MULTIMEDIA DATASETS FOR ANOMALY DETECTION: A SURVEY

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ABSTRACT

Audio or video anomaly datasets play a crucial role in automated surveillance. The range of applications expand from outlier object/situation detection to the detection of life-threatening events. This research area has been active for more than 1.5 decades, and consequently, more and more datasets dedicated to anomalous actions and object detection have been created. Making use of these public anomaly datasets enable researchers to compare various anomaly detection frameworks with the same input data. This survey aims to address the lack of a comprehensive comparison and analysis of public datasets for audio, video, and audio-visual based anomaly detection. It also assists in selecting the best dataset for benchmarking frameworks. Additionally, we discuss gaps in the existing dataset and future direction insights toward developing multimodal anomaly detection datasets.

Index Terms—dataset survey, video anomaly detection, audio-visual anomaly detection, surveillance

1. INTRODUCTION

Anomaly detection corresponds to finding unexpected behavior in data [1]. Detection of anomalies can offer important insights into a large number of monitoring, safety-critical, commercially, or scientifically significant real-world applications such as extreme climate event detection, disaster forecast, mechanical fault detection, disease outbreak detection, fire/blast detection, fraud detection, network intrusion detection, etc. The topic has been studied in a variety of research areas and application domains due to its broad applicability. Additionally, due to wide availability of cheap microphones and CCTV cameras and fast audio/video processing power, applications relying on these modalities have seen a tremendous growth. In recent years, we have experienced a significant rise in automated audio/video surveillance applications such as biometric-based person identification, alarm-based CCTV scene monitoring, automatic detection of traffic rule violations, audio-based machine fault detection, audio-video based anomalous behavior recognition, etc. Manual monitoring of scenes, deployed with hundreds of CCTV cameras or microphones, by human personnel is not scalable as well as error-prone due to its own human limitations. Therefore, automated scene analysis and alarm raising have been in demand for the detection of anomalous events/objects and consequently avoiding any hazardous situations. Consequently, the topic has been under investigation since long, and many frameworks for anomaly detection have been proposed. To evaluate and compare with other frameworks, common datasets are used by the researchers. Towards this end, many anomaly datasets have been created. Datasets have been created in literature either based on a specific type of anomaly, or for generic anomaly detection applications. In case of audio, datasets are mainly developed for specific anomaly detection. In the case of video, some are specifically focused on certain types of anomaly, while others are more generic. Scene monitoring using video has gained more attention compared to audio since spatial information, motion information, appearance information, etc., are available in video to analyze the situation/object. However, relying solely on visual data implies a number of assumptions about the CCTV cameras’ uninterrupted and robust performance. Besides this, some anomalous situations may go undetected if we consider only audio or video from the target scene. Therefore, using audio and video together as complementary information has been in focus in a variety of applications recently [2].

In this survey, we discuss the existing video, audio, and audio-visual datasets for anomaly detection and facilitate a detailed comparison of these datasets based on various parameters, which will help researchers to choose suitable datasets for specific constraints and applications. To the best of our knowledge, there exists only one short survey paper [3] on a video dataset published in 2016. We present video datasets from diverse applications, audio datasets, audio-visual datasets in a structured manner. Additionally, there are more than fifteen new datasets contributed to the video anomaly detection domain after the year 2016, which generates the need to explain and compare those datasets.

The rest of the paper is organized as follows. The public video datasets for anomaly detection are discussed in the next section. In Section 5, we present a discussion on video datasets. Section 4 covers the public audio datasets. A discussion about the audio datasets have been provided in Section 5. We present public audio-visual datasets in Section 6. Further comparison of audio-visual dataset is presented in Section 7. Section 8 has a discussion on future directions. Finally, we
conclude the paper in Section 9.

2. VIDEO ANOMALY DATASETS

In this section, we discuss the publicly available video datasets that are being used or can be used for anomaly detection. There are more than 30 datasets for the purpose. We can categorize the video datasets into three major categories based on the nature of anomalies present in them. They are heterogeneous anomaly datasets, specific, and others. Datasets that do not contain some specific kind of anomalies but are diverse in nature are categorised as heterogeneous. On the other hand, some datasets that contain specific kind of anomalous events or objects are categorized as specific anomaly datasets. Further, specific anomaly datasets are divided in two sub-categories; the first one consists of datasets that involve people in the majority and events/actions are around them, the other sub-category has datasets that are built around traffic related events. There are some other datasets that are not primarily developed for anomaly detection but other sub-tasks of scene monitoring such as detecting group formation, tracking people, counting people, human interaction/action classification, etc. We keep such public datasets in other datasets categories. We discuss them in this paper as they can also be utilized for generic scene surveillance or can be useful in creating some giant anomaly datasets. The above-discussed taxonomy is shown in Fig. 1.

2.1. Heterogeneous Anomaly datasets

The datasets discussed here possess diverse kind of anomalies including rare objects as well as events events. Some examples of anomalies in these datasets are presence of cart/bicycle/motor-car on pedestrian area, person throwing papers, fight, run, etc. There are only 8 datasets in this category. Majority of the datasets were collected from the institute of the authors who created the dataset. Now, we will be discussing the public video datasets having heterogeneous anomalies.

Fig. 2. Representative frames for the UCSD Peds1 and Peds2 dataset. First row shows normal frames and second row shows abnormal frames. First two columns are from Peds1 and last column is from Peds2 sequences.

2.1.1. UCSD dataset

The UCSD dataset is a widely used and non-staged anomaly dataset. It was recorded at the University of California, San Diego, in the year 2010. The dataset was collected by deploying a stationary camera mounted at an elevation overlooking pedestrian walkways. The dataset records two different scenes: Peds1 and Peds2. For each of the scenes, the train-test is clearly specified, where the train has only normal samples, and the test has normal as well as abnormal samples. Peds1 has 34 short clips for training, and 36 clips for testing, whereas Peds2 has 16 training and 12 testing clips. Frames in each of the datasets are of the same size and almost the same number of frames (200 frames in each clip of Peds1 and 120-180 frames each clip of Peds2). Along with frame-level annotations, pixel-level annotations (10 test clips for Peds1 and 12 test clips for Peds2) are also provided for anomaly localization in the frame. The number of people on the pathways varied from low to crowded in this dataset. Video seg-
ments containing the only pedestrian are regarded as normal events. The presence of wheelchairs, bikers, skaters, cycles, small carts, people in wheelchairs, and people walking across a walkway or grass were some common anomalies observed in the footage. Some normal and abnormal frames of this dataset are shown in Fig. 2. Despite its wide popularity, the dataset has some shortcomings. Relatively small data in terms of frame count, total abnormalities, variety of anomalies, and presence of appearance-based anomalies only, etc., are some of the deficiencies.

2.1.2. Avenue dataset

The Avenue dataset [5] is another widely used dataset, captured in CUHK campus avenue and published in 2013. It consists of short video clips recorded in an outdoor environment. The camera is placed such that it looks at the side of a building with a pedestrian walkway in front of it. Anomalies are mostly staged and consist of actions such as a person throwing papers or a backpack into the air, running, and loitering. Some normal and abnormal frames of this dataset are shown in Fig. 3. A slight camera shake is also present in some of the clips. The training volume has a total of 16 clips and consists of only normal events. The testing volume has 21 clips with both normal and abnormal events. The clips are recorded at 25 Frame Per Second (FPS) and have a resolution of 640 × 360. Clips' duration varies in 1-60 seconds. Both pixel-level and frame-level ground truth is available; hence frame-level, as well as pixel-level evaluation, can be done. Like UCSD Peds1, Peds2, this dataset also has few and fewer variable anomalies.

2.1.3. ARENA dataset

The ARENA dataset [6] was published as a part of the PETS2014 challenge. ARENA stands for ‘Architecture for the REcognition of threats to mobile assets using Networks of multiple Affordable sensors’. It was recorded within the framework of the EU project ARENA. The dataset was recorded by installing four cameras (Resolution: 1280 x 960 pixels, frame rate: 30 FPS) with no overlap at the crossing path and car park in the University of Reading. The samples frames from the four cameras are shown in Fig. 4. It offers 22 acted scenarios of abnormal behavior around the parked vehicle. They are categorized into three categories which are (1) Something is wrong: Abnormal behavior that however cannot be considered as a real threat, (2) Potentially criminal: The security of the driver, the vehicle or any contained asset is in danger, and (3) Criminal behavior: The security/safety of the driver, the vehicle or any contained asset has been breached.

2.1.4. ShanghaiTech Campus dataset

The ShanghaiTech Campus dataset [7], released in 2017, is one of the largest video anomaly datasets, which is recorded by deploying CCTV cameras at multiple places on the ShanghaiTech campus. It covers a diversity of 13 different scenes with different illumination, camera angle, and area of surveillance scenes. There are 330 training videos (normal events) and 107 testing videos (normal and abnormal events), each with a resolution of 480 × 856 pixels. The dataset has a total of 317398 frames. It contains 130 abnormal events with frame-level and pixel-level annotation. Anomalies are mainly staged, which includes fighting, robbing, jumping, fighting, and vehicle (skaters, bicycle) in pedestrian areas, etc. Some example anomalies can be seen in Fig. 5. The dataset does

![Sample frames from the four cameras in ARENA dataset (image source [6]).](image)

![Representative frames for the ShanghaiTech dataset. First row shows normal frames and second row shows abnormal frames.](image)

![Representative frames for the ShanghaiTech dataset. First row shows normal frames and second row shows abnormal frames.](image)
not adhere to the single scene formulation since it is designed to be used to learn a single model for anomaly detection. One can assume it to be 13 different datasets, each having one scene, but then the dataset will be too small, and sometimes negligible anomalies present.

Fig. 6. The Sample frames with abnormality in bounding boxes in some frames from LV dataset (image source [8]).

2.1.5. LV dataset

The Live Videos (LV) dataset [8] published in the year 2017 is a rich collection of realistic videos captured by surveillance cameras in challenging environmental conditions such as changing illumination and camera motion. It has 30 video clips representing 30 different scenarios which are collected from online sources. The total duration of this dataset is 3.93 hours. The frame rate and resolutions of the clips are variable. Minimum and maximum resolution are (176 × 144) and (1280 × 720), whereas the frame rate is in range (7.5 - 30). The dataset has a total of 34 anomalous events (68989 frames) from 14 unique categories. The anomalous event is Fighting, people clashing, arm robberies, thefts, car accidents, hit and runs, fires, panic, vandalism, kidnapping, homicide, cars in the wrong-way, people falling, loitering, prohibited u-turns and trespassing. Some frames from different clips with anomaly localization as bounding boxes are shown in Fig. 6. Each clip has some normal and some abnormal frames. Authors provide frame-level annotation along with bounding boxes for the events of interest. The dataset is useful for modeling security threat based anomaly events

2.1.6. UCF-Crime dataset

The UCF-Crime dataset [9], released in 2018, is a large collection of internet videos taken from hundreds of different cameras resulting in a diversity of scenes. It includes 1900 untrimmed surveillance footage, out of which 950 footage have normal events, whereas the remaining 950 belongs to predefined 13 categories of criminal activities. It includes events like Abuse, Arrest, Arson, Assault, Accident, Burglary, Explosion, Fighting, Robbery, Shooting, Stealing, Shoplifting, and Vandalism. Some of the frames from normal and abnormal clips are shown in Fig. 7. The dataset also specifies a predefined train-test split. It has 800 normal and 810 anomalous videos for training and 150 normal and 140 anomalous videos for testing purposes. Each video has a frame rate of 30 and resolution 320×240. For evaluation, video-level, i.e., frame-level annotation, is only available for this dataset. The dataset spans over multiple scenes; hence it may not be useful for the applications or model which deals with a single scene. Also, the dataset is more inclined to activity detection.

Fig. 7. Representative frames for the UCF Crime dataset. First row shows normal frames and second row shows abnormal frames.

2.1.7. Street Scene dataset

Street Scene [10] is another large volume dataset (203257 frames in total) that was recently released (the year 2020). It consists of 46 training (normal events) and 35 testings (normal and abnormal) video sequences captured from a static USB camera looking down on a two-lane street with bike lanes and pedestrian sidewalks. Videos were collected at various times during two consecutive summers and mainly during the daytime. It captured a variety of activities like cars driving, turning, stopping, and parking; pedestrians walking, jogging, and pushing strollers; and bikers riding in bike lanes. Additionally, the videos have moving shadows and

Fig. 8. Representative frames for the Street Scene dataset. First row shows normal frames and second row shows frames with anomalies.
non-stationary backgrounds such as movement in tree leaves, flag due to wind, etc. There are a total of 56,847 and 146,410 frames for training and testing, respectively, each of resolution 1280 x 720 pixels. The test videos contain natural anomalies such as pedestrians jaywalking across the road, pedestrians loitering on the sidewalk, bikers on the sidewalk, bikers outside a bike lane, cars making u-turns, cars parked illegally, cars outside a car lane, etc. These test videos reported a total of 205 anomalous events spread over 17 categories. For each testing video, ground truth annotations are provided in the form of bounding boxes around each anomalous event in each frame. Representative frames from this dataset are shown in Fig. 8.

Fig. 9. Representative frames for the ADOC dataset. First row shows normal frames and second row shows frames with anomalies.

2.1.8. ADOC dataset

The ADOC [11] is the longest untrimmed dataset for video anomaly detection that was added in the year 2020. Moreover, it is recorded at a single scene (a university campus area) over consecutive 24 hours. It captured a variable number of people flow and the presence of rare objects in the scene. The versatile range of illumination change, shadow size, and sparse range of people count in the scene make the dataset more challenging. The video turns to grey image mode from RGB during the night, and spotting anomalies under such low illumination will be difficult. Fig. 9 shows some of the anomalies in the night scene. The second and third column of the second row shows the presence of cart (left-top corner of the second column) and a person with stature (bottom-middle of the third column). The video is recorded at 30 Hz and 320 × 240 resolution. The presence of canoe is treated abnormal object here. The dataset has limited use due to its very short duration and only one example of anomaly.

Fig. 10. Representative frames of the Canoe dataset. The left frames is a normal frames and right one is an abnormal frame.

2.2. Specific Anomaly datasets: Crowd Surveillance based

The datasets discussed here have few specific anomalies in crowd scenarios. These datasets can be used for various tasks such as crowd counting, tracking people, person re-identification, group dispersion/formation identification, crowd behavior analysis, etc. Some of the datasets were gathered from publicly accessible sources such as Getty Images, Pond5, YouTube, and Flickr or through public cameras. Others were collected from the institutes with the same name as the dataset. Now, we will be discussing the public datasets with crowd-related specific anomalies in increasing order of their release year.

2.2.1. Canoe dataset

The Canoe dataset [12] is a 34-second sequence recorded near a river. It was released in 2008. The clip shows a flow of water and the appearance of a canoe after 22 seconds in the clip. The video is recorded at 30 Hz and 320 × 240 resolution. The presence of canoe is treated abnormal object here. The dataset has limited use due to its very short duration and only one example of anomaly.

2.2.2. Subway dataset

The Subway dataset [13], released in 2008, comprises two sub-datasets, ‘Subway Exit’ and ‘Subway Entrance’, captured with a CCTV at a subway exit and entrance location, respectively. The videos are recorded at a frame rate of 25 FPS and 512 × 384 resolution. These datasets were the largest one-chunk video (Subway Exit: 43 minutes 16 seconds, Subway Entrance: 1 hour 36 minutes 9 seconds) anomaly datasets till the year 2019. Anomalies in these videos are identified

\[\text{Available upon request}\]
as what would interest a security guard in the subway entry and exit area. However, only some fixed classes of anomalies are considered and annotated here. Walking in wrong direction, entry without payment, loitering near the exit were some staged anomalies in these videos. Only frame-level sparse annotations are available; pixel-wise annotations are missing. There is no explicit train-test separation. Usually, the first 5-20 minutes of video, which are from normal class, is used for training and the rest for testing by the researchers. Some of the normal and abnormal frames are shown in Fig. 11.

2.2.3. UMN dataset

The UMN dataset [14] released in 2009 includes panic-driven crowd videos from the University of Minnesota. The videos are recorded at 30 FPS and 320 × 240 resolution. The dataset has 11 short clips of 3 scenes of people roaming around an outdoor field (total 48 seconds), an outdoor courtyard (total 77 seconds), and an indoor hallway (total 138 seconds). Each clip starts with people walking in different directions and ends in a sudden evacuation scenario. Sample normal and abnormal frames are shown in Fig. 12. The dataset is staged and has only one type as well as a single anomalous event per clip. Also, the dataset does not specify any train-test split and does not provide spatial annotations.

2.2.4. Web dataset

The Web dataset [14] was published along with UMN dataset in 2009 to study abnormal crowd behavior. The dataset is build of 12 normal and 8 abnormal crowd videos taken from the sites like Getty Images and ThoughtEquity.com. The videos have different resolutions and FPS. The normal crowd videos span 4-102 seconds, and abnormal crowd videos span 2-29 seconds. The normal crowd behavior includes Pedestrian walking, marathon running, etc., and scenes of panic-escape, protesters clashing, and crowd fighting are some abnormal crowd behavior in this dataset. Each video has a single type of crowd movement. Overall this small dataset has less variability and complexity and hence a less challenging crowd movement dataset. Fig. 13 shows sample frames of the normal and abnormal sequences.

2.2.5. PETS2009 dataset

The PETS2009 dataset [15] released in 2009 includes normal and abnormal sequences of a crowd walking and evacuating
scenes. The sequences are recorded at 7 FPS with two resolutions, 786×576 and 720×576. The dataset is not primarily meant for anomaly detection but different tasks such as analysis of group activities, counting people, tracking individuals, estimation of local dispersion, crowd formation, and splitting, etc. Estimation of the start and end of such activities can also be another task. People running in one direction or evacuation can be anomalies to be detected in these datasets. Overall, this dataset is more suitable for crowd analysis than anomaly detection. Some of the normal frames and abnormal frames are shown in Fig. 14.

**Fig. 15.** Representative frames for different clips in Anomalous Behavior datasets. Frames in the first and third rows are normal whereas frames in second and fourth rows are abnormal.

### 2.2.6. Anomalous Behavior datasets

In [16], authors released 6 video sequences for anomalous object or behavior detection in the year 2010. The video sequences are from a different scenario with illumination effects, scene clutter, variable target appearance, rapid motion, and camera jitters. All 6 sequences are manually annotated by creating a grid on the frames. These video sequences are briefly discussed below.

**Boat-Sea:** It is a video sequence capturing a sea view. The flow of water is normal behavior, and the appearance of a boat is treated abnormal here. This clip is recorded at 19 FPS with resolution 720×576 and has a total duration of 1 minute 56 seconds.

**Boat-River:** It is similar to the Boat-Sea sequence. It records a river view. The appearance of a boat is treated abnormal here too. The total length of this clip is 1 minute 8 seconds. It is shot at 5 FPS and 704× 576-pixel resolution.

**Caouflage:** This sequence is acted by one person. The presence of the person has treated anomaly here. It is of 54-second duration shot at 29.97 FPS with 320× 240-pixel resolution.

**Airport-WrongDir:** This sequence has footage of people passing from a gate for a security check. The camera is mounted at the top, and hence the top view of people is visible. People going in the opposite direction are treated anomaly here. It is of 1 minute 39-second duration with 300×300 resolution and a frame rate of 25 Hz.

**Bellevue:** This is a gray-scale video showing a traffic scene at different times of the day. Cars entering the intersection from the left or right is considered illegal turn here and hence anomaly. The video is of 4 minutes 51 seconds duration and has a resolution of 320 × 240, recorded at 10 FPS. It has 2918 frames, out of which the first 200 frames, which are normal, are used for training.

**Train:** This is most challenging compared to all the above sequences. This clip is shot inside a moving train with camera jitters and rapidly varying illumination as the train passes inside a tunnel. The total length of this clip is 12 minutes. It is shot at 25 FPS and resolution of 288×386. The movement of people inside the train is regarded anomaly here.

In all the above datasets, the rare phenomena or appearance of a rare object is treated anomaly. Multiple video sequences are useful for anomaly detection in different scenarios. However, a very constrained amount of anomaly, event, and duration of clip limits the utility of this dataset. Sample frames from the normal and abnormal class for each of these clips are shown in Fig. 15.

**Fig. 16.** Sample frames from Rodriguez’s dataset (image source [17]).
2.2.7. Rodriguez’s dataset

Rodriguez’s dataset [17] for crowd analysis purposes was released in 2011. It was created using video crawling from search engines and stock footage sources (e.g., Getty Images and YouTube) (Fig. 16). It has 520 video footage of dense crowds. Along with the enormous number of crowd recordings, the dataset contains ground truth trajectories for 100 individuals chosen at random from the population of all moving persons. The dataset can also be used for anomalous trajectory detection. Authors [17] used this dataset for tracking rare and abrupt event detection too. This refers to the detection of motion of an individual not following the global pattern of motion in the crowd (shown in Fig. 17).

2.2.8. Hockey dataset

The Hockey dataset [18] is a violence detection video dataset published in 2011. The dataset has activities with violence and non-violence from a hockey game in the same scene setting. Specifically, the authors collect 1000 clips of action from hockey games of the National Hockey League (NHL) (representative frames in Fig. 18). Each clip has 50 frames with a resolution of 720x576 pixels. Annotation is done on clip level with the binary label as fight and non-fight. The dataset is available on request to authors.

2.2.9. Movie dataset

The Movie dataset [18] is also designed specifically for violence detection along with the Hockey dataset described above. To generalize the fight scene, authors collect fight scenes from various movies. Specifically, the authors collect 100 clips with fights and 100 clips with non-fight scenes. Since the clips are from different sources, resolutions are multiple.

2.2.10. UCF Crowd dataset

The UCF dataset [19] for crowd analysis was released in 2012 by the ‘Center for Research in Computer Vision’ group at UCF institute. It was acquired from the web and PETS2009
challenge. It has a total of 38 videos comprising outdoor crowds, palaces, and traffic scenes. It is also mainly designed for a few crowd behaviors type categorization like merging crowd, circulating crowd, blocking crowd, etc. Some of these crowd behavior types are shown in Fig. 20. Although, it has few anomalies such as rare motion pattern of an individual/group (similar to Rodriguez’s dataset), scene evacuation (from PETS2009 dataset), etc.

Fig. 21. Sample frames from Voilent-Flows dataset (image source [20]).

2.2.11. Violent-Flows dataset

The Violent-Flows dataset [20] is a crowd dataset released in 2012. It consists of 246 videos (average length of 3.60 seconds) collected from the web. All the videos are resized to 320×240 resolution. The collection has a wide range of scene types, video qualities, and surveillance scenarios. However, from an anomalous standpoint, it comprises only a few specific types of anomalies, all of which fall under the category of crowd violence. Some representative frames are pasted in Fig. 21.

Fig. 22. Representative frame with trajectories of crowd in Grand central station dataset (image source [21]).

2.2.12. Grand Central Station dataset

The Grand Central Station dataset [21] is a continuous video sequence captured inside the New York Grand Central Station (Fig. 22). It was published in the year 2012. The footage has mainly crowd movements. It can be used for person counting, tracking, crowd behavior analysis, and public surveillance. The camera is mounted at a high elevation. The total length of the video is 33 minutes and 20 seconds. It has a resolution of 720×480 and a frame rate of 25. The dataset also provides the KLT keypoint trajectories from the video. The dataset can also be used for detecting an anomalous or rare walking pattern.

Fig. 23. Representative frames showing different scenes from the AGORASET dataset.

2.2.13. AGORASET dataset

The AGORASET dataset [22] is a synthetic video dataset published in 2012. Twenty-six avatars with variable shapes and colors were generated to create the synthetic scenes. Some of the scenarios are shown in Fig. 23. A total of 7 categories of scenes were developed using crowd models proposed by Helbing et al. [23], exhibiting different patterns of crowd movement. The different scene includes humans in a free environment, two environments with obstacles, an evacuation through a door, a dispersion, a rotation similar to the Mecca crowd scene, and an unstructured crowd. The Mental Ray Physical Sky model [24] is used for the scene rendering process. Approximately 23 videos with 1 minute of average duration were created. They have a resolution of 640×480 pixels and 30 FPS. Along with the synthetic videos, the authors provide the associated pedestrian information (position of pedestrians, associated velocity) and its continuous analog quantities (such as density) and the pedestrian segmentation masks. This dataset has few anomaly samples, such as evacuation and dispersion scenarios. However, the synthetic scene is too simple (plain background and constant illumination) to be a realistic scene.

2.2.14. Meta-Tracking for Video Scene Understanding dataset

The Meta-Tracking for Video Scene Understanding dataset [25] was developed in 2013. It is mainly col-
lected from online video repositories and is best suited for holistic crowd movement analysis. It is largely collected from UCF data, the change detection.net database, YouTube, and a personal database. The videos are from 12 different scenes, with each having 300-8000 frames. Some of the scenes include a marathon, a religious pilgrimage, an Indian market, pedestrian traffic, etc. Representative frames are shown in Fig. 24. The resolution of videos is in the range 320×240 to 720×404 with variable frame rate too. The clips have varying crowd densities. The dataset can be used for crowd-based surveillance, behavior analysis, counting, tracking, group detection, etc.

2.2.15. PWPD dataset

The Pedestrian walking route dataset (PWPD) dataset was published in the year 2015. It is a 1-hour crowd surveillance video recorded in a terminal station. It provides 12,684 complete trajectories of people from the time they enter the scene to exit time. The video has 100,000 frames with a resolution of 1920×1080 recorded at 25 FPS. Authors uniformly sample each 20th frame from the video, and thus the frame rate of annotation is 1.25. The trajectories from these frames are manually annotated. Some trajectories are shown in Fig. 25. The average and the maximum number of pedestrians observed in each frame are 123 and 332, respectively. This dataset is a larger dataset with a dense crowd and complex scene. It is useful for tracking people end to end in the scene and walking pattern-based anomalous behavior analysis.

2.2.16. RE-DID dataset

The RE-DID (Real-Life Events-Dyadic Interactions Dataset) dataset is a fight detection dataset published in 2015. It has 30 real footage from car-mounted Dash-Cams, and mobile phones scraped from YouTube (see example frames in Fig. 26). The length of clips varies from 20 to 242 seconds. Also, the clips have variable lighting conditions, weather conditions, camera views, and resolutions. Clips were upsampled to a fixed resolution of 1280x720 for homogeneity. The dataset recorded a total of 73 instances of fight scenes in its 30 clips. The start and end of fight scenes are annotated along with bounding box information.
2.2.17. MED dataset

The Motion-Emotion dataset (MED) [28] was published in 2016. It has 31 video sequences (554 × 235, 30 FPS) recorded at two different indoor scenarios and variable lighting conditions. There is a total of 29713 normal frames and 13913 abnormal frames. The video mainly records pedestrians, which are regarded as normal events. A group of people acted out a predefined script which led to anomalies in the dataset. Anomalies in this dataset are categorized into 4 different classes, which are panic, fight, congestion, and presence of obstacle or unattended object. Some of the example frames for normal and abnormal classes are shown in Fig. 27. The dataset is also annotated with six categories of emotions and hence can be used for emotion detection as well.

2.2.18. CCTV-Fights dataset

The CCTV-Fights dataset [29], released in 2019, is a database of real fight scenes. It has 1000 clips collected from YouTube by using search keywords like CCTV Fight, Mugging, Violence, Surveillance, Physical violence, etc. The clips were generally CCTV footage or recorded from mobile cameras. Some example frames are pasted in Fig. 28. A total of 280 videos of various types of fight scenes were acquired, with each ranging from 5 to 12 minutes. Further, 720 additional clips (3-7 seconds each) of real fights from other sources (mobile cameras, dash-cams, drones, helicopters) were added to the database. Thus it has a total of 100 videos. Frame-level annotation is available for this dataset.

2.3. Specific Anomaly datasets: Traffic Surveillance based

The datasets discussed here are mainly developed for traffic monitoring. Some examples of anomalies in these datasets are wrong direction, illegal parking, illegal turn, accidents, etc. Now, we will be discussing the public datasets having traffic-related specific anomalies. Although, some of these datasets also have non-traffic-related datasets. Since they are released together so we have discussed them together.

2.3.1. i-Lids dataset

The i-lids dataset [30] was released as a bag and vehicle detection challenge in AVSS 2007. It mainly focused on two specified anomalous situations. The first is abandon baggage detection, and the other is parked vehicles in a no parking zone (representative frames in Fig. 29). Abandoned baggage and illegal parking of vehicles are clearly defined for the specified scene in the challenge. The dataset has 7 video sequences, 3 for the first task and 4 for the other. The data collection site are various locations in the UK. For baggage detection, a train station is selected, and for vehicle detection, a suburban street is chosen. The primary event in street videos includes the left-lane vehicle going up, the right-lane vehicle going down, vehicle turning, pedestrian crossing the road. The street clips have slight camera motion and light variations. The database has a total of 35000 frames with resolution 720×576 sampled at 25 Hz.

2.3.2. QMUL dataset

The QMUL dataset [31], published in the year 2008, is intended for traffic surveillance applications. The authors [31] recorded a one-hour video with a 25 frame rate is recorded at a busy traffic junction. There are four roads, two walkways, and numerous buildings in the background. It also has a significant number of cars, bicycles, and pedestrians, as well as lighting changes making the scene complex. The events include vehicles straight driving, turning, waiting for the red lights, and pedestrians crossing the road. The authors identified 4 vehicle flow types (trajectories) in the video. Any event interrupting the normal traffic flow, vehicles not following the
allowed set of trajectories, rare behavior of vehicles, etc., are regarded anomalies here. Authors also categorized observed anomalies into 3 categories: A (Abnormal behaviors that are visually obvious), B (Rare and ambiguous behaviors), and C (Abnormal behaviors supported by weak evidence). Some example of anomalies with their category and clip number is given in Fig. 30. The database has 112 non-overlapping clips, manually extracted from the one-hour footage resulting in a total of 22 minutes of duration. All the clips are resized to a resolution of 360×288 pixels. 73 clips (22000 frames) were used for training, and 39 clips (12000 frames) were used for testing. For annotations, authors manually examined each frame exhaustively. 3 clips from the test set and 5 clips from the train set are identified as anomalous.

2.3.3. U-turn dataset

The U-turn traffic dataset [32], released in 2009, consists of eight short clips. Six clips are recorded in a university, and the rest two are acquired by a static camera positioned at a road intersection and viewing the traffic (Fig. 31). Anomalies in the first six clips are rare objects/events such as abandoned baggage, a car, a person running, etc., and the rest two clips have anomalies as illegal u-turns. Each of the clips has mainly one type of anomaly. The clips have the same resolution (360 × 240) but variable FPS (15-30). Normal and abnormal representative frames from some of the clips are shown in Fig. 31. The authors consider some very specific objects/events as anomalies; on the contrary presence of cycle in the last column of the figure is not regarded anomaly, just the abandoned baggage was of interest. Further, the very short duration of clips (18-407 seconds), an environment with stationary background, and less crowd make it less challenging.

2.3.4. ldiap dataset

The ldiap dataset [33] released in 2009 is another video dataset for traffic surveillance. The dataset is recorded at a traffic-controlled road junction. It has approximately 45 minutes of video recorded at 25 Hz with a resolution of 288×360. Some of the observed anomalies in this dataset are people crossing the road at the wrong place (far away from zebra crossing), vehicles parked at the pedestrian path, or vehicles stopping ahead of the stop line while the stop sign is red, etc. The dataset has fewer anomalies, and the video has zoomed view of traffic; thus, only a small portion of road traffic is visible at any point in time (see Fig. 32).

2.3.3. U-turn dataset

The U-turn traffic dataset [32], released in 2009, consists of eight short clips. Six clips are recorded in a university, and the rest two are acquired by a static camera positioned at a road intersection and viewing the traffic (Fig. 31). Anomalies in the first six clips are rare objects/events such as abandoned baggage, a car, a person running, etc., and the rest two clips have anomalies as illegal u-turns. Each of the clips has mainly one type of anomaly. The clips have the same resolution (360 × 240) but variable FPS (15-30). Normal and abnormal representative frames from some of the clips are shown in Fig. 31. The authors consider some very specific objects/events as anomalies; on the contrary presence of cycle in the last column of the figure is not regarded anomaly, just the abandoned baggage was of interest. Further, the very short duration of clips (18-407 seconds), an environment with stationary background, and less crowd make it less challenging.
2.3.5. IITH Accidents dataset

The IITH Accidents dataset [34] published in 2018 is focused on road accident detection tasks. It offers real footage collected from multiple CCTV cameras deployed in Hyderabad city in India. Few scenes are shown via Fig. 33. Videos are recorded at 30 FPS. Each clip starts with some normal frames, some accident events followed by normal frames. There are a total of 127138 normal and 863 abnormal frames. The authors used 94720 normal frames for training. For testing, 32417 normal and 863 abnormal (accident) frames were used. The dataset has only one type of anomaly, limiting its applicability for generic surveillance.

2.3.6. HTA dataset

The HTA dataset [35] was released in 2020. It is curated from the Berkeley DeepDrive [36] collection, which contains 100k high-resolution dashcam recordings (1280 × 720, 30FPS) from vehicles in New York and the Bay Area. Authors select only highway clips that are of good visual quality. The dataset is intended to be utilized by self-driving cars for anomaly detection or monitoring other vehicles. This dataset is different from other existing anomaly detection datasets in terms of frequent camera motion and dynamic scene changing scenarios. Five types of anomalies, namely speeding vehicle, speeding motorcycle, vehicle accident, close merging vehicle, and halted vehicle, were observed in this dataset. Some of the abnormal samples and normal samples are pasted via Fig. 34. The training set contains 286 videos of normal traffic clips, whereas the test set has 78 normal and 25 abnormal traffic condition footage. For this dataset, too, only temporal annotations are available.

Fig. 34. Representative frames for the HTA dataset. First row shows normal frames and second row shows abnormal frames.

2.3.7. NVDIA AI CITY dataset

These are traffic surveillance datasets [37] offered under AI City Challenge organized by NVIDIA. Till now, a total of 5 challenges from 2017-2021 have been organized. The challenge provides large datasets from real traffic footage collected in the wild as well as some synthetic footage. The main tasks in these challenges are turn counting, multi-camera-based vehicle re-identification/tracking, anomaly detection (e.g., crashes, stalled vehicles, etc.), natural language-based vehicle track retrieval, etc. The dataset can be acquired by filling a dataset request form provided on the dataset website.

2.4. Additional datasets

The datasets discussed here are not primarily meant or suitable for anomaly detection but other tasks such as human activity classification, group analysis in crowded scenarios, specific object detection, human behavior classification, people tracking, counting, etc. However, they have the potential to be used for anomaly detection after re-annotating them. Multiple short datasets can be merged for this purpose too. These public datasets are discussed below.

Fig. 35. Representative frames for the CAVIAR dataset (image source [38]).

2.4.1. CAVIAR dataset

The CAVIAR dataset [38] released in 2004 is primarily meant for activity detection. It has video clips from two indoor scenarios. The dataset was recorded from webcams deployed in two different indoor scenarios; the first is the entrance lobby of the INRIA Labs at Grenoble, France, and the second scenario is a shopping center in Lisbon (Fig. 35). Most of the activities of interest were acted out by the CAVIAR project team members. Some of the activities include people walking alone, meeting with others, window shopping, entering and exiting shops, fighting, leaving a package in a public place, etc. Videos in both scenarios are recorded at 25 FPS and 384 × 288 resolution. Annotations of people in all frames are provided as bounding boxes.

2.4.2. MIT Traffic dataset

The MIT Traffic dataset [39] is a 90-minute long traffic surveillance video sequence published in the year 2008. A traffic scenario with walking pedestrians and moving vehicles in a far-field at a street junction is captured in this video. It has 168822 frames with resolution 720×480 recorded at 30 FPS. The video footage is divided into 20 clips where 10 clips were used for training, and the other 10 clips were used
for testing by the authors. For each clip, the ground truth of pedestrians of some sampled frames is manually labeled. The dataset is mainly used for car/pedestrian detection/tracking. Fig. 36 shows some samples frames with marking on pedestrians (green) and vehicles (red).

Fig. 36. Sample frames from the MIT Traffic dataset. Vehicle motions are marked by red color and pedestrian motions are marked by green color (image source [39]).

2.4.3. BEHAVE dataset

The BEHAVE dataset [40] was published in 2010, mainly for the purpose of detecting different human activities in outdoor environments. The dataset has four video clips (640x480, 25 FPS) from two different outdoor scenes (representative frames in Fig. 37). The four videos have lengths 52 minutes 11 seconds, 19 minutes 26 seconds, 56 minutes 59 seconds, and 21 minutes 22 seconds, respectively. Out of these four videos, the only first video is chunked into 8 sub-videos and annotated yet. Authors annotate start and end frames of activities taking place in the video. The bounding boxes around humans are also provided to localize the actions. Actions are mainly human-centric and categorized into 10 classes such as people walking in a group, two groups of people approaching each other, one group chasing another, groups fighting, groups splitting from one another, etc. Action such as fighting, running can be of interest to be detected for the purpose of crime-oriented abnormal behavior detection.

Fig. 37. Representative frames from the two outdoor scene in the BEHAVE dataset. These frames also show some potential anomalies.

2.4.4. VIRAT dataset

The first release of the VIRAT dataset [41] in 2011 is mainly meant for activity recognition in an outdoor environment. It records various daily-life activities from 16 different outdoor scenes. Frames from some of the scenes are shown in Fig. 38. The dataset is important in terms of realistic scenes, diverse types of human actions and human–vehicle interactions, and environmental noise such as clutter, camera shake. Videos are collected at multiple sites distributed throughout the USA. Two releases of the dataset are available, being 2.0 the current one. Annotations for objects (person, vehicle) and events are available in the form of bounding boxes. The dataset can be used to detect context-based anomalies like wrong parking, standalone vehicle on the road, etc.

Fig. 38. Few example scene from the VIRAT dataset (image source [41]).

2.4.5. CUHK Square dataset

The CUHK Square dataset [42] was recorded in a similar fashion to the MIT Traffic dataset in the year 2012. It offers
one continuous footage of 60 minutes captured by a stationary camera overlooking traffic. Compared to MIT Traffic, it has more challenging perspective distortion. A total of 352 frames uniformly sampled from the first 30 minutes and 100 frames uniformly sampled from the last 30 minutes are annotated and used for train and test, respectively. This dataset is also mainly used for person/vehicle detection/tracking. Since it offers untrimmed footage of traffic, it can also be used for traffic analysis or surveillance.

Fig. 40. Example frames in the Mall dataset. Person with baby-Carrier, cleaning material, walking stick in above frames can be regarded anomalies.

2.4.6. Mall dataset

The Mall dataset [43], published in 2012, was collected from a public surveillance camera deployed in a shopping mall. It has 2000 video frames taken at 12 FPS with resolution 640×480. It provides annotations of 60,000 pedestrians in this dataset. The head position of pedestrians is provided. This dataset covers a more diverse range of crowd density, activity patterns, illumination conditions compared to the UCSD dataset. It also has more perspective distortion, which results in larger differences in the size and appearance of objects at different depths of the scene, as well as a higher occurrence of occlusion. This dataset can be used for person counting, tracking, crowd behavior modeling, etc. People running, presence of baby-cart can be considered as anomalies in this dataset (see Fig. 40). However, the annotation is mainly done for tracking and counting.

Fig. 41. Example frames from the Collective Motion dataset (image source [44]).

2.4.7. Collective Motion dataset

The Collective Motion dataset [44] was published in the year 2013, mainly for the purpose of estimating collectiveness in crowd videos. It has clips from 62 different crowded scenes (see representative frames from a different scene in Fig. 41). The database contains 413 video clips, where 297 videos were collected by authors and 116 videos were taken from Gitty Images. Each clip has roughly 100 frames and a variable amount of collective motions. Clips are annotated with three levels of motion as low, medium, and high with the help of 10 annotators.

Fig. 42. Example frames from the CUHK Crowd dataset (image source [45]).

2.4.8. CUHK Crowd dataset

As the name suggests, the CUHK Crowd dataset [45] is mainly focused on group profiling from crowd scenarios. It was published in 2014. It is a large dataset with 474 video clips collected from different sources. 419 clips are taken from Pond5 and Getty Images, and the rest 49 are collected by authors. The video clips are from different environments such as shopping malls, airports, parks, etc., (some example frames from different scenes are shown in Fig. 42). They vary in terms of crowd densities and shapes. The number of frames and resolution are also not static in these clips. Authors provide gKLT tracker-based trajectories for each video clip. Also, locations and velocities of tracked feature points and annotate the group label of each point is made available.

2.4.9. Group Detection datasets

Few datasets such as BIWI, GVEII, and Student003 are specially developed and used for group detection in the crowd. Trajectories and groups information is provided for all these datasets. See some sample frames for these datasets in Fig. 43 and 44. The datasets can also be utilized for crowd analysis, people counting, tracking, etc. They are described below.

BIWI: The BIWI dataset [46] was released in the year 2009,
offers two scenes, namely ETH and Hotel. These scenes (ETH and Hotel) are recorded outside a university and at a bus stop, respectively. This dataset is mainly used for group detection and crowd surveillance. 750 different pedestrians are encountered in each scene. The motion patterns in this dataset are more varied and chaotic.

**GVEII:** The GVEII dataset released in the year 2015 is also meant for group detection. It is a single sequence dataset (resolution 1280×720) recorded from a camera mounted at a high elevation. The dataset was collected by ImageLab at the University of Modena and Reggio Emilia and has 2400 frames.

**Student003:** The Student003 dataset is used for group formation/dispersion/detection task. It was released in the year 2015 by ImageLab at the University of Modena and Reggio Emilia. It has a resolution of 720×576 and contains more than 5,000 frames. The dataset is challenging as the density of the pedestrians is significantly high, and there are multiple entry and exit points present in the scene. These datasets show densely populated real-world environments with hundreds of non-linear trajectory variations. Couples walking together, groups crossing each other, and groups forming and dispersing are some of the challenging crowd scenarios here.

**MPT-20x100:** The MPT-20x100 dataset released in the year 2015 is composed of 20 clips of 100 frames each. It has a variety of videos captured from a public camera placed at different crowded places such as malls, streets, etc. Thus it offers a high number of pedestrians and heterogeneous scene conditions.

**2.4.10. WorldExpo’10 dataset**

The WorldExpo’10 dataset, published in 2015, is one of the largest video datasets for crowd counting acquired from Shanghai 2010 WorldExpo. The video sequences were obtained from 108 CCTV cameras stationed there, each with a different bird view, and thus cover a wide range of scenes (see some frames in Fig. 45). There is a total of 1132 video clips, 1127 clips of 1-minute each for training and 5 clips of 1 hour each for testing. Frames are uniformly sampled from each of these video sequences and annotated. For training, set frames are sampled at a width of 15 seconds, resulting in 3380 frames (from 1132 clips). For test frames, sampling is done at a width of 30 seconds, resulting in a total of 600 frames (from 5 clips). The dataset provides 199923 annotated pedestrians (labeled at the centers of their heads) from train and test frames. The pedestrian count in the scene ranges from 1 to 220.

**2.4.11. MuseumVisitors dataset**

The MuseumVisitors dataset was published in the year 2015. It is under construction. The dataset is aimed for various crowd-based analysis tasks such as group detection, occlusion handling, tracking, re-identification, gaze estimation, and behavior analysis. The dataset was collected by deploying three IP cameras inside the National Museum of Bargello in Florence. It captures data from two scenarios: the first one consists of individuals watching artwork, and the second scenario consists of groups of people watching artwork (some frames are pasted in Fig. 46). The data is recorded at 5 frames per second and with a resolution of 1280×800 pixels. The dataset has a total of 4808 frames with ground-truth annotation for each pedestrian in the form of bounding boxes.

**2.4.12. S-Hock dataset**

The S-Hock dataset was released in the year 2015. It is aimed at analyzing the behavior of spectator crowds at stadiums. Particularly, 5 cameras from multiple angles were installed focusing on a different part of the stadium. A full HD camera (1920×1080, 30 FPS, focal length 4mm) for the ice rink, another one for a panoramic view of all the bleachers, and 3 high-resolution cameras (1280×1024, 30 FPS, focal length 12mm) focusing on different parts of the spectator crowd was installed. The dataset is unique compared to other crowd datasets as the people are semi-static, centered most of the time on a unique position/seat. This dataset can be used for multiple spectator crowd analysis purposes such as spectator recognition and segmentation, global head orientation, automatic highlight production, gesture segmentation, and social signal processing. It has 31 seconds long 15 sequences for each camera; thus, in total, it has 75 clips. The annotation is done with the help of an annotator and some surveys from the spectator crowd itself. For each frame, multiple information that is interesting for crowd analysis were annotated. They are as follows: people detection (full body bounding boxes), head detection (bounding boxes of head), head pose (left, right, down, etc.), body position (sitting, standing, etc.), posture (crossed arms, elbows on legs, hands on hips, etc.), locomotion (walking, jumping), action/interaction (waving arms, whistle), supported team (which one), best action (most exciting action), social relation (if know the neighbor). An example of the spectator and rink from one of the cameras is shown in Fig. 47. Each person from the crowd is...
Fig. 44. Example frames with groups marked in various Group Detection datasets. Fig. (a-e) are from MPT-20x100, Fig. (f) is from GVEII, and Fig. (g), (h) are from the two sequence (Eth and hotel) from BIWI dataset (image source [46]).

Fig. 45. Some representative frames from the worldExpo’10 dataset (image source [47]). Person heads are marked in red color.
2.4.13. WWW dataset

The WWW dataset [50] published in 2016 is the largest crowd video dataset collected in the wild. It has 10000 clips from 8257 scenes. Authors built this dataset from various online sources such as surveillance footage, Getty Images, Pond5, YouTube, and movies. They used keywords such as street, stadium, rink, marching, chorus, graduation, etc., for collecting crowd-related videos from these sources. The diversity in the collected video makes it complete and suitable for crowd surveillance. It has more than 8 million frames with 640×360 resolution. The clips are annotated with the help of 19 annotators. Crowd attributes such as Who is in the crowd? Where is the crowd? And why is the crowd here? is provided. A total of 94 meaningful attributes covering common crowded places, subjects, actions, and events were specified in the allowed annotation list. See an example of annotation with sample frames in Fig. 48.

2.4.14. Crowd-11 dataset

The Crowd-11 dataset [51] is one of the largest crowd datasets consisting of 6272 video clips, released in 2017. It is collected using web scraping. Some of videos are also selected from existing public crowd datasets (WWW [50], CUHK [45], Violent-Flows [20], Worldexpo’10 Crowd Counting dataset [47], Agoraset [22], PETS [15], UMN [14], WWW [50], Hockey Fight and Movies [18]). The procedure
to prepare the dataset from these sources is elaborated in the paper. Moreover, the authors provide the list of URLs on email request. Videos have variability of resolutions, ranging from 220 × 400 to 700 × 1250. Authors model the crowd type as different flow types studied in fluid dynamics are label the crowd dataset into 10 different categories which are Gas Free, Gas Jammed, Laminar Flow, Turbulent Flow, Crossing Flows, Merging Flow, Diverging Flow, Static Calm, Static Agitated, and Interacting Crowd (see Fig. 49). And the last class is of no crowd. Thus the dataset can be seen as 11 class classification problem too.

Initial datasets for video based anomaly detection consisted of simple events, scenarios, and a very constrained amount of anomalies. The anomalies are mainly performed by a group of people intentionally and therefore lack a natural flow of events. They are of very short duration too. The presence of a few rare objects or events in clean background events was regarded anomaly there. Some examples of such datasets are Canoe (a boat occurs in scene one time and this is regarded anomaly), UMN (few people acted for sudden evacuation which is regarded anomaly here), Web (panic-escape, crowd fighting is regarded anomaly), Subway entrance/exit (the wrong direction is regarded anomaly), various sub-clips in abnormal behavior dataset (appearance of only one type of rare object/event), etc. Later datasets were consists of more types of anomalies and scene variability such as UCSD, AVENUE, ARENA, ShanghaiTech. In contrast, some recently developed datasets are gigantic in terms of duration and variability of scene and events such as UCF-Crime, VI-RAT, LV, ADOC, HTA, Rodriguez’s, etc. They leverage the online sources of CCTV footage and public videos and curate large databases of realistic video clips from our daily life. The developed dataset over time for anomaly detection offers a rich and large collection of datasets. They are equipped with a variety of events, actions, the scene complexity level of scene and events and thus offers a large collection to select application-specific dataset for anomaly modeling. Some datasets are suitable for generic scene monitoring, such as UCSD, ADOC, AVENUE, ShanghaiTech, etc., while others are suitable for specific classes of anomaly detection such as Subway entrance/exit, UMN, Web, i-Lids, etc. Further, some datasets offering detection of specific anomaly classes are important datasets to be used for frameworks intended for life-threatening event detection, such as UCF-Crime, LV, NVIDIA AI CITY, etc.

We present a systematic comparison and remark on video datasets discussed in Section 2. For this, we describe these datasets on various attributes through Tables 1 to 6. Table 1 shows a broader category of datasets according to the type of anomalies present. In the first category, i.e., heterogeneous anomalies, the included anomalies are of different categories,
i.e., any object, situation, the appearance of people which are rare in that dataset, is treated anomaly. Object/scene representation requires considering both motion and appearance for the detection of such anomalies. This dataset category allows researchers to focus on generic anomaly detection framework development. On the other hand, datasets with specific anomalies, which are further categorized as crowd and traffic-based, poses a constraint on the allowed type of anomalies. Crowd-specific ones have mainly focused on one type crowd-centric anomaly event. Datasets for traffic surveillance are mainly focused on vehicle trajectory-related anomalies such as illegal turns, vehicle passing from restricted areas, etc. Frameworks to detect such contextual anomalies must consider the trajectories of vehicles in any form. And these frameworks then do not focus on anomalies other than trajectory-related. These datasets are specially designed for evaluating traffic surveillance systems. The additional dataset category has video datasets that are not primarily meant for anomaly due to a lack of anomaly-related annotations and dataset formulation. However, they can be reformulated and be utilized for anomaly detection. We compare datasets through Tables 2-6 following the sequence of categories mentioned in Table 1 and the year of their release (increasing order).

For each dataset, we list the year of publication, the approximate number of times it is refereed by researchers, and the applications where it has been used for benchmarking through Table 2. The number of times a dataset is referred also signifies how many times it is used for benchmarking. However, it is not exactly equal because there are many papers that just mention the particular dataset paper for a survey paper, use the approach provided along with the dataset, referred to compare with own dataset, etc. Also, the dataset which can be applied for benchmarking in multiple applications gets more references. Additionally, We can observe that a dataset published earlier has been referenced more compared to a recently released one. Recently released datasets are less cited as they are younger but normally provide better ground truth information. For some datasets such as Canoe, PET2009, QMUL, etc., the number of references is less, in spite of being released a long time ago. This may be due to various reasons such as the dataset website is not maintained, annotations are not sufficient/poor, the dataset is recorded under too many constraints to look unrealistic, has constrained amount of anomalies, etc., resulting in limited applicability of the dataset. The column showing the area of application gives an idea of different applications where the data has been used for benchmarking. Table 4 shows the following attributes: if the video is recorded in continuation, i.e., it is untrimmed (column 2), the dataset is recorded from how many locations (column 3), where is the data recorded (column 4), the recording location is indoor or outdoor (column 5), what is the density of people in the scene (column 6). Continuity (yes or no) and location (how many) helps to see the applicability of a dataset for the task at hand such as if the aim is to examine the context adaptation of anomaly detection framework, then the footage should be untrimmed as well as recorded at a single location [162]. The adaptive models need sufficient data to learn the context on their own and adapt over time; hence a dataset with too short clips from different spatial and temporal aspects is not useful for evaluation. For datasets having multiple recording locations, we mention the exact number of locations if countable or provided by authors; otherwise, we write it as multiple. Information about dataset collection scene, i.e., whether it is a mall or an airport or a traffic junction, etc., may help to choose scene-specific dataset for the evaluation of specific surveillance frameworks. Also, whether the dataset is recorded indoor or outdoor may help to evaluate the robustness or claim that the frameworks work in indoor and/or outdoor scenarios. Some works are specifically designed to handle crowded scenes, whereas some work only for low density of people; thus, the information of density in a dataset may help to choose suitable datasets for evaluations. In Table 3, we add details of anomalies and annotation. In the ground truth column, the availability type of annotation is provided. Some dataset gives only clip level annotation; if a clip is annotated anomalous, then it is assumed that anomaly is present or spanned to all the frames in the clip. The assumptions hold true in most cases, especially for small databases, but it is not scalable to validate this assumption for larger datasets. Hence, some frames may be wrongly annotated. Frame-level annotations are more precise and accurate. For some datasets, pixel-level annotations are also provided, which are helpful for models which aim to precisely localize the occurrence of an anomaly in the spatial domain along with the temporal domain. Pixel-wise annotations are too precise but difficult to manually do; therefore, some datasets such as Train, Bellevue, Boat-Sea, BoatRiver, Airport-WrongDir, etc., first divide the frame into grids (a grid can have multiple pixels) and then annotates the grids that can be served for spatial anomaly localization. Some also provide the rectangle bounding boxes around the area of interest, i.e., anomalous object/person. Some datasets, especially for people tracking crowd datasets, provide the trajectories and anomaly information on these. Some datasets in additional dataset category viz. S-Hock and WWW offer categorical information such as head position, body position, details of scene (who is there, what is in the scene, where is it located), etc. We list the nature of anomalies, i.e., anomalies are acted or naturally occurred if acted, then how many actors were there, how many distinct types of anomalies are there in the dataset, and some examples of anomaly events through columns 3 to 6. Getting anomalous natural events for human-centric anomaly datasets is difficult; therefore, many of the datasets have acted as anomalies. The acted events add unrealistic flavor, and hence less complex anomaly events are generated. Generally, traffic surveillance-related datasets get natural anomaly samples as accidents, illegal turns, or other...
4. AUDIO ANOMALY DATASETS

Audio anomaly detection is gaining a lot of attention in many applications in various fields, such as traffic surveillance, industries, music, medicines, etc. Unlike for video, not many datasets for audio are available for study. A few datasets have been created based on applications and further provided publicly. In this section, we describe and discuss the features of publicly available audio datasets.

4.1. MIVIA road audio events dataset

The MIVIA road audio events dataset [163] was released in the year 2014. It was mainly intended for road surveillance applications [163, 164]. Originally, 59 samples of crashes and 45 of tire skidding, together with the sound of 23 different road locations, were collected. Thus, in total, a collection of 400 events, namely tire skidding with the duration of 522.5 seconds and car crashes for a duration of 326.38 seconds, were created. The duration for background audio amounted to 2732 seconds. The audios are available as wav files and have been recorded and sampled at 32 kHz, quantized at 16 bits per PCM sample. The signal-to-noise ratio for the data is 15 dB. In order to account for cross-validation experiments, these events are divided into 4 folds of 100 events each. Each fold comprises a number of audio files of a duration of about 1 minute, wherein a series of dangerous events are superimposed to a regular road background sound. Each audio file consists of a different background sound in order to simulate a number of different real situations.

4.2. AudioSet soundscape

AudioSet Soundscape dataset was collected for the experiment carried out in [165] from different ecosystems. A total of over 2750 hours of audio recordings were collected. In order to detect anomalies, each recording was embedded with 0.96 seconds of eco-acoustic data in 128-dimensional feature space from Google’s AudioSet dataset. AudioSet is a collection of over 2 million human-labeled, short audio clips from a wide range of sources available on YouTube [166]. The majority of the sound clips in AudioSet are unrelated to natural soundscapes, with the largest sections comprising of music, human speech, and machine noise, such as gunshots and chainsaws. The dataset collected from different ecosystems has been mentioned below. A summary of the datasets collected has been described in Table 7.

4.2.1. Sabah, Malaysia

Two datasets were collected from lowland rainforests across a gradient of habitat degradation in Sabah, Malaysia. It was collected between February 2018 and June 2019 across an ecological gradient encompassing primary forest, logged forest, cleared forest, and oil palm sites.
| Dataset            | Year | # Ref. | Area of Application                                                                 |
|--------------------|------|--------|-------------------------------------------------------------------------------------|
| USCD Ped1          | 2010 | 1196   | crowd profiling/counting [53,54], anomaly detection [55,56], crowd density estimation [57] |
| UCSD Ped2          | 2010 | 1196   | anomaly detection [58,59], crowd profiling/counting [53], action classification [60] |
| Avenue             | 2013 | 588    | anomaly detection [61,62], crowd profiling/counting [53], action classification [60] |
| ARENA              | 2014 | -      | abnormal activity/behaviour detection [63,64,65], group walking event detection [66] |
| ShanghaiTech       | 2017 | 214    | anomaly detection [61,68], action classification [60], crowd counting [69]           |
| LV                 | 2017 | 21     | anomaly detection [70,71,72], panic detection [73]                                  |
| UCF-Crime          | 2018 | 468    | anomaly detection [74,75], action classification [60]                                |
| Street Scene       | 2020 | 27     | anomaly detection [76], road surveillance [77]                                      |
| ADOC               | 2020 | 2      | anomaly detection [76]                                                              |
| Canoe              | 2008 | 43     | anomaly detection [79,80]                                                          |
| Subway Entrance    | 2008 | 810    | Anomaly detection [79,80], abnormal behavior modeling [81,82]                       |
| Subway Exit        | 2008 | 810    | Anomaly detection [79,80], abnormal behavior modeling [81,82]                       |
| UMN                | 2009 | 1691   | anomaly detection [4,79], abnormal crowd behaviour detection [83,84], crowd aggregation detection [85], crowd escape behaviour detection [86] |
| Web                | 2009 | –      | anomaly detection [87]                                                             |
| PETS2009           | 2009 | 54     | tracking [88,89], crowd profiling/counting [53,90], crowd analysis [54], human detection [91,92], person re-identification [93], crowd escape behaviour detection [86] |
| Train              | 2010 | 106    | anomaly detection [59,78,93]                                                        |
| Belleview          | 2010 | 106    | anomaly detection [78,94]                                                            |
| Boat-Sea           | 2010 | 106    | anomaly detection [78,95]                                                            |
| Boat-River         | 2010 | 106    | anomaly detection [78,82]                                                            |
| Camouflage         | 2010 | 106    | anomaly detection [82]                                                              |
| Airport-WrongDir   | 2010 | 106    | anomaly detection [82,96]                                                            |
| Rodriguez's        | 2011 | 255    | crowd profiling/counting [90], crowd saliency detection [97], tracking [89], crowd analysis [98], crowd segmentation [99] |
| Movie              | 2011 | 316    | violence detection [100,101,102,103]                                                |
| Hockey             | 2011 | 316    | violence detection [102,103,104]                                                    |
| UCF Crowd          | 2012 | 265    | abnormal crowd detection [105], crowd profiling/counting [90], crowd saliency detection [97], crowd segmentation [106] |
| Violent-Flows      | 2012 | 337    | abnormal crowd behaviour detection [83], violence detection [100,102]                |
| Grand Central Station | 2012 | 326   | pedestrian trajectory prediction [107], pedestrian behavior modeling [108], crowd behavior analysis [109,110], human re-identification [111], tracking [112,113], crowd counting [54,114] |
| Dataset          | Year | # Ref. | Area of Application                                                                 |
|------------------|------|--------|-------------------------------------------------------------------------------------|
| AGORASET         | 2012 | 31     | panic behaviour detection [115], crowd flow tracking [116], crowd motion classification [117], crowd behaviour analysis [118] |
| Meta-tracking    | 2013 | 62     | tracking [119, 120], measuring collectiveness [119], anomalous walking pattern detection [120] |
| PWPD             | 2015 | 195    | trajectory prediction [122], anomaly detection [122], pedestrian speed detection [123], crowd behaviour analysis [124] |
| RE-DID           | 2015 | 24     | fight detection [127] |
| MED              | 2016 | 35     | anomaly detection [125], panic detection [126] |
| CCTV-Fights      | 2019 | 20     | fight detection [127] |
| t-Lids           | 2007 | –      | abandon baggage detection [128], traffic surveillance [129] |
| QMUL             | 2008 | 9      | vehicle tracking [112], trajectory classification [130], anomaly detection [131, 132, 133] |
| U-Turn           | 2009 | 244    | traffic based anomaly detection [134, 135, 136] |
| Idiap            | 2009 | 148    | anomaly detection [132, 133], recurrent activity mining [137] |
| IITH Accidents   | 2018 | 56     | road accident detection [134] |
| HTA              | 2020 | 1      | anomalous motion detection [135] |
| NVDIA AI CITY    | 2021 | –      | multi-camera based vehicle re-identification/tracking [138], traffic anomaly detection [139] |
| CAVIAR dataset   | 2004 | 185    | tracking [89], violence detection [140], pedestrian detection [141], re-identification [142], face detection [143], anomalous behaviour detection [144], abandon baggage detection [128], body pose detection [145] |
| MIT Traffic      | 2008 | 891    | crowd behavior analysis [109], vehicle tracking [112], recurrent activity mining [137] |
| BEHAVE dataset   | 2010 | 174    | anomalous behaviour/activity detection [129], violence detection [146] |
| VIRAT            | 2011 | 649    | Activity recognition/forecasting [147], Surveillance Video Summarization [148] |
| CUHK Square      | 2012 | 137    | people/vehicle detection [149] |
| Mall             | 2012 | 503    | crowd density estimation [57], crowd counting [54] |
| Collective Motion| 2013 | 230    | group collectiveness or crowd analysis [150] |
| CUHK Crowd       | 2014 | 252    | pedestrian trajectory prediction [107], Crowd aggregation detection [105], crowd segmentation [106, 121], anomaly detection, tracking, person counting, crowd behaviour analysis [151], pedestrian behavior modeling [108], pedestrian speed detection [123], crowd counting [152] |
| WorldExpo’10     | 2015 | 904    | pedestrian trajectory prediction [107], Crowd aggregation detection [105], crowd segmentation [106, 121], anomaly detection, tracking, person counting, crowd behaviour analysis [151], pedestrian behavior modeling [108], pedestrian speed detection [123], crowd counting [152] |
| MuseumVisitors   | 2015 | 12     | user interest profiling [153], group identification/tracking [148] |
| S-Hock           | 2015 | 44     | head counting [154, 155], head pose detection [156], crowd analysis [157] |
| WWW              | 2016 | 34     | crowd analysis [158] |
| Crowd-11         | 2017 | 15     | crowd analysis [159, 160] |
| BOSS             | 2017 | 5      | attack detection [161], people detection [52] |
### Table 4. Comparison of video datasets based on data collection information

| Dataset          | Continuity | Location | Scene             | Indoor/Outdoor | Density       |
|------------------|------------|----------|-------------------|----------------|---------------|
| USCD Ped1        | no         | 1        | campus (walkway at UCSD) | outdoor        | high/medium   |
| UCSD Ped2        | no         | 1        | campus (walkway at UCSD) | outdoor        | high/medium   |
| Avenue           | no         | 1        | campus (avenue)    | outdoor        | medium/low    |
| ARENA            | no         | 4        | campus (University of Reading) | outdoor        | low           |
| ShanghaiTech     | no         | 13       | campus (Shanghai Tech) | outdoor        | medium/low    |
| LV               | no         | 30       | multiple           | both           | high/medium/low|
| UCF-Crime        | yes        | 1        | campus (walkway)   | outdoor        | high/medium/low|
| Street Scene     | no         | 1        | road (two-lane street) | outdoor        | medium/low    |
| ADOC             | yes        | 1        | campus (walkway)   | outdoor        | high/medium/low|
| Canoe            | yes        | 1        | river              | outdoor        | low           |
| Subway Entrance  | yes        | 1        | subway entrance    | indoor         | medium/low    |
| Subway Exit      | yes        | 1        | subway exit        | indoor         | medium/low    |
| UMN              | no         | 3        | field, courtyard, hallway | both           | medium        |
| Web              | no         | multiple | multiple           | both           | dense/high    |
| PETS2009         | no         | 8        | university         | outdoor        | medium        |
| Train            | yes        | 1        | inside train       | outdoor        | low           |
| Belleview        | no         | 1        | road (intersection) | outdoor        | medium        |
| Boat-Sea         | yes        | 1        | sea                | outdoor        | low           |
| Boat-River       | yes        | 1        | river              | outdoor        | low           |
| Caouflage        | yes        | 1        | room               | indoor         | low           |
| Airport-WrongDir | no         | 1        | security check     | indoor         | medium        |
| Rodriguez's      | no         | multiple | multiple           | outdoor        | dense         |
| Hockey           | no         | 1        | Ice hockey         | indoor         | medium/low    |
| Movies           | no         | multiple | movies             | both           | medium/low    |
| UCF Crowd        | no         | multiple | multiple           | outdoor        | dense         |
| Violent-Flows    | no         | multiple | multiple           | both           | dense         |
| Grand Central Station | yes      | 10       | terminal station   | indoor         | medium/high   |
| AGORASET         | no         | multiple | multiple           | indoor         | high/dense    |
| Meta-tracking    | no         | multiple | multiple           | outdoor        | low/high/dense|
| PWPD             | yes        | 1        | terminal station   | indoor         | medium/high   |
| RE-DID           | no         | multiple | multiple           | both           | low/medium    |
| MED              | no         | 3        | campus (walkways)  | outdoor        | high/medium   |
| CCTV-Fights      | no         | multiple | multiple           | both           | low/medium    |
| i-Lids           | no         | 2        | railway station, road | outdoor        | low/medium    |
| QMUL             | no         | 1        | road (traffic junction) | outdoor        | medium/high   |
| U-Turn           | no         | 4        | road (intersection), university | outdoor        | medium/low    |
| idiap            | yes        | 1        | road               | outdoor        | low/medium    |
| IITH Accidents   | no         | multiple | road (intersection, junction) | outdoor        | medium        |
| HTA              | no         | multiple | multiple           | outdoor        | medium/low    |
| NVIDIA AI CITY   | no         | multiple | multiple           | outdoor        | high/medium/low|
| CAVIAR           | no         | 3        | entrance lobby, shopping centre | indoor        | medium/low    |
| MIT Traffic      | yes        | 1        | road (intersection) | outdoor        | medium/high   |
| BEHAVE           | yes        | 2        | campus (parking)   | outdoor        | medium/low    |
| VIRAT            | no         | 16       | parking            | outdoor        | medium/low    |
| CUHK Square      | yes        | 1        | road               | outdoor        | medium/high   |
| Mall             | yes        | 1        | shopping mall      | indoor         | medium/high   |
| Collective Motion| no         | 62       | multiple           | outdoor        | high/dense    |
| CUHK Crowd       | no         | multiple | multiple           | outdoor        | high/dense    |
| WorldExpo'10     | no         | 108      | Shanghai 2010 WorldExpo | outdoor        | high/dense    |
| MuseumVisitors   | no         | 3        | Museum             | indoor         | low/medium    |
| S-Hock           | no         | 5        | stadium            | indoor         | medium/high   |
| WWW              | no         | 8257     | multiple           | both           | high/dense    |
| Crowd-11         | no         | multiple | multiple           | both           | high/dense    |
| BOSS             | no         | 10       | inside train       | indoor         | medium/low    |
| Dataset | Ground truth | Nature of Anomaly | # Actor | Types of Anomaly | Example anomalies/event |
|---------|-------------|------------------|---------|------------------|------------------------|
| USCD Ped1 | frame/pixel | natural | none | 5 | bikers, small carts, walking across walkways |
| USCD Ped2 | frame/pixel | natural | none | 5 | bikers, small carts, walking across walkways |
| Avenue | frame | acted | 1-3 | 5 | loitering, running, throwing objects, new object |
| ARENA | frame | acted | 1-5 | 8-12 | abnormal behaviour, threats |
| ShanghaiTech | frame/pixel | both | 2-5 | <10 | bicycle, small carts, fight, etc. |
| LV | frame/bounding box | natural | none | 14 | realistic security threats |
| UCF-Crime | clip/frame | natural | none | 13 | abuse, arrest, assault, accident, burglary, etc |
| Street Scene | frame/pixel | natural | none | 17 | jaywalking across road, pedestrians loitering, u-turns |
| ADOC | frame/pixel | natural | none | 27 | walking with balloons/umbrella/dog/suitcase, person on vehicle, crowd gathering, etc |
| UCF Crowd clip | natural | none | <5 | anomalous trajectory |
| Violent-Flows | clip | natural | none | <5 | anomalous trajectory |
| Grand Central Station | bounding box | natural | none | <3 | rare walking pattern |
| AGORASET trajectories | synthetic | – | <3 | evacuation, dispersion |
| Meta-tracking trajectories | natural | none | <3 | anomalous trajectory |
| RE-DID | frame/bounding box | natural | none | 1 | fight |
| MED | frame | acted | ≈5-15 | 5 | Panic, fight, congestion, obstacle, neutral |
| s-Lids | frame | natural | none | 2 | abandon bag, illegally parked vehicle |
| U-Turn | clip | natural | none | <5 | unusual traffic trajectory, rare behaviour of vehicles |
| Idiap | frame | natural | none | <4 | illegal u-turns, running, abandon baggage |
| IIITH Accidents | bounding box | natural | none | 1 | accidents |
| HTA | frame | natural | none | 5 | accident, speeding vehicle, close merge, |
| NVIDIA AI CITY | – | – | – | accidents |
| CAVIAR | frame/pixel | both | 2-4 | <5 | leaving object, fighting, run, chase, etc. |
| MIT Traffic | bounding box | natural | none | <3 | road surveillance |
| BEHAVE | frame/pixel | both | 2-5 | <4 | fighting, chasing, run |
| VIRAT | frame/pixel | natural | none | <3 | wrong parking, standalone vehicle |
| CUHK Square | bounding box | natural | none | <3 | road surveillance related |
| Mall | bounding box | natural | none | <3 | running, baby carrier |
| Collective Motion | clip | natural | none | <3 | crowd based behaviour modeling |
| CUHK Crowd | trajectories | natural | none | <3 | crowd based behaviour modeling |
| WorldExpo’10 | bounding box | natural | none | <2 | unusual walking pattern |
| MuseumVisitors | bounding box | natural | none | <2 | unusual walking pattern |
| S-Hock | categorical/bounding box | natural | none | <4 | shout, interesting events in game |
| WWW | categorical | natural | none | <4 | anomalous behaviour modeling |
| Crowd-l1 | frame | both | – | <4 | anomalous behaviour modeling |
| BOSS | frame | acted | 2-13 | <4 | Harass, panic |
Table 6. Specifications of video datasets

| Dataset          | Release Year | Duration     | Total Frames | Total No. of Videos | Resolution | FPS | Camera motion |
|------------------|--------------|--------------|--------------|---------------------|------------|-----|---------------|
| USCD Ped1        | 2010         | ≈ 5-7 min    | 14000        | 34(N)+36(AN)        | 238x158    | -   | none          |
| UCD Ped2         | 2010         | ≈ 2-3 min    | 4560         | 16(N)+14(AN)        | 360x240    | -   | none          |
| Avenue           | 2013         | 20 min 26 sec| 30652        | 16(N)+23(AN)        | 640x360    | 25  | slight in few |
| -                 | 2014         | -            | -            | 22                  | 1280 x 960 | 30  | none          |
| ShanghaiTech     | 2017         | ≈ 3-3.5 hrs  | 317398       | 330(N)+107(AN)      | 856x480    | 24  | none          |
| LV               | 2017         | 3.93 hrs     | -            | 30                  | multiple   | multiple | in some      |
| UCF-Crime        | 2018         | ≈ 128 hrs    | ≈ 13 million | 950(N)+950(A)       | 320x240    | 30  | slight in few |
| Street Scene     | 2020         | ≈ 3-4 h      | 203257       | 46(N)+35(AN)        | 1280x720   | 15  | none          |
| ADOCS            | 2020         | 24 hrs       | 259127       | 4                   | 2048 x 1536| 3   | none          |
| Canoe            | 2008         | 34 s         | 1050         | 1                   | 320 x 240  | 30  | none          |
| Subway Entrance  | 2008         | 96 m 9 s     | 144225       | 1                   | 512x384    | 25  | none          |
| Subway Exit      | 2008         | 43 m 16 s    | 64900        | 1                   | 512x384    | 25  | none          |
| UMN              | 2009         | 4 min 17 sec | 7710         | 11 (available as 1)| 320x240    | 30  | none          |
| Web              | 2009         | 7 min 35 sec | 11,962       | 12(N)+8(A)          | multiple   | multiple | slight jerks |
| PETS2009         | 2009         | ≈ 1-2 hrs    | 42182        | 59                  | 768x576    | 7   | none          |
| Train            | 2010         | 12 min       | 19218        | 1                   | 288x386    | 25  | moving        |
| Belleview        | 2010         | 4 min 51 sec | 2918         | 1                   | 320 x 240 | 10  | jitter        |
| Boat-Sea         | 2010         | 1 min 56 sec | 450          | 1                   | 720x576    | 19  | none          |
| Boat-River       | 2010         | 1 min 8 sec  | 250          | 1                   | 704x576    | 5   | none          |
| Camouflage       | 2010         | 54 sec       | 1629         | 1                   | 320x240    | 29.97| none          |
| Rodriguez’s      | 2011         | 10 hrs 24 min| -            | 520                 | 720x480    | -   | none          |
| Hockey           | 2011         | 27 min       | 50000        | 1000                | 720x576    | -   | none          |
| Movie            | 2011         | 6 min        | -            | 200                 | multiple   | multiple | in some      |
| UCF Crowd        | 2012         | ≈11 min      | ≈16320       | 38                  | multiple   | multiple | none          |
| Violent-Flows    | 2012         | 14 min 6 sec | 22,156       | 246                 | 320x240    | multiple | significant   |
| Grand Central Station | 2012 | 33 min 20 sec | 50910 | 1 | 480x720 | 25 | none |
| AGORASET         | 2012         | ≈20 min      | >33641       | 23                  | 640x480    | 30  | none          |
| Meta-tracking    | 2013         | –            | >4000        | 12                  | multiple   | multiple | none          |
| PWPD             | 2015         | 1 hour       | 5000         | 1                   | 1920x1080 | 1.25| none          |
| RE-DID           | 2015         | <2 hrs       | -            | 30                  | 1280X720   | multiple| in some       |
| MED              | 2016         | ≈24-25 min   | 43,626       | 31                  | 554x235    | 31  | none          |
| CCTV-Fights      | 2019         | ≈10 hrs      | >1000        | multiple            | multiple   | multiple | in some      |
| i-Lids           | 2007         | ≈24 min      | 35000        | 7                   | 720x576    | 25  | none          |
| QMUL             | 2008         | 22 min       | 34000        | 104(N)+8(A)         | 360x288    | 25  | none          |
| U-Turn           | 2009         | ≈20 min      | ≈25182       | 8                   | 360 x 240 | multiple| none          |
| Idiap            | 2009         | 44.13 min    | 66324        | 1                   | 288x360    | 25  | none          |
| ITHA Accidents   | 2018         | –            | 128001       | 30                  | none       | none  |              |
| WWW              | 2020         | ≈ 4 hrs      | ≈ 0.4 million| 286(N)+107(AN)      | 1290x720   | 30   | moving        |
| CAVIAR dataset   | 2004         | ≈17-18 min   | 26419        | 28                  | 384 x 288 | 25  | none          |
| MIT Traffic      | 2008         | 90 min       | 168822       | 20                  | 720x480    | 30  | none          |
| Airport-WrongDir | 2010         | 1 min 39 sec | 2200         | 1                   | 300x300    | 25  | none          |
| BEHAVE dataset   | 2010         | ≈2.5 hrs     | 225024       | 4                   | 640x480    | 25  | none          |
| VIRAT            | 2011         | 29 hrs       | ≈ 3 million  | 354                 | multiple   | multiple | varying      |
| CUHK Square      | 2012         | 60 min       | -            | 720 × 576           | -          | none  |              |
| Mall             | 2012         | –            | 2000         | 1                   | 640x480    | <2   | none          |
| Collective Motion| 2013         | –            | ≈41300       | 413                 | –          | –    | none          |
| CUHK Crowd       | 2014         | –            | 474          | multiple            | multiple   | multiple | none          |
| WorldExpo’10     | 2015         | 1427 min     | 3980         | 1132                | 576x720    | 1/30, 1/15| none          |
| MuseumVisitors   | 2015         | ≈17 min      | 4808         | 3                   | 1280x800   | 5   | none          |
| S-Hock           | 2015         | ≈39 min      | 69750        | 75                  | 1920x1080 | 30   | none          |
| WWW              | 2016         | –            | >8 million   | 10,000              | 640x360    | 30   | none          |
| Crowd-11         | 2017         | ≈ 4-6 hrs    | 621196       | 6,272               | multiple   | multiple | none          |
| BOSS             | 2017         | 27 min       | 40500        | 129                 | 720x576    | 25   | moving        |
Table 7. AudioSet_Sounscape Dataset

| Location            | Time of recording                  | Total hrs | Sampling rate |
|---------------------|------------------------------------|-----------|---------------|
| Sabah, Malaysia     | February 2018 - June 2019          | 274 hrs   | 44.1 kHz      |
|                     | Tascam: 274 hrs 40 min             |           |               |
|                     | Audiomoth: 748 hrs 16 kHz          |           |               |
| Ithaca, New York    | January 2016 - December 2019       | 797 hrs   | 48 kHz        |
|                     | From May 2017                       | 638 hrs   | 48 kHz        |
| New Zealand         | 8-20 December, 2016                | 240 hrs   | 32 kHz        |
| Sulawesi            | August 2018                        | 64 hrs    | 48 Hz         |
| Republic of Congo   | December 2017 - July 2018          | 238 hrs   | 8 kHz         |

Tascam dataset: In this, 20 minutes sound files were recorded at a sampling rate of 44.1 kHz. At each site, one 20 minutes file was recorded per hour, resulting in a total of 27 hours 40 minutes recording.

Audiomoth dataset: In the Audiomoth dataset, continuous recording of sound was carried out in consecutive 5 minutes sound files, sampled at 16 kHz, resulting in a total of 748 hours of audio. Audiomoths were secured to trees.

4.2.2. Ithaca, New York

From the protected temperate broadleaf forests in Sapsucker Woods, Ithaca, New York, two datasets were collected.

The first dataset was collected continuously over 3 years, between January 2016 and December 2019 (inclusive) from only one location. Data was audio-digitized at a sampling rate 48 kHz and comprised of a total of 797 hours of audio.

The second dataset comprises 24 hours of audio dated from 13 May 2017 across an area of 220 acres. The audio was recorded continuously in consecutive 1-hour files, sampled at 48 kHz, with recorders attached to trees at eye height. A total of 638 hours of audio was collected.

4.2.3. New Zealand

Audio data was collected from the protected temperate broadleaf forests in Abel Tasman National Park, New Zealand, by deploying 10 units of semi-autonomous recorders from the New Zealand Department of Conservation from 8 to 20 December 2016. Of these, 5 units were installed on the mainland and the other 5 on Adele Island. Continuous recording of audio was performed in consecutive 15 minutes files, audio-digitized at 32 kHz, with recorders attached to trees at eye height. A total of 240 hours of audio was collected.

4.2.4. Sulawesi

In Sulawesi, audio was recorded from protected lowland tropical rain forests, Tangkoko National Park. Continuous recording of audio was carried out from four locations during August 2018, in consecutive 40 minutes files, sampled at 48 Hz. A total of 64 hours of audio was collected.

4.2.5. Republic of Congo

Audio data was collected from 10 sites of protected and logged lowland rainforest in and surrounding NouabaléNdoki National Park between the period from December 2017 to July 2018. Continuous recording of audio was carried out in consecutive 24 hours files, sampled at 8 kHz. Habitat types spanned mixed forest and Gilbertiodendron spp. from within a protected area, areas within a 6-year-old logging concession, and within active logging concessions. Recorders were installed at the height of 7 to 10 meters from ground level and suspended below tree limbs. Overall, 238 hours 20 minutes of audio were taped.

4.3. DCASE 2017 dataset

The 2017 DCASE Challenge Task 2 [167] was released in the year 2017. It comprises an audio dataset for the detection of infrequent sound events from a set of artificially created mixtures. The background recordings in the audio dataset have been collected from the TUT Acoustic Scenes 2016 development dataset [168], which consists of 30 seconds audio recordings from 15 distinct acoustic indoor as well as outdoor environments, as mentioned in Table 8. Each acoustic scene comprises of 78 segments, totaling 1170 samples, resulting in the final audio of 39 minutes.

Four rare sound events are included in the database for anomaly detection. These are baby cry (106 training, 42 test instances, mean duration 2.25 seconds), glass break (96 training, 43 test instances, mean duration 1.16 seconds), and gunshot (134 training, 53 test, mean duration 1.32 seconds). The sound events are recorded at levels of +6Db, 0Db, and -6Db when compared to the background audio (Event-to-Background Ratio). The events have been recorded in the 24-bit format and at the sampling rate of 44.1 kHz.

4.4. ICBHI 2017 dataset

The ICBHI 2017 dataset [169] was collected and made available in the year 2017 for medical purposes, such as for respiratory anomaly classification. For the same, data were acquired from the International Conference on Biomedical and Health Informatics (ICBHI) Challenge 2017, task 1 [170].
The respiratory sounds for this challenge were collected from 128 patients, resulting in an audio recording of over 5.5 hours. A total of 920 audio clips were recorded, where each recording consists of one to four distinct types of cycles, namely Crackles, Wheezes, Crackles and Wheezes, and Normal accompanied by onset and offset time labels. The recording lengths of the cycles varied from 0.2 to 16.2 seconds, with an unbalanced number of cycles, i.e., 1864 cycles for Crackles, 886 for Wheezes, 506 for Crackles and Wheezes, and 3642 Normal cycles. The entire set of audio recordings comprise different lengths from 10 to 90 seconds, with a wide range of sampling frequencies varying from 4 to 44.1 kHz.

### 4.5. SMD anomaly detection dataset

The SMD Anomaly Detection Dataset [171] was released in year 2018. The audio recordings for this dataset were acquired from a Surface-Mount Device (SMD) assembly machine. Two sets are provided in this data: C-line and B-line. In this dataset, one production C-line is considered normal, and the rest everything is abnormal. Three anomalous categories have been described in this dataset, viz., change in assembly part (from C-Line to B-line), the addition of artificial noise (in order to represent broken internal components), and removal of grease in the same production C-line. For anomaly detection using the SMD dataset, 2048 samples transmuted into frequency domain with an overlap length of 512 samples, and a sampling rate of 16300 Hz. The spectrogram so obtained was split into 32 columns and represented about 1.5 seconds. A total of 2100 segments for C-line were designed, out of which 2000 segments were used for the training dataset and the rest 100 as testing data. The anomalies were introduced only in the testing dataset. The audio records used in the experiment have been listed in Table 9.

| Category             | Length |
|----------------------|--------|
| C-line (Normal)      | 24:49  |
| Non-greased line (Anomaly) | 15:53 |
| C-line with intermittent noise (Anomaly) | 06:08 |
| B-line (Anomaly)     | 11:00  |

### 4.6. MIMII DUE dataset

MIMII DUE audio dataset [172] was developed in the year 2019. It comprises of Malfunctioning Industrial Machine Investigation and Inspection with domain shifts due to variations in operational and environmental conditions (MIMII DUE). It is a subset dataset used in the creation of DCASE 2021 Challenge Task 2. Hence, the dataset is entirely similar to the data that is included in the development as well as the additional training dataset. It includes normal and anomalous audios from five distinct types of industrial machines: fans, gearboxes, pumps, slide rails, and valves. Each category comprises data from two domains, i.e., the source domain and target domain, collected in different conditions like the speed of operation or noise from the environment. The anomalous conditions for each machine type are mentioned in Table 10. The entire dataset comprises audio recordings for more than 420000 seconds. Each single-channel 16-bit audio sample is a recording of 10 seconds, sampled at 16 kHz. For the source domain in each section, the training dataset comprises 1000 audio clips, whereas the test data consists of around 100 audio clips of normal and 100 for anomalous conditions. For the target domain, each section contains only three audio clips for the training data, whereas the test data comprises around 100 sound recordings of normal and 100 for anomalous conditions.

### 4.7. ToyADMOS dataset

The ToyADMOS dataset [173] was released in the year 2019. It refers to a machine operating sounds dataset consisting of approximately 540 hours of normal machine operating sounds and over 12000 samples of anomalous audio collected using four microphones, sampled at the rate of 48 kHz. The ToyADMOS dataset consists of three sub-datasets for three types of anomaly detection in machine operating sounds (ADMOS).
tasks. A different toy is considered in each task: product inspection (toy car), fault diagnosis for a fixed machine (toy conveyor), and fault diagnosis for a moving machine (toy train). In order to simulate different noise levels, individual recordings of machine-operating sounds and environmental have been carried out. The dataset for each task comprises over 180 hours of normal machine-operating sounds and over 4000 samples of anomalous sounds collected at a sampling rate of 48 kHz. All audio events were stored as different wav files classified into two types: individual (IND) and continuous (CNT). Each of the three sub-datasets consists of three types of acoustic data: normal, anomalous, and environmental. Normal sound refers to the operating sound when the target machine normally performs in accordance with its specified characteristics. Anomalous sound is defined as the operating sound when the target machine is forced to perform anomalously by intentionally altering its elements or by adding foreign parts. The anomalous conditions for each miniature machine have been mentioned in Table 11. Environmental noise refers to the noise used for the purpose of simulation of a factory environment. For this purpose, noise samples such as collision, drilling, pumping, and airbrushing were assembled from various locations in an actual factory. The sub-datasets used in the ToyADMOS dataset are described below. The total audio duration and number of samples for each sub-dataset are summarized in Table 12.

4.7.1. Toy car

The toy car sub-dataset contains normal and anomalous audio clips of a toy car called “mini 4WD”. It is mainly designed for the purpose of product inspection. Each IND normal and anomalous wav file was of a duration of 11 seconds, recording 1350 IND samples in each case and channel, resulting in 66 hours of IND normal sounds. In the case of CNT recordings, approximately 150 CNT samples were recorded for each case and channel. A total number of 135 hours of CNT normal sounds was recorded, which made half the total length of CNT files. In order to add anomalous sounds, parts of the machine, namely scale and N-scale. Each normal and anomalous wav-file of IND sounds was of a duration of 11 seconds, recording a total of 1350 IND samples for each case and channel. In total, 66 hours of IND normal sounds were recorded. For CNT data, 74 audio samples were recorded for every case and channel, resulting in a total of 197 hours of CNT normal sounds. Anomalous sounds were taped by intentionally altering the first/last carriage and straight/curved railway track. A total of 270 anomalous sound samples were recorded with the help of these combinations (54 patterns). In addition, environmental noise was recorded only once for 12 hours.

4.7.2. Toy conveyor

The toy conveyor sub-dataset contains normal and anomalous audio clips of a toy conveyor fixed on a desk. It is mainly designed for the purpose of fault diagnosis of a fixed machine. Three different sizes of the conveyor were considered as ‘cases’ in this sub-dataset. Each normal and anomalous wav-file of IND sounds was of a duration of 10 seconds, recording a total of 1800 IND samples for each case and channel. In total, 60 hours of IND normal sounds were recorded. For CNT data, at least 124 audio samples were taped in each case, resulting in a total of 120 hours of CNT normal sounds. In order to add anomalous sounds, parts of the machine, namely tension pulley, trail pulley, and belt, were intentionally altered or voltage was excessively lowered/raised. A total of 355 anomalous sound samples were recorded with the help of these combinations (60 patterns). In addition, environmental noise was recorded only once for 12 hours.

4.7.3. Toy train

The toy train sub-dataset contains normal and anomalous audio clips of HO-scale (large) and N-scale (small) model railways. It is mainly designed for the purpose of fault diagnosis of a moving machine. Four cases were designed for this sub-dataset. Each ‘case’ is configured by combining two kinds of trains, i.e., commuter and a bullet, and scales, viz., HO-scale and N-scale. Each normal and anomalous wav-file of IND sounds was of a duration of 11 seconds, recording a total of 1350 IND samples for each case and channel. In total, 66 hours of IND normal sounds were recorded. For CNT data, 74 audio samples were recorded for every case and channel, resulting in a total of 197 hours of CNT normal sounds. Anomalous sounds were taped by intentionally altering the first/last carriage and straight/curved railway track. A total of 270 anomalous sound samples were recorded with the help of these combinations (54 patterns). In addition, environmental noise was recorded only once for 12 hours.

4.8. LIFE DYNAMAP dataset

Detection of anomalous noise events in the LIFE DYNAMAP project makes use of audio events of real road traffic noise (RTN) of the ring road surrounding the city of Barcelona [174]. These audio events are synthetically combined with anomalous noise events (ANE) samples. The synthetic noise events have been gathered from free online repositories and consist of up to 15 noise types: horns, ambulance sirens, car collisions, church bells, birds, crickets, rain, thunders, etc. The noise-free field recordings of road traffic were obtained at a sampling rate of 48 kHz and a broadband linear frequency range of 4.2 Hz - 22.4 kHz. An overall length of 250 seconds of acoustic samples of RTN and 300 seconds of ANE were used for training. Each noise type in the mixtures was adjusted to obtain RTN-ANE ratios of -6 and -12 dB.

4.9. ToyADMOS2 dataset

The ToyADMOS2 dataset [175] is also a subset of the dataset for DCASE 2021 Challenge Task 2. This dataset consists of operating sounds for miniature machines for detecting anomalous sounds under domain shift conditions. It comprises of two audio categories, viz., toy car and toy train.
### Table 11. Anomalous conditions for each miniature machine in the ToyADMOS dataset

| Parts      | Condition | Toy car   | Toy conveyor | Toy train   |
|------------|-----------|-----------|--------------|-------------|
| Shaft      | -Bent     | Tension Pulley | -Excessive tension | First Carriage | -Chipped wheel axle |
| Gears      | -Deformed | Tail Pulley | -Excessive tension | Last Carriage | -Chipped with axle |
|            | -Melted   |            | -Removed     |             |              |
| Tires      | -Coiled (plastic ribbon) | Belt | -Attached metallic object 1 | Straight Railway Track | -Broken |
|            | -Coiled (steel ribbon) | |            |             | -Obstructing stone |
| Voltage    | -Over voltage | Voltage | -Over voltage | Curved Railway Track | -Broken |
|            | -Under voltage |            | -Under voltage |             | -Obstructing stone |

### Table 12. Audio collection in ToyADMOS dataset

|                      | Toy car | Toy conveyor | Toy train |
|----------------------|---------|--------------|-----------|
| # of IND normal sounds per case and channel | 1350 samples | 1800 samples | 1350 samples |
| Total hours           | 66 hours | 60 hours     | 66 hours  |
| # of CNT normal sounds per case and channel  | ≈150 samples | at least 124 samples | 74 samples |
| Total hours           | 135 hours | 120 hours    | 197 hours |
| # of IND anomalous sounds per case and channel | ≈250 samples | 355 samples | 270 samples |
| Total hours           | 72 samples | 144 hours    | 96 hours  |

### Table 13. Anomalous conditions for each miniature machine in the ToyADMOS2 dataset

| Parts      | Anomaly  | Toy car   | Toy train   |
|------------|----------|-----------|-------------|
| Shaft      | -Bent    | Carriage  | -Flat tire  |
| Wheels     | -Damaged | Railway track | -Broken shaft |
| Gears      | -Deformed| -Melted   | -Disjointed |

4.9.1. **Toy car:**

This sub-dataset consists of normal and anomalous sound clips of a toy car. It is mainly designed for the purpose of product inspection. Each recorded sample is of a duration of 12 seconds. Thus, there are a total of 35k samples times five channels, resulting in a total of over 177k audio samples. The anomalies were produced by an intentionally damaging shaft, gears, and tires of the machine to the depth three levels. This resulted in producing over 8k samples of anomalous audios, including 300 patterns of their combinations.

4.9.2. **Toy train:**

The toy train sub-dataset is designed for the detection of faults in a moving machine. Here, similar to the toy car sub-dataset, each recorded sample is of a duration of 12 seconds. Thus, there are a total of 35k samples times two mic types, resulting in a total of over 71k audio samples. The anomalies were produced by an intentionally damaging shaft, gears, and tires of the machine to the depth three levels. This resulted in producing over 8k samples of anomalous audios, including 300 patterns of their combinations.

The anomalous conditions for each sub-dataset are described in Table 13.

4.10. **DCASE 2021 dataset**

The 2021 DCASE Challenge Task 2 [176] was released in the year 2021. It comprises normal/ anomalous operating sounds from seven different kinds of machines, viz., Fan, Gearbox, Pump, Slide rail (also called slider), ToyCar, ToyTrain, and Valve. Each recording in the dataset is 10 seconds, single-channel audio consisting of sounds of a machine as well as its related equipment and environmental sounds. The dataset is categorized into three subsets: development dataset, additional training dataset, and evaluation dataset.

4.10.1. **Development dataset**

The development dataset includes three sections for each type of machine, where each section comprises training as well as test data. Each section comprises of (i) around 1000 clips of normal audio in a source domain for the purpose of training, (ii) three clips of normal audio in a target domain for training, (iii) around 100 clips of both normal as well as anomalous audio in the source domain for testing, and (iv) around 100 clips of both normal as well as anomalous audio in the target domain for testing.
4.10.2. Additional training dataset

Additional training dataset comprises another three sections for each type of machine. Each section includes (i) around 1000 normal audio clips in the source domain for training and (ii) three clips of normal audio clips in the target domain for training.

4.10.3. Evaluation dataset

The evaluation dataset provides test clips for three sections for each machine type, similar to the additional training dataset. Here, each section comprises (i) test audio clips in the source domain and (ii) test audio clips in the target domain, where none of the clips has a condition label (i.e., normal or anomaly).

5. DISCUSSION ON AUDIO DATASETS

In this section, a discussion on various audio datasets described above has been carried out. Table 14 gives a description of the datasets based on applications. As it can be seen from the table, so far, most of the anomaly detection applications have used DCASE 2017 database, followed by the MIVIA road audio event dataset. The datasets have been used for applications in different fields, such as in industries for machine monitoring and inspection, road surveillance, etc. A dataset for anomaly detection in respiratory patterns in human bodies has also been created. Most of the datasets have been artificially generated by deliberately adding anomalies and made available to the public recently. The year of release for every dataset has also been mentioned in the table.

Table 15 describes expressively the type of anomalies that are present in various datasets, along with some examples. As it can be seen from the table, most of the audio datasets have been created artificially, except for ICBHI 2017 dataset, which records the natural respiratory sounds from a human body. The datasets have been created at various indoor and outdoor locations, such as industry, roads, forests, etc. Since it is difficult to generate natural audio datasets consisting of anomalies, hence anomalies have been generated deliberately to simulate the system for its detection and for future anomaly detection applications. Some of the anomalies that have been generated are mentioned for every dataset in the table. Table 16 gives the specifications of the audio samples collected for different datasets. The specifications include the time duration of each dataset, the number of samples collected, and the sampling rate for audio-digitization. It can be from the table that the duration of audio for different datasets varies from a few seconds to a number of hours. AudioSet soundscape dataset has the longest duration of audios, followed by ToyADMOS2 and ToyADMOS datasets. A very small recording of 550 seconds has been collected for the LIFE DYNAMAP project.
Table 15. Comparison of audio datasets based on anomaly information

| Dataset                        | Scene  | Indoor/Outdoor | Nature of anomaly | # of anomalies | Example anomalies                                      |
|-------------------------------|--------|----------------|-------------------|----------------|-------------------------------------------------------|
| MIVIA road                    | outdoor| artificial     | 2                 | crashes and tire skidding                              |
| AudioSet Soundscape           | nature | both           | random            | music, human speech, machine noise, etc.               |
| DCASE 2017 city               | outdoor| artificial     | 3                 | baby cry, glass break, gun shot                        |
| ICBHI 2017 human body         | indoor  | natural        | 3                 | crackle, wheeze, crackle and wheeze                    |
| SMD industry                  | indoor  | both           | >15               | non-greased line, B-line, C-line to B-line             |
| ToyADMOS industry             | indoor  | artificial     | 23                | wing damage, clogging, gear, contamination etc.        |
| LIFE DYNAMAP dataset          | road    | outdoor        | 15                | horns, church bells, birds, thunder etc.               |
| ToyADMOS2 industry            | industry| indoor         | 8                 | bent shaft, melted gears, flat tire etc.               |
| DCASE 2021 industry           | industry| indoor         | >30               | wing damage, clogging, chipped wheel, axle etc.        |

Further, from the table, it can be seen that the sampling rate for different audio datasets varies between the range of 4kHz to 48 kHz. The sampling rate of 48 kHz has been mostly considered for audio digitization in various datasets. Also, for ICBHI 2017, there is no fixed value of sampling rate for the data; rather, it varies between the range of 4 to 44.1 kHz. Thus, different sampling rates have been used as per the requirement of the tasks.

6. AUDIO-VISUAL DATASETS

So far, we have discussed a number of publicly available datasets for video and audio anomaly detection applications individually. Since a course of actions consist of both audio and video components dependant on each other, hence, audio-visual analysis can result in more accurate results compared to audio and video recordings being used independently. In this present section, we describe the available audio-visual datasets for anomaly detection in various applications. All the public audio-visual datasets contain specific kind of anomalies, therefore no further categorization is done.

6.1. Human–human Interactions dataset

The Human-human Interaction dataset developed in 2014 aimed at stressful situation detection in human-human interactions at help-desks. Generally, this stressful situation which is also regarded anomaly, is generated due to various reasons such as there is a case of emergency, communication is not running smoothly, or problems are not solved as expected, etc. These situations are reflected in hand gestures and speech, which also reflect the emotional state of a person. Thus analyzing gestures and speech can also help in detecting stressful situations, i.e., anomalies. Authors create such a dataset with the help of a multicultural group of nine professional actors (4 male, 5 female). Four scripted scenarios were designed and asked to be performed by the actors that create a stressful situation in human-human interaction. The actors were divided into two disjoint groups and played each script twice; thus, a total of eight sessions were recorded, resulting in 32.24 minutes. Each scene has an employee and a customer. In few cases, there were three visitors in front of the service desk. Two cameras, one facing to the customer’s face and the other to the employee and the complete scene, were installed. Each person has a microphone clipped to their shirt. Representative frames for both the camera are shown in Fig. 51. Video of the customer, i.e., the image on the left of Fig. 51 is taken for analysis in the paper. The audio has Dutch and English speech depending upon one’s nationality. Moreover, they were not provided any detailed script of conversation but asked to create a source of conflict in between. The recordings were annotated on a scale of 5, where label 1 was attributed to normal situations, 2 and 3 to moderate stress levels, and 4 and 5 to extremely negative situations.

Fig. 51. First camera showing the details of the visitor’s behavior (left) and an overview shot by the second camera (right) in Human–human Interactions dataset.

6.2. VSD dataset

The VSD dataset is an audio-visual dataset for violence detection. The dataset is developed as a part of the MediaEval Affect task for the detection of violent scenes in movies. The clips are curated from 18 movies from the different genres such as extremely violent ones, war movies, action movies, movies with no violent content, etc.
Table 16. Specifications of audio datasets

| Dataset | Total duration | No. of samples | Sampling rate |
|---------|----------------|----------------|---------------|
| MIVIA   | 3580 seconds   | -              | 32 kHz        |
| AudioSet Soundscape: Ithaca, New York | #1: 797 hrs | - | 48 kHz |
|         | #2: 638 hrs    | -              | 48 kHz        |
| AudioSet Soundscape: Sabah, Malaysia | Tuscam: 27 hrs 40 min | - | 44.1 kHz |
|         | Audiomoth: 784 hrs | - | 16 kHz |
| AudioSet Soundscape: New Zealand | 240 hrs | - | 32 kHz |
| AudioSet Soundscape: Sulawesi | 64 hrs | - | 48 kHz |
| AudioSet Soundscape: Republic of Congo | 238 hrs 20 min | 1170 | 8 kHz |
| DCASE 2017 | 39 min | - | 44.1 kHz |
| ICBHI 2017 | > 5.5 hrs | - | 4 to 44.1 kHz |
| SMD | ≈ 1 hour | 2048 | 16.3 kHz |
| MIMII DUE | >420000 sec | 32157 | 16 kHz |
| ToyADMOS | ≈ 540 hrs | >12000 | 48 kHz |
| LIFE DYNAMAP dataset | 550 sec | - | 48 kHz |
| ToyADMOS2 | 604 hrs | ≈264k | 48 kHz |
| DCASE 2021 | ≈82 hours | 29463 | 16 kHz |

The total duration of the training set is 28 hours 34 minutes, and that of the test set is 6 hours 44 minutes. Seven visual violence categories and three audio violence categories were identified. For video, they are as follows: the presence of blood, fights, presence of fire, presence of guns, presence of cold weapons, car chases, and gory scenes; for audio, they are: gunshots, explosions, and screams. The start and end frames of these violent events are annotated.

6.3. EMOLY dataset

The EMOLY dataset [194] was published in 2018. The dataset is made of speech and facial video records of subjects which also contains controlled anomalies. This is the first dataset of its kind. The dataset constitutes 123 audiovisual recordings of face and voice from 41 student participants (11 females and 30 males) from the age group of 22±2 years. Each participant had to read 11 slides made from the French version of the tale “the handless maiden” (“La jeune fille sans main”) from Brothers Grimm. 37 participants were native French speakers, and 4 were non-native French speakers. Anomalous facial expression and speech were triggered by inducing anomalous content in the slide show. Participants were unaware of this aim. They were just asked to read the tale to the camera as if they were telling the tale to a child. The purpose was to get expressive speech and facial expressions from them. The dataset was collected in three rounds, i.e., each subject went through all slides three times. In the first round, the session was without anomaly. In the second session, different backgrounds in the slides and rotated text were incorporated to induce anomalies in participants. In the third session (done after a week delay), they were asked to perform anomalous acting of their choice. Annotation is done with the help of eleven members of the EXPRESSION research team at IRISA. Manual annotations of the sample on which an anomaly inductor has been triggered are made available by the authors. Additional information about each subject, such as age, gender, French native, self-measurement of oral abilities, etc., are also available.
6.4. XD-Violence dataset

The XD-Violence dataset [195], released in the year 2020, is the largest audio-visual dataset for violence detection. Authors consider six classes of violence, namely Abuse, Car Accident, Explosion, Fighting, Riot, and Shooting. The choice is such that they are frequently occurring and important from a safety point. The clips are collected from movies and YouTube (in-the-wild scenes), resulting in violence from various sources such as movies, cartoons, sports, games, music, fitness, news, live scenes, captured by CCTV cameras, captured by hand-held cameras, captured by car driving recorders, etc. A total of 91 movies (violent and non-violent) were used to collect violent and non-violent events. Further, text search queries were used to collect both types of events from YouTube. The dataset has 2405 violent videos and 2349 non-violent videos, resulting in a total duration of 217 hours. The author also specified a train-test split as 3954 videos (1905 violent and 2049 non-violent) in the training set and 800 videos (500 violent and 300 non-violent) in the test set. For each violent video, labeling is done with the help of multiple human annotators. They marked the start and end frame of the violent event. There can be multiple labels to the same frame, i.e., multiple types of violence can co-occur; hence multiple labels are available. Some of the sample frames representing violence and non-violence are shown in Fig. 54.

6.5. BAREM dataset

BAREM stands for Behaviour Analysis for Reverse Efficient Modeling. Released in the year 2021, BAREM is an audio-visual dataset consisting of humans interacting with the e-service platform. BAREM dataset was designed for automatic detection of changes in the behavior of a user while interacting with e-service [196]. Thus, the level of frustration was considered an anomaly for the task. A total of 18 subjects, consisting of 11 men and 7 women, were considered for collecting the database. The dataset has been created in a geographical area that is unfamiliar to the subject. The main target was to create a frustrating environment for the subjects by proposing frustrating and challenging tasks within a time frame of 20 minutes. Four tasks have been created, as mentioned in Table [17] Thus, with each subject being given the mentioned tasks, a total of 72 videos were generated. Two annotations have been performed: manual and subject self-evaluation. The dataset has been summarised in table [18]. RGB videos and 16-bit depth images of the face and upper body of the subject were recorded at a frame rate of 25 frames per second.

7. DISCUSSION ON AUDIO-VISUAL DATASETS

In this section, we present a discussion on the audio-visual datasets described in the previous section. There are very few audio-visual datasets for anomaly detection. These datasets focus on the specific type of anomaly. VSD dataset, XD-Violence dataset, etc., consist of only fight events, EMOLY dataset has an anomalous mood of a person as an anomaly, Human-human interaction dataset has agitation behavior as an anomaly. Apart from having one class of anomaly, the datasets are mainly recorded in a controlled environment (except for fight anomaly, which is easy to collect, too) by some human actors. The existing audio-visual dataset is good for application-specific anomaly detection, but there is a lack of the same for generic scene surveillance. Some researchers have tried collecting such datasets, but they are not released publicly due to privacy or legal issues.

Table [19] lists the audio-visual datasets with their year of release, number of citations, and its application. We can see that datasets for agitation detection (Human-human Interaction) and violence detection (VSD and XD-Violence) have been much in use compared to others due to their applicability in real threat indication. The audio-visual datasets have been designed and made available to the users recently. Different areas of applications have been covered for these datasets. Some of these include anomalous expression detection, violence detection, detection of stress in a particular situation, etc.

Table [20] details dataset collection, viz., whether the dataset is untrimmed, at how many locations the dataset is collected, scene in the dataset, environment of the dataset, and the density of moving objects in the scene. It can be observed from the table that none of the datasets is collected in continuation and hence is not suitable for evaluation of adaptive anomaly detection frameworks. The dataset collection scenarios are mostly limited to indoor, except for VSD and XD-Violence, which consist of both indoor and outdoor environments. The datasets for violence detection, which are mainly collected from real CCTV footage, have high density; otherwise, the rest other datasets which contain actors have

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\[5\] Available upon request
Table 17. Task description for the BAREM dataset anomaly generation

| Task | Description |
|------|-------------|
| Task 1 | The subject is provided with an email and username, and is asked to sign up on the platform. **Cause of frustration:** The username provided to the subject is already in existence, thus leading to an error message during registration process. The subject must select another username in order to accomplish the task. |
| Task 2 | Here, the subject has to fill up data about two children. The objective is to give a sense of accomplishment to the subject and beef up the frustration level in the succeeding task. |
| Task 3 | The subject has to book school transportation for the first child. A part of data must be obtained from a document that is provided during the start of the scenario. It is an essential requirement to upload a file available on the computer in dual formats. **Cause of frustration:** The first attempt while uploading the first file will cause a format error. The subject will have to perform the upload again with the second file. |
| Task 4 | The subject has to now book school transportation for the second child. **Cause of frustration:** Essential data related to the itinerary is lacking, making task completion out of the question. This results in a strong impact on the subject’s level of frustration. |
low density.

Dataset comparison on the basis of anomaly information is presented in Table 21. All the datasets have frame-level annotations, and some acted anomalies too. The type of anomalies is only one except for the datasets for violence detection, which consist of 8 anomalies for VSD and 6 for XD-Violence datasets. Some of the example anomalies include fights, stress, explosions, abuse, car accident, shooting, frustration, etc.

Table 22 provides details about features and specifications of the audio-visual clips. Mainly, information about the total number of videos and total duration is made available by the authors. The datasets for violence detection records the largest length of 217 hours compared to others; this is because violence event is comparatively less rare to occur and hence easily available in CCTV-footage. The total number of videos available for XD-Violence is maximum, i.e., 4754, followed by EMOLY dataset consisting of 123 videos. Least number of videos have been provided in the Human-human interaction dataset, with the total duration of 32.24 minutes. Clips have been recorded at multiple resolutions and at multiple frame rates. However, the sampling rate of audios recorded in the databases have not been made available by the authors. Few clips from VSD as well as XD-Violence datasets consist of camera motion, thus making them challenging for further analysis.

8. DISCUSSION: TOWARDS THE FUTURE

During the last decade, there has been a drastic shift from datasets with less number of anomaly samples and total duration to datasets with diverse range of anomalies and gigantic volume. It may be observed that availability of datasets with crime specific anomalies have facilitated development of automated surveillance framework for crime detection. For videos, the category spans as detection of explosion, abuse, panic-escape, assault, accident, violence, fight, etc. In case of audios, they span as detection of gunshot, shout, etc. Further, for audio-visual dataset, the categories span as riots, detection of fight and violence detection. By analyzing the applications and anomalies present in the datasets discussed across Section 2 to 7 we can see that they mainly have specific types of anomalies. There are very few datasets of heterogeneous nature (listed in Section 2.1). This is almost zero in audio-visual category. This arises a strong need to develop datasets having diverse ranges of anomalous samples. Also, the datasets in audio-visual category mainly contain acted anomalies which limits its usefulness. Even if some acted situation/events needs to be added, it should in such a manner that it appears natural and contains the necessary amount of variations mimicking the real life.

Apart from this, all the existing multimedia datasets lack anomalies with concept drift. If an event/object is regarded anomaly in a dataset, it is always regarded as an anomaly, no matter how frequent it may occur in distant future. This is due to the fact that datasets are too short to contain this effect. We should pay attention that the datasets which are more than a duration of 5-10 hours are not suitable here because the samples are collected from different time-stamp, location, and have only specific anomalies in rare amount. Thus, shift of a sample from abnormal class into normal class is not observed. These existing datasets are useful for specific anomaly detection, particularly crime oriented anomaly detection, traffic rule violation etc. However, generic scene monitoring, where raising an alarm for interesting events which may not always be crime oriented, is demanded for future applications like smart city surveillance. There are attempts to record long untrimmed footage at one place, e.g., QMUL, ADOC, etc., however, the authors do not attempt to provide annotations in accordance with concept drift.

9. CONCLUSION

This paper presents a survey of multimedia datasets for anomaly detection to researchers working toward automated surveillance. The structured comparison of datasets on various attributes also helps to understand the datasets better. There is a large number of short-length and giant video datasets available. Some are developed for generic scene surveillance, whereas some are specific anomaly datasets. The number of datasets for the heterogeneous anomaly is far less compared to specific anomaly datasets. There are too many additional video datasets discussed which are not annotated or used for anomaly but can be re-used to create bigger datasets. In the case of audio, datasets are mainly developed for machine surveillance such as defect detection, fault detection, etc. Generally, surveillance using audio alone in outdoor scenes is not efficient due to the presence of multiple auditory signals superimposed together. However, when they are analyzed together with video, they can offer crucial and complementary information about the target scene. But the datasets developed towards audio-visual surveillance are far less compared to that for audio or video. There are a few audio-visual datasets for a specific action such as fight, agitation detection. A recently released dataset, namely the EMOLY dataset, has used only the upper body of individuals and their speech in-
### Table 19. Applications of various audio-visual datasets

| Dataset          | Year | # Ref. | Area of Application                                      |
|------------------|------|--------|----------------------------------------------------------|
| Human-human Interaction | 2014 | 23     | Detection of stressful situations at a help-desk         |
| VSD              | 2015 | 43     | violence detection                                       |
| EMOLY            | 2018 | 1      | abnormal expression detection                            |
| XD-Violence      | 2020 | 15     | violence detection, anomaly detection                     |
| BAREM            | 2021 | 0      | Behaviour Analysis for Reverse Efficient Modeling         |

### Table 20. Comparison of audio-visual datasets based on data collection information

| Dataset          | Continuity | Location | Scene | Indoor/Outdoor  | Density          |
|------------------|------------|----------|-------|-----------------|------------------|
| Human-human Interaction | no        | 1        | help-desk | indoor          | low              |
| VSD              | no         | multiple | multiple | both            | high/medium/low  |
| EMOLY            | no         | 1        | lab    | indoor          | low              |
| XD-Violence      | no         | multiple | multiple | both            | high/medium/low  |
| BAREM            | no         | 1        | e-service platform | indoor      | low              |

### Table 21. Comparison of audio-visual datasets based on anomaly information

| Dataset          | Ground truth | Nature of Anomaly | # Actor | Types of Anomaly                                      | Example anomalies/event |
|------------------|--------------|-------------------|--------|------------------------------------------------------|-------------------------|
| Human-human Interaction | frame | acted | 9 | 1 | stress | |
| VSD              | frame | both | - | 8 | fights, fire, gunshots, cold weapons, car chases, gory, explosions, screams | |
| EMOLY            | frame | both | - | 1 | anomalous expression | |
| XD-Violence      | frame | both | - | 6 | abuse, car accident, explosion, fight, riot, shoot frustration | |
| BAREM            | frame | both | - | 18 | frustration | |

### Table 22. Specifications of audio-visual datasets

| Dataset          | Release Year | Total Duration | Total No. of Frames | Total No. of Videos | Video resolution | FPS (video), Camera motion |
|------------------|--------------|----------------|---------------------|---------------------|------------------|----------------------------|
| Human-human Interaction | 2014 | 32.24 min | - | 8 | - | - | none |
| VSD              | 2015 | 35 hrs 18 min | - | 25 | multiple | multiple | in some |
| EMOLY            | 2018 | - | - | 123 | - | - | none |
| XD-Violence      | 2020 | 217 hrs | - | 4754 | multiple | multiple | in some |
| BAREM            | 2021 | ≈ 6 hrs | ≈ 5,40,000 | 72 | - | 25 | none |
formation to facilitate abnormal behavior detection. However, there is a strong need to develop more audio-visual datasets for generic scene surveillance. We believe the survey presented in this article will help the prospective researchers who intend to contribute datasets or research in this field.

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