing reviews predominantly discuss conventional Machine learning techniques [34-36], rather than the latest state of the art approaches that rely on Deep Learning.

3. Datasets used in Crowd Behaviour Analysis

Because of the intricate characteristics of detecting anomalous crowd behavior problem, multiple diverse datasets are dedicated to addressing the problem is public. Within this segment, we will classify the datasets based on the primary objective accomplished by each individual. This segment is divided into two parts, in first datasets consists motion anomaly detection and second part focus for action anomaly detection.

3.1 Motion anomaly detection-based dataset

The datasets in this area are intended to depict various motion models for outliers. Here are the most commonly utilized datasets for detecting irregular motion:

UCSD Pedestrian dataset [38]

This dataset is quite prominent in the literature. There are two distinct video sets, named Peds1 and Peds2. Peds1 consists of 34 movies for testing, of which 36 are videos. Peds2, on the other hand, includes a series of 16 training videos and 12 testing videos. Each clip consists of around 200 frames, which corresponds to a duration of 20 seconds. The resolution of each frame is 158×238. The primary differentiation between Peds1 and Peds2 is in the mode of pedestrian movement.

CUHK Avenue dataset [39]

It is also known as Avenue Dataset. CUHK Avenue record contains 16 records training and 21 test videos, 15328 frames for training and training 15324 test. Again, a normal sample is produced by pedestrian's parallel to the camera plane. People moving in other directions, Weird movement patterns and moving vehicles are taken into account become abnormal. In this case, the ground truth of the anomalous object is denoted with a box that defines its boundaries, and the assessment criteria are Intersection over Union (IU) between detection and ground truth.

UMN dataset [40]

The UMN dataset is a synthetic dataset made up of three separate scenarios, totaling 4 minutes and 17 seconds (7725 frames). In every scene, an unorganized crowd walks into the scene, and then everyone starts fleeing, which is labelled as an anomaly. The purpose of this dataset is to identify changes in crowd movement with excellent precision.

ShanghaiTech Campus dataset [41]

The ShanghaiTech Campus dataset is composed up of 330 training and 107 testing videos that shot across the campus in 13 different scenarios. Strange things in the area create anomalous events, as do pedestrians moving at unusual speeds (running or lounging) and in odd directions.

3.2 Action anomaly detection-based dataset

The datasets provided in this subsection's major task is to identify when a person in the scene demonstrates deviant behaviour. Typically, uncivil actions, such as theft, fighting, snatching, etc., is what is regarded as abnormal. The following datasets are the most pertinent for identifying behavioural anomalies:

BEHAVE dataset [42]

The BEHAVE Interactions dataset consists of 4 video sequences with a combined running time of 2 hours. Fighting is mostly responsible for anomalies. Only the initial sequence has all of the annotations. It is broken up into 8 pieces, each of which is ground truth at the frame level.

CAVIAR dataset [43]

The CAVIAR test case situations dataset includes a collection of films from two distinct locations: the lobby of a lab building and a hallway in a mall. Each scenario has a number of video clips. A single individual or group of individuals performs an alternate act in every recording. The majority of the oddities in this dataset are brought about by pedestrian fights.

BOSS dataset [44, 45]

The BOSS dataset is a collection of 19 scenes sequences inside a moving train and displays diverse interactions between groups of people, from individual people to crowds of more than 10 pedestrians, in both normal and deviant ways. Every scene has many cameras recording the event from various angles. Anomalies in this dataset include collective panic, fallen persons, and fights.

UT Interactions dataset [46, 47]

The UT Interactions dataset is a collection of 20 movies, each lasting about a minute, that showcase six distinct categories of human-human interactions: handshakes, pointing, hugs, pushing, kicking, and punching. Each video includes a number of exchanges as well as distracting passersby. The objective is to accurately identify and categories the kind of subject contact. For these encounters, ground-truth labels are given, incorporating time intervals and restricting bounds.

UCF-Crime dataset [48, 49]

The UCF-Crime dataset was created in 2018 and contains 1900 videos divided into 13 categories: abuse, arrest, arson, assault, road accident, burglary, explosion, fighting, robbery, shooting, stealing, shoplifting, and vandalism. At the first stage, detection and localization of generic anomalies are proposed, followed by particular anomaly

classification at the subsequent stage. This dataset is especially intriguing because of its vast size (almost 13 million samples) and originality.

Peliculas dataset and Hockey Fight dataset: [50, 51]

The Peliculas dataset includes 100 small clips of movie fights and more than 100 videos of everyday events. The Hockey Fight dataset also includes 500 small clips from each class. These two datasets have commonly been utilized in systems for violence detection, which is a job for recognizing action anomalies.

XD-Violence dataset [52]

A sizable audio-visual dataset called XD-Violence is used to identify violence in videos. However, earlier studies either lack depth (e.g., short-clip classification and a single scenario) or are undersupplied (e.g., a single modality and manually created features based multimodality). In order to solve this issue, we first make available the 217-hour long, large-scale, multi-scene dataset XD-Violence, which contains 4754 untrimmed films with poor labels and audio signals.

UBI Fights dataset [53]

UBI-Fights is a brand-new, large-scale dataset that consists of 80 hours of fully annotated video. It focuses on a specific anomaly detection while still offering a broad variety of combat scenarios. Consisting of 1000 videos, of which 216 feature fight scenes and 784 depict ordinary daily occurrences. In order to prevent disruptions to the learning process, all extraneous video segments such as video introductions and news were deleted.

Kumbh Mela dataset [54]

It is a new video dataset for crowd counting of around 6 h containing approximately 600 K frames. The drone feed was recorded on various times to gather the ground truth information. The video was shot by the Motilal Nehru National Institute of Technology (MNNIT) in Allahabad, India, using a drone on various occasions at the Ganga Ghat. Because it is private, it cannot be found online.

Abnormal Behaviors HAJJ dataset [55]

Authors gathered nine movies from the annual Hajj pilgrimage in Saudi Arabia, where people attend from all over the world with diverse backgrounds and traditions. All of the collected videos are kept in mp4 format. The gathered videos show people acting strangely or abnormally in large gatherings. High resolution cameras were used to record these videos. These videos were then divided into training and testing sets after being cropped. Each set includes 9 quick videos.

CamNuvem dataset [56]

The total number of videos in the CamNuvem collection is 972, comprising 486 unusual films that were gathered from websites like Facebook, YouTube, and other social media platforms. The introductions and ends of the films were cut out since they were not captured by the security camera. All of the strange films feature robbery-related activity. The number of videos in this category was divided into 437 for the training set and 49 (10%) for the test set. All the videos were adjusted to 320 × 240 px and 30 fps.

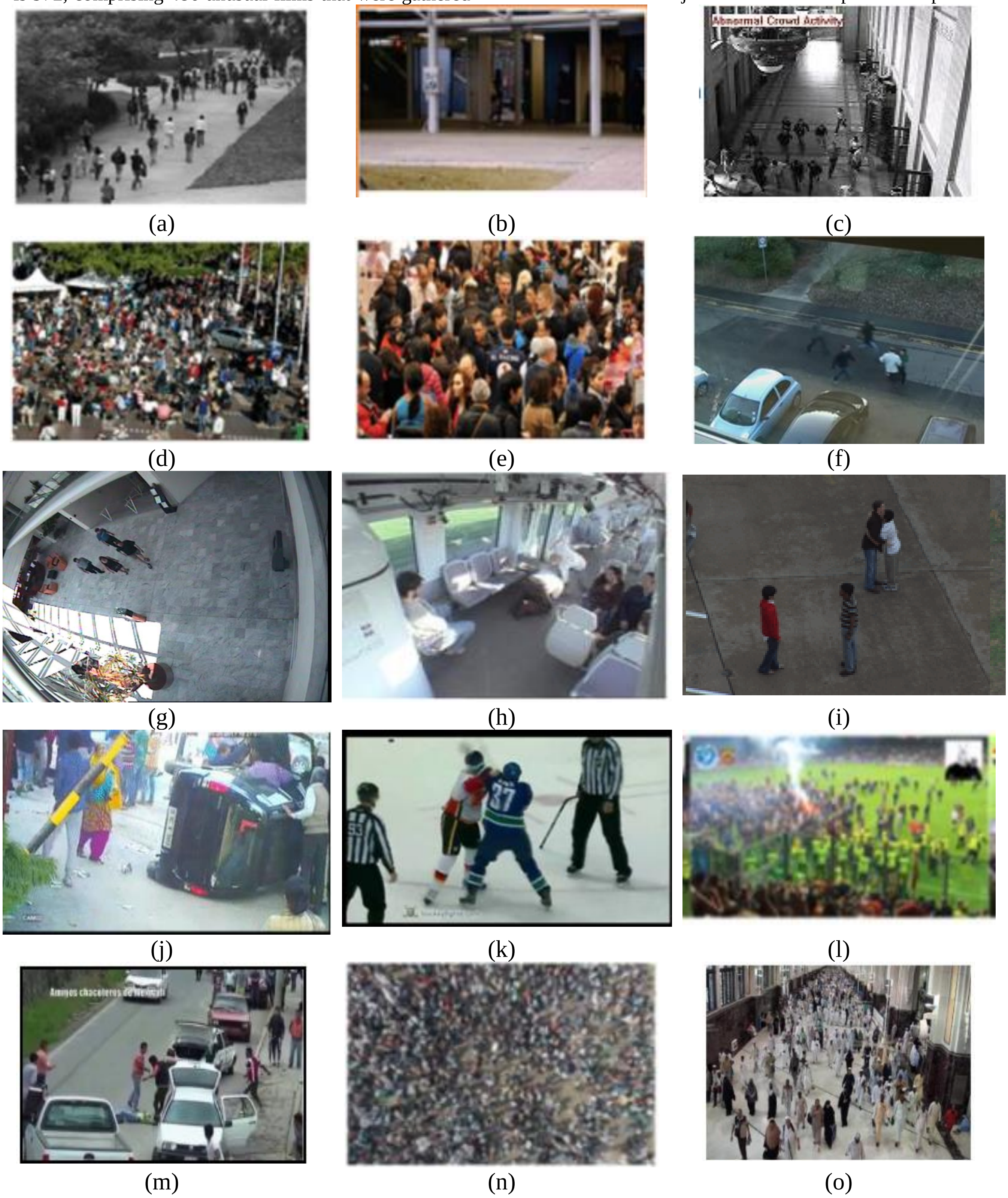

Fig.3.1. a) UCSD, b) CUHK Avenue, c) UMN dataset d) ShanghaiTech Campus Part A, e) ShanghaiTech Campus Part B, f) BEHAVE, g) CAVIAR, h) BOSS, i) UT Interaction, j) UCF Crime, k) Hockey Fight, l) XD-Violence, m) UBI Fight, n) Kumbh Mela, o) Hajj v1

4. Deep Learning Techniques for Crowd Behaviour Analysis

The fundamental element that decides which deep neural network (DNN) is used for the type of the input data determines the crowd behaviour analysis task. Based on the degree of label availability, the following are the kinds of approaches for detecting anomalies using Deep Learning: (i) Supervised based, (ii) Semi-supervised based, (iii) Unsupervised based, (iv) Deep Active learning based, (v), Transfer Learning-based, (vi) Deep Reinforcement Learning based, (vii) Deep Hybrid Models based [60].

4.1 Supervised Learning based deep learning technique

These methods feed the model with annotated data as input. Starting with starting parameters, supervised DL networks iteratively update these parameters via a back-propagation technique to obtain a better estimate for the desired output [61]. Supervised deep learning based classification models primarily consist of extraction of features networks and classification networks. A binary and a multiclass are the two types of classifiers that are specifically trained for use in supervised networks in anomaly detection applications.

4.2 Unsupervised Learning based deep learning technique

With the use of this method, learning can be done without labelled data. In order to help anomaly detection by identifying patterns within the data, it learns the intrinsic data properties such as distance or density to differentiate between normal and aberrant data. Large video datasets and powerful computing power are prerequisites for the success of unsupervised video anomaly detection approaches. Due to the algorithms not requiring training on annotated data, this approach offers the benefit of being cost-effective for detecting outliers [61, 63].

4.3 Semi-supervised Learning based deep learning technique

It is expected that every training instance has a single class label in the semi-supervised technique, which uses datasets with weakly labelled examples. This method creates a discriminative barrier around the typical instances in this situation. As a result, test instances that do not belong to the majority class are flagged as anomalous. This technique benefits from both supervised and unsupervised techniques. This technique has the benefit of requiring the least amount of labelled data, which is one of its benefits.

4.4 Deep active based deep learning technique

In order to optimize training and boost performance, an algorithm frequently requests labels from human annotators, a process known as active learning. Active learning is a method that analyzes data sets and assumes that the model needs to be updated differently for each sample within the same data set. Examples that demonstrate high performance are given preference for inclusion in the training set. This is carried out to enhance model performance, lessen the incidence of false positives, and cut labelling expenses. With the help of a domain expert, active learning introduces proper priors to lessen the ambiguous character of anomalies in the anomaly detection framework. Additionally, it addresses the problems of an unbalanced dataset and idea drift by only requiring a small number of labels to improve model performance [64, 65].

4.5 Transfer learning based technique

There are typically two methods for training Neural Networks: Scratch learning and Transfer learning. During the process of Scratch learning, a network begins with randomly assigned initial weights. This kind of learning takes a lot of data, strong computing, and a lot of processing time. In order to tackle these hurdles, the concept of Transfer Learning has been suggested as a method to overcome these obstacles. Transfer learning is a method that enables you to apply the information you obtain from one task to another to execute related tasks more effectively. To accomplish this, the second task begins with the weights and parameters that were discovered during the first work. By doing so, the total amount of training data and computational resources required to obtain good performance can be minimized [61, 66-68].

4.6 Deep Reinforcement based deep learning

One of the main goals of a deep reinforcement based method is an active search for novel classes of anomalies outside the scope of the labelled training data. This approach develops a balance between utilizing its existing data model and searching for new classes of abnormalities. As a result, it can increase the collection of anomalies it searches for without limiting itself to the examples provided by leveraging the tagged anomaly data in order to enhance detection accuracy. The main idea behind applying Reinforcement Learning to problem-solving concerns is that an agent will be able to learn from the environment by interacting with it and reaping rewards for particular acts; this idea is derived from human's natural manner of learning via their experiences.

4.7 Deep Hybrid Models based deep learning technique

The hybrid models integrate many models in a way that enhances anomaly detection for streaming video. Additionally, these models perform well when given input data with large dimensions, such as video data. Deep hybrid models mostly employ deep neural networks for feature extraction and conventional machine learning methods for activity anomaly detection.

Table 1. Deep Learning Techniques and Datasets for Crowd Beahviour Analysis

Year	Type	Approach and Architecture	Anomaly	Target	Dataset	Ref.
2018	Supervised	CNN (VGG-16 LSTM)	Kicking, pointing punching, pushing	Human	UT-Interaction-Data	[72]
2018	Supervised	FCNs	Car Skateboarder Wheelchair Bicycle, Wrong direction	Human	UCSD, Subway	[73]
2019	Supervised	CNN	Walking, jogging, fighting, kicking, punching	Human	CMU, UTI PEL, HOF WED	[74]
2019	Supervised	2D CNN	-	Vehicle, Human Animal, Bird Mixed	CVML Crowd Variety	[103]
2019	Supervised	Modified 3D ConvNet	Violent	Human	Crowd violence	[75]
2019	Supervised	Optical Flow CNN	Panic, running fast speed, crash	Human Vehicle	UCSD, UMN	[76]
2020	Supervised	CNN, RNN	Use mobile in class, fighting, fainting	Human	KTH, CAVIAR	[77]
2020	Unsupervised	CNN, Conv-LSTM	People littering, skateboard, Discarding items, loitering	Human	CUHK Avenue, UCSD Ped 1, UCSD Ped 2	[78]
2020	Supervised	CNN, KNN	Injury	Human	UMN	[79]
2020	Supervised	CNN, MII Optical Flow	Escape or panic situation	Human	UMN, PETS2009	[80]
2020	Unsupervised	RNN, 2D CNN	Violence	Human	Hockey, Violent-Flow, Real-Life Violence Situations	[81]
2020	Supervised	VGGNet-19 Binary SVM	Running, Carts Bikers, Skateboarder	Human	UMN, UCSD-ped1	[69]
2020	Supervised	Optical Flow	Panics, loitering, running, throwing objects	Human	UCSD, UMN CUHK Avenue ShanghaiTech	[83]
2021	Unsupervised	3D-CNN LSTM	Panics, fighting, protest	Human	UMN, CAVIA, Web	[84]
2021	Supervised	CNN Residual LSTM	Fighting, explosion, accidents, shooting, robbery, shoplifting, burglary	Human	UCF-Crime, UMN, Avenue	[85]
2021	Reinforcement Learning	Faster CNN	Car, bicycle	Vehicle	UCSD	[86]
2021	Supervised	CNN	Density	Human	HAJJ-Crowd	[104]
2021	Supervised	Conv-LSTM	Violence	Human	Standard crowd anomaly	[87]
2021	Unsupervised	Vgg-16 and LSTM	Non-pedestrian	Human Cars	UCSD Ped2 CUHK Avenue	[88]

2021	-	GRU, FFN (Human skeleton, GRU-FFN)	Running, falling down, robbing, fighting	-	ShanghaiTech, Avenue	[89]
2021	-	CNN (3D-ConVNet)	Robbery, fight	-	Behave, Caviar	[90]
2021	-	CNN, GAN(3D-ConVNet)	Crime	-	CUHK Avenue, ShanghaiTech	[71]
2021	-	LSTM, AEs (Convolution AE and sequence to sequence LSTM)	Sudden running	-	UMN	[92]
2022	Unsupervised	GAN	Biking, fighting, vehicle, running	Human Vehicle	CUHK Avenue, UCSD Campus, ShanghaiTech	[93]
2022	Supervised	CNN, RNN KNN, Optical Flow	Bicycles, skateboards, wheelchairs	Human Vehicle	CUHK Avenue UCSD, ShanghaiTech, UR fall	[24]
2022	Supervised	Optical Flow GAN	Standing, sitting, sleeping, running, moving in opposite, non-pedestrian	Human Cars Wheelchairs	UMN, UCSD, HAJJ datasets	[27]
2022	-	RNN (LSTM and GRU)	Fall, fight	-	Camera	[96]
2022	-	RNN, CNN 3D-ConVNet, LSTM	Violence	-	RLVS, Hockey, Violent flow	[97]
2022	-	CNN (ConvLSTM)	Robbery, fight hijack, harassment	-	Abnormal Activities	[98]
2022	-	CNN, LSTM (YOLOv5, ConvLSTM)	Smoking, playing cards, fighting	-	Hockey fight, Cigarette smoker, Playing cards	[99]
2022	-	CNN, LSTM (ConvLSTM)	Begging, Drunkenness, Fight, Harassment, Hijack, Knife Hazard, Robbery, and Terrorism	-	Abnormal Activities (96.19%)	[100]

5. Conclusion

As an AI language model, we have try to reach out to access all the information about all research papers published until 2022. However, we can offer some information on the constraints of crowd anomaly detection according to the available studies. One of the key constraints of crowd anomaly detection is the difficulty in distinguishing between anomalous behavior and legitimate variations in crowd behavior. This can result in false positives or false negatives, which can be problematic in real-world scenarios where the consequences of an incorrect decision can be significant. Another limitation is the reliance on data collection and processing methods that can be time-consuming and resource-intensive. Crowd anomaly detection typically involves collecting large amounts of data from multiple sources, such as video feeds and sensor networks, and processing this data to identify anomalies. This can be challenging, especially in real-time applications where data needs to be analyzed and acted upon quickly. Another limitation is the need for human expertise to interpret and analyze the results of crowd anomaly detection algorithms. While machine learning and other AI techniques can help automate the process to some extent, human experts are still needed to make decisions based on the output of these algorithms.

Finally, the ethical implications of using crowd anomaly detection systems also need to be considered. These systems can be used for a variety of purposes, including public safety and security, but they can also be used to monitor and control the behavior of individuals in ways that may be deemed inappropriate or even unethical. As such, it is important to carefully consider the potential risks and benefits of using these systems and to ensure that they are used in an ethical and responsible manner.

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