A Survey on Deep Learning Techniques for Video Anomaly Detection

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Abstract Anomaly detection in videos is a problem that has been studied for more than a decade. This area has piqued the interest of researchers due to its wide applicability. Because of this, there has been a wide array of approaches that have been proposed throughout the years and these approaches range from statistical-based approaches to machine learning-based approaches. Numerous surveys have already been conducted on this area but this paper focuses on providing an overview on the recent advances in the field of anomaly detection using Deep Learning. Deep Learning has been applied successfully in many fields of artificial intelligence such as computer vision, natural language processing and more. This survey, however, focuses on how Deep Learning has improved and provided more insights to the area of video anomaly detection. This paper provides a categorization of the different Deep Learning approaches with respect to their objectives. Additionally, it also discusses the commonly used datasets along with the common evaluation metrics. Afterwards, a discussion synthesizing all of the recent approaches is made to provide direction and possible areas for future research.

Keywords video understanding · video processing · anomaly detection · deep learning · computer vision

1 Introduction

Surveillance videos have been increasingly present in various establishments in order to monitor human activity and prevent crime from happening. It goes without saying that there needs to be someone behind watching the videos and signaling an alert whenever something different from normal is happening. However, these events do not happen very often and that
most of the time, the person monitoring these videos would see nothing out of the ordinary (Sultani et al. 2018). These unusual events can be thought of as anomalies which can be defined as patterns that do not conform to what is considered normal. The task of finding these nonconforming patterns is called anomaly detection (Chandola et al. 2009). Because of this, researchers have been trying to create a robust anomaly detection algorithms that can automate the process of monitoring and detection of unusual events in surveillance videos.

An example of a simple anomaly case can be seen in Fig. 1 where the normal regions are denoted by $N$ and anomalies are those denoted by $O$. As seen in the figure, anomalies tend to clearly lie outside what is normal. However, these anomalies can, in fact, be close to normality which is illustrated by $O_2$.

Anomaly detection is a challenging task due to number of reasons: first, the definition of an anomaly may vary from one context to another (Medel and Savakis 2016; Sabokrou et al. 2017). Second, the different possibilities of what constitute an anomaly might be are boundless (Luo et al. 2019). Third, anomalous data points, especially with real-world data, tend to lie closely to what might be defined as normal (Vu et al. 2017). Lastly, extracting robust features from the data even if anomalies seldom appear (Ribeiro et al. 2018). The mentioned list does not entirely capture all of the possible reasons which make the problem hard but these main points are what researchers have been considering for the past years when proposing new solutions to the problem.

Around a decade ago, most of the researchers have focused on trajectory-based anomaly detection (Jiang et al. 2011; Calderara et al. 2011; Tung et al. 2010; Li et al. 2013). The main idea is if the objects of interest are not following the learned normal trajectories, the video will be tagged as an anomaly. However, one major drawback of this approach is occlusion since the approach heavily relies on continuously monitoring the objects of interest (Sabokrou et al. 2017; Narasimhan and S. 2018). Due to these drawbacks, there was an emphasis on using low-level features for feature extraction instead (Sabokrou et al. 2017). These approaches based on low-level features rely on the use of appearance, motion, and texture features (Mehran et al. 2009; Li et al. 2014; Zhang et al. 2016; Wang et al. 2018; Kim and Grauman 2009; Benzeth et al. 2009). Various representations have been used in order to represent these aspects of the video such as in the approach of (Mehran et al. 2009) where they used social force maps to model motion of the crowds. Similarly, pixel-motion
properties were used by Benezeth et al. (2009) to model behavior. Meanwhile, Kim and Grauman (2009) made use of optical flows which are then used as inputs to the mixture of probabilistic principal component analysis (MPPCA) model, thus, creating a more compact feature representation. However, features based on motion are not enough which is why there were proposed approaches that make use of both. An example is the approach of Li et al. (2014) where their approach makes use of mixture of dynamic textures (MDTs) that utilize temporal normalcy and discriminant saliency detectors to model spatial normalcy. Likewise, Zhang et al. (2016) used support vector data description for spatial features and optical flow for motion features. In contrast, Wang et al. (2018) used spatially localized histogram of optical flows and uniform local gradient pattern-based optical flows. Most of these techniques and methods, specifically on these “traditional” approaches, have been discussed in great detail in the works of Kaur et al. (2018); Li and min Cai (2016); Popoola and Wang (2012).

Despite the proven success of these traditional approaches on benchmark datasets, they are still ineffective when used in a different domain. Furthermore, they are unable to adapt to anomalies that they have never seen before (Hu et al. 2016; Medel and Savakis 2016). For these reasons, recent works have mostly explored the use of Deep Neural Networks for the task of anomaly detection. These neural networks automatically learn useful and discriminant features on their own which removes the hassle of creating handcrafting features (Krizhevsky et al. 2017). This also makes it more adaptive when used on different domains. Deep learning was proven to be effective for a variety of computer vision tasks such as feature extraction in images (Yan et al. 2016), image classification (Krizhevsky et al. 2017), object detection (Zoph et al. 2018), video analysis (Mei and Zhang 2017), face detection (Lopes et al. 2017), visual question answering (Malinowski et al. 2017) and many other tasks.

As mentioned previously, there are existing works that have discussed various anomaly detection methods for videos (Kaur et al. 2018; Li and min Cai 2016; Popoola and Wang 2012). However, due to the recent traction in the use of deep learning techniques on this field, the goal of this paper is to provide a closer look into these deep learning techniques. This entails providing organization as to how the approaches are related to one another, the rationale as to why these methods have been proposed, and summarizing the conclusions which they have presented in a clear manner. In addition, it would also be necessary to discuss datasets and evaluation metrics which have mostly been used by these approaches. It would also be insightful to determine how these datasets and metrics would scale well when dealing with real-world anomaly detection. Different researchers have created different environmental setups making some of them incomparable. Thus, the performances of the approaches discussed will not be included to avoid confusion and misinterpretation.

The paper is organized as follows: the first section serves as an introduction to the survey. Second, deep learning anomaly detection techniques will be discussed in detail. Third, the mostly used datasets will be tackled. Fourth, the commonly used evaluation metrics will be presented. Fifth, a section for discussion is allocated to synthesize all of the approaches and datasets mentioned. Lastly, the concluding remarks coupled with recommendations as to what directions this area of research could possibly go.

2 Deep Learning in Anomaly Detection for Videos

Deep learning techniques mostly focus on creating new architectures or crafting components that can be suitable for a specific problem. Since deep learning methods have been
successful in a number of varied use cases (Yan et al. 2016; Krizhevsky et al. 2017; Zoph et al. 2018; Mei and Zhang 2017; Lopes et al. 2017; Malinowski et al. 2017), most of these networks or architectures might be similar to each other. An example of which would be with Krizhevsky et al. (2017) where they used Convolutional Neural Networks for image classification. However, almost the same network is also used for face recognition (Lopes et al. 2017). Because of this, the presented categories below would group these approaches specifically with respect to their final objectives instead of network architecture or learning strategy. Examples of these include using reconstruction error or providing an anomaly score. In line with this, there are four (4) identified categories namely: using reconstruction error or reconstruction-based methods, framing the problem as a classification problem, predicting future frames, and computing for an anomaly score. A quick summary of all these techniques are provided in Table 1.

2.1 Using Reconstruction Error

Reconstruction error has already been used in various traditional anomaly detection techniques (Popoola and Wang 2012). The basic assumption of using reconstruction error is that the reconstruction error for normal samples would be lower since they are closer to the training data. On the other hand, the reconstruction error is assumed or expected to be higher for samples which are not normal (Gong et al. 2019; Sabokrou et al. 2016).

More formally, let $x$ be a video segment or video frame and let $g$ be a neural network that reconstructs $x$. The reconstruction error can be defined as a function $f$ such that is computes for error between $x$ (the original input), and $g(x)$ which is the reconstruction Eqn 1. This concept has been extended recently by making use of deep learning techniques to reconstruct various scenes.

$$e = f(x, g(x))$$

(1)

Different from usual feedforward networks, one type of neural network that is able to reconstruct input data is called an autoencoder. The autoencoder is a neural network that has the capability to encode an input into a more compact representation while retaining important and discriminative features. It also has the ability to decode this particular encoding back to its original form (Baldi 2011). A visual schematic of an autoencoder is shown in Fig. 2 where the diagram illustrates a simple architecture of an encoder where the left-hand side is the input to the autoencoder $X$, the middle portion is the encoded representation (sometimes called the latent vector or code) of $X$, and the right-hand side is the decoded encoding called $X'$.

Most approaches whose goal of using reconstruction error as a means to identify anomalies base their method on autoencoders. One such method is introduced by Hasan et al. (2016) where they posited that in comparison to sparse coding, the objective function of an autoencoder is more efficient. They have also said that it is able to preserve spatio-temporal information while encoding dynamics. Their approach made use of combining 2D convolutions to autoencoders wherein the 2D convolutions take as input specific raw video segments. Conventionally, inputs to a Convolutional Neural Network is a 2D image having the third channel as the color channel (Krizhevsky et al. 2017). However, in their approach, the third dimension is instead composed of stacked grayscale frames, allowing the model to encode both spatial and some temporal information for reconstruction.

Similarly, the work of Medel and Savakis (2016) also framed the problem as a reconstruction problem. The approach makes use of a convolutional long short-term memory
wherein the Long Short-Term Memory (LSTM) Network is a type of neural network that is capable of learning long-term dependencies of the data (Hochreiter and Schmidhuber 1997). Despite not being explicitly an autoencoder, their approach also makes use of an encoder-decoder structure. Given an input sequence of video frames, the convolutional long short-term memory extracts relevant features along the spatial and temporal dimension in such a way that the last time step is used as the encoding. The decoder unravels the encoding and then reconstructs the frames which can then be used to compute the reconstruction error for anomaly detection.

The proposed approach of Ribeiro et al. (2018) closely resembles that of Hasan et al. (2016). The main difference is that the low-level features such as optical flow and edges are used as inputs alongside the raw frames. In addition, they have also presented how these features affect the convolutional autoencoder with regard to detecting anomalies.

Another method was proposed by Sabokrou et al. (2016) where they have used two different autoencoders for the task: one is a regular autoencoder and the other is a sparse autoencoder. A sparse autoencoder is an autoencoder but has an additional sparsity penalty. This penalty encourages fewer neurons to activate. This constraint allows the network to learn relevant information without reducing the number of nodes in the hidden layers. Their approach involves two steps, the first step is to compute the sparsity value from cubic patches of the videos, if it is below a specific sparsity threshold, another set of patches are extracted around that patch for reconstruction.

According to Zhao et al. (2017), the approach of Hasan et al. (2016) which makes use of temporal cuboids by stacking frames in the third dimension, does not necessarily retain the temporal information. Based on their work, a reason for this is that 2D convolutions operate on the frames spatially. Putting this in the perspective of the approach of Hasan et al. (2016), the third channel is represented along each of the channels of the first feature map which rarely preserves temporal information. To solve this, Zhao et al. (2017) proposed the use of 3D convolutions as a means to retain temporal information during the convolution process. Since it is data intensive, they have also applied data augmentation to increase their samples.

As claimed in the work of Zhou et al. (2019), one weakness of the approach of Medel and Savakis (2016) is that spatial and temporal aspects of the inputs are encoded separately by the convolutions and the long short-term memory. This implies a broken relationship between the two during the encoding process. Furthermore, it was also stated by Zhou et al.
that the approach proposed by Medel and Savakis (2016) was not able to make use of existing pre-trained networks. These networks have shown remarkably improved performances once it has been applied to other domains. Hence, their proposed method makes use of a feature learning subnetwork that combines motion and appearance features into an image. Afterwards, it is then used as an input to a pretrained network for feature extraction. Moreover, they have proposed a novel subnetwork called sparse coding to network (SC2Net) to compute for the sparsity loss and reconstruction loss from the extracted features.

Among all of the approaches, Gong et al. (2019) have posited that most of the works on reconstruction generally assume that the anomalous instances will have a high reconstruction error. Based on these works, this assumption does not necessarily hold true mainly because there might be instances where an autoencoder is able to generalize well. This poses a problem since it might accurately reconstruct anomalous instances as well. To mitigate this problem, they have introduced a new autoencoder which has the capability to store encodings into memory. The main difference from previous approaches is that instead of directly feeding the encoding to the decoder, the encoding is treated as a query. This query is expected to return closest normal patterns in memory which is instead used for decoding. In the event that an anomaly is to be reconstructed, it would have a high reconstruction error because the memory only has normal memory items.

2.2 Using Future Frame Prediction

A different perspective on the problem was presented by Liu et al. (2018). They support the claim of Gong et al. (2019) stating that autoencoders might also accurately reconstruct anomalous frames. Since anomalies can be viewed as events that do not conform with certain expectations, Liu et al. (2018) suggested a frame prediction approach might be a more natural way to view the problem. Mathematically speaking, given $x_t$ which is the video segment or frame $x$ at time $t$, future frame prediction can be expressed as a function $h$ predicting the next segment as shown in Eqn 2:

$$x_{t+1} = h(x_t)$$

In deep learning, there is a specific type of neural network is used for generating new data with the same statistics as the training data. This network which is called generative adversarial network (GAN) (Goodfellow et al. 2014). This architecture has two main parts. The first one is a generator whose job is to mimic the original data distribution. Meanwhile, the second network is called a discriminator that gives a probability of whether or not the input is coming from the generator.

The approach of Liu et al. (2018) made use of a generator-discriminator structure, likened to that of a generative adversarial network. They used the U-Net architecture (Ronneberger et al. 2015) for future frame prediction as the generator because of its exemplary performance in image-to-image translation. While the discriminator at the end of the network determines whether or not the predicted frame is anomalous.

Some works on reconstruction also have the capability for predicting future frames such as in the work of Hasan et al. (2016). Their approach has the ability to encode both spatial and temporal aspects of the video by allowing the autoencoder to learn it from a sequence of video segments (discussed in more detail in Section 2.1). It is because of this exact same reason that it can also predict future and past frames given a center frame. Based on their methodology, by padding the center frame with zero values, their model can extrapolate the near future and near past of the center frame.
Moreover, some of the previous works actually leverage future frame prediction in the process of reconstructing the current frame. An example of this is the work of Zhao et al. (2017) where their network learns the future frames along with the task of reconstruction in a different branch of the network. Similarly, Medel and Savakis (2016) also has a separate branch in parallel that learns how to predict the future. Despite their similarities, they both have big differences as to how future frame prediction is used. Medel and Savakis (2016) makes use of future frame prediction to identify interest points within the video. On the contrary, in the approach of Zhao et al. (2017), the future frame is actually included in the computation of the loss to guide the network to extract temporal features. In addition, it is also included in the reconstruction score which combines the prediction loss and the reconstruction loss.

2.3 Using Classifiers

Despite the sophisticated methods that rely mainly on reconstruction loss and future frame prediction, there are also still a handful of approaches that cast the problem as a classification problem. The classification problem can be viewed as a function \( j \) that takes as its input a frame or video segment \( x \) whose output \( y \) is a class or category as seen in Eqn 3.

\[
y = j(x), y \in \mathbb{R}
\]  

(3)

Because of imbalanced datasets, these methods focus mostly on how to create compact, efficient, and robust features. The approach of Sabokrou et al. (2017) tries to solve this problem by proposing a competitive cascade of deep neural networks. The cascade is composed of two stages where the first stage is a small stack of autoencoders which hierarchically models the normality of the video patches. The other one is a Convolutional Neural Network which takes as input video patches that the autoencoders could not handle and would need further probing. The classifier used for the approach is a Gaussian Classifier.

On the other hand, Narasimhan and S. (2018) proposed a method that makes use of local and global descriptors whose aim is utilize both spatial and temporal domains. For local features, they made use of an image similarity metric on the video cubic patches to represent the temporal and spatial features. Meanwhile, the global features are represented by the latent vector of the trained autoencoders. After creating both local and global features, it is then fed to an autoencoder which selects important features that are discriminative enough for anomaly detection. Finally, these features are fed into Gaussian classifiers separately for local and global descriptors and then combined to detect anomalies.

Most of the above mentioned methods, even those in the previous sections, make use of Convolutional Neural Networks. However, Sabokrou et al. (2018) has mentioned problems with regard to using these networks, one of which is that these networks are too inefficient for patch-based methods. Examples of approaches that made use of patches are as follows: Narasimhan and S. (2018); Sabokrou et al. (2016); Sabzalian et al. (2019); Sabokrou et al. (2018); Medel and Savakis (2016). For this reason, they have proposed a possible solution to the problem which makes use of the discriminative power of a pre-trained model without having to tweak it Sabokrou et al. (2018). More specifically, they use the intermediate layer to generate the features that will be fed to a Gaussian Classifier. In the event that a low confidence is generated by the classifier, it is sent to another convolutional layer on top of the best intermediate layer for further probing.
| Year | Author          | Type                                      | Main Contribution                                                                 |
|------|-----------------|-------------------------------------------|-----------------------------------------------------------------------------------|
| 2016 | Medel et. al.   | Reconstruction & Future Frame             | Convolutional Long Short-Term Memory                                              |
| 2016 | Hasan et. al.   | Reconstruction                            | Fully 2D Convolutionist Autoencoder                                               |
| 2016 | Sabokrou et. al.| Reconstruction                            | Sparse Autoencoder + Autoencoder                                                  |
| 2016 | Hu et. al.      | Scoring                                   | Deep Neural Network + Slow Feature Analysis                                        |
| 2017 | Narasimhan et. al.| Classification                          | Sparse Denoising Autoencoders                                                     |
| 2017 | Sabokrou et. al.| Classification                            | Cascade of Deep Convolution Neural Networks + Autoencoders                         |
| 2017 | Zhao et. al.    | Reconstruction & Future Frame             | Spatiotemporal Autoencoder                                                        |
| 2018 | Sabokrou et. al.| Classification                            | Deep-Anomaly                                                                      |
| 2018 | Sultani et. al. | Scoring                                   | Multiple-Instance Learning                                                        |
| 2018 | Ribeiro et. al. | Reconstruction                            | Low-level Features + 2D Convolution Autoencoder                                    |
| 2018 | Liu et. al.     | Future Frame                              | Future Frame using U-Net                                                           |
| 2019 | Landi et. al.   | Scoring                                   | Localization before Feature Extraction                                            |
| 2019 | Sabzailan et. al.| Scoring                                 | Traditional + Deep Learning Features                                              |
| 2019 | Zhu et. al.     | Scoring                                   | Optical Flow as inputs to Multiple-Instance Learning                              |
| 2019 | Zhou et. al.    | Reconstruction                            | AnomalyNet: a unified approach                                                    |
| 2019 | Gong et. al.    | Reconstruction                            | Autoencoder + memory module + attention-based addressing                           |
| 2019 | Lin. et. al.    | Scoring                                   | Multiple-Instance Learning + Social Force Maps                                    |
| 2019 | Santos et. al.  | Classification                            | Transfer Learning + Transfer Component Analysis                                    |
| 2019 | Luo et. al.     | Scoring                                   | Sparse Coding-inspired Deep Neural Network                                         |
| 2019 | Ionescu et. al. | Classification                            | Object-Centric Convolutionist Autoencoders                                         |
| 2019 | Xu et. al.      | Classification                            | Adaptive Intra-Frame Classification Network                                        |
| 2020 | Fan et. al.     | Scoring                                   | Gaussian Mixture Fully Convolution Variational Autoencoders                        |
Similar to Sabokrou et al. [2018], the proposed approach of dos Santos et al. [2019] took advantage of the available pre-trained models. They have investigated the generalization of feature spaces of Convolutional Neural Networks without requiring additional labels. In their experiments, they used transfer component analysis (Pan et al. 2011) which attempts to learn a certain subspace that is shared by different domains. They have concluded that generalization through different domains.

Most of the methods mentioned previously make use of extracting either global or local features without taking the objects of interest into account. The approach of Ionescu et al. [2019] makes use of a single-shot detector (SSD) (Liu et al. 2016) on each frame of the video. After isolating the objects, a convolutional autoencoder is used to learn deep unsupervised features thereby allowing the algorithm to focus on the objects in the scene. Furthermore, they have instead casted the problem of anomaly detection as a multi-class classification problem rather than an unbalanced binary classification problem or a one-class problem. To generate the artificial classes, they have used clustering on the set of features generated by the convolutional autoencoder where each cluster represents a different type of normality. A one-versus-rest classifier is trained which discriminates between the clusters. If the highest classification score is negative, meaning the sample does not belong to any cluster, it is tagged as anomalous.

Similar to Ionescu et al. [2019], Xu et al. [2020] also framed the problem as a multi-class classification problem as opposed to either a one-class or a binary classification problem. In line with this, they also took note of the fact that most of the previous approaches were able to effectively identify subregions representations of anomalies. However, for most of the approaches, there is a wide array of inputs and outputs such as optical flows, patches, or gradients. This inspired the approach of Xu et al. [2020] which tries to unify all of these approach by creating a network called the adaptive intraframe classification network that takes the raw inputs, computes for motion and appearance features, and determines whether or not the sample is anomalous.

### 2.4 Using Scoring Methods

Some researchers have instead, framed the problem as a regression problem wherein the goal is to provide an anomaly score which will then be used as a means to determine whether or not a video segment or a frame is anomalous (Landi et al. 2019; Sultani et al. 2018). The scoring methods can be viewed as a function \( k \) such that it takes a video segment or frame \( x \) as its input. It outputs a real number \( z \) representing the anomaly score as seen in Eqn 4.

\[
z = k(x), z \in \mathbb{R}
\]

The proposed approach of Hu et al. [2016], makes use of their novel sum squared derivative to score the features generated by their approach. This basically determines if the sequence of frames is anomalous. Prior to their scoring method, they combined both deep learning and slow feature analysis (Wiskott and Sejnowski 2002) in order to learn semantic-level representations given raw video frames. It is also worth noting that their approach has an online variant, thereby making their approach adaptive.

The approach of Sultani et al. [2018] made use of a multiple instance learning to identify anomalies in video segments based on weakly-labelled videos (labels are on a video-level and not frame-level). Their approach uses C3D, a 3D Convolutional Neural Network that learns spatiotemporal features by exposing the model to large-scale video datasets (Tran.
et al., 2015). These spatiotemporal features are then fed to fully connected layers for generating the anomaly score. The backpropagation of the error is guided by the principle of multiple instance learning, allowing the model to learn anomalous segments despite having weak labels. This idea was taken up by Zhu and Newsam (2019) where, instead of using C3D, they made use of computing for the optical flows which are then fed to a temporal augmented network. Their proposed approach also makes use of an attention mechanism (Vaswani et al., 2017) that allows the network to identify which features are important to look at. Similarly, Lin et al. (2019) also built upon this idea where they proposed a dual-branch network that incorporates motion into the initial network introduced by Sultani et al. (2018). The approach of Lin et al. (2019) adapts the same network of Sultani et al. (2018) as the first branch with a modification wherein an attention module (Vaswani et al., 2017) was added after the feature extraction layer. The second branch is similar in structure as the first branch except that it takes as an input social force maps (Mehran et al., 2009) computed from the raw images to represent motion.

Meanwhile, the approach of Sabzalian et al. (2019) makes full use of the effectiveness of traditional and deep learning features for anomaly detection. Their proposed approach starts by identifying the foreground of the video by using optical flows. Once the regions of interest have been identified, a pre-trained Convolutional Neural Network is used to extract features alongside computing for traditional features like histogram of gradients and histogram of optical flows. These three features are combined by making use of an iteratively weighted nonnegative matrix factorization method (Sabzalian et al., 2019). Afterwards, the features are clustered and the discrimination of whether or not the sample is an anomaly will be done via a voting system.

Aside from framing the problem as a regression problem, Landi et al. (2019) proposed to make use of locality when computing for the anomaly score. The approach is similar to that of Sultani et al. (2018) except that their approach extracts a tube from the video which in a way localizes and adjusts the level of granularity when extracting features. From their experiments, they have shown that locality or, more specifically, zoning in on one region where the anomalous event takes place actually helps the method to accurately compute anomaly scores.

Sparse coding for anomaly detection is an approach that learns a dictionary which attempts to encode all normal events (Lu et al., 2013). By revisiting sparse coding, Luo et al. (2019) proposed temporally-coherent sparse coding to model the coherence between neighboring events for normal frames. These temporal features are then combined with spatial features learn from pre-trained networks across different scales for a normality score. Note that the features extracted pass through a Stacked Recurrent Neural Network autoencoder to generate the final features for scoring.

Past works demonstrated the effectiveness of autoencoders and that normal samples can be associated with at least one Gaussian Mixture Model. Because of this, Fan et al. (2020) proposed an end-to-end neural network called the Gaussian Mixture Fully Convolutional Variational Autoencoder to model anomalies and to predict them. Their model is trained on image and dynamic flow patches wherein both of them are separately fed into different networks. This basically captures separate motion and appearance features. Afterwards, joint probabilities are used to detect both appearance and motion anomalies via a sample energy-based method.
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Table 2: Overview of Benchmark Datasets

| Dataset      | Frames | Scene | Labels | Resolution | Anomalies                          |
|--------------|--------|-------|--------|------------|------------------------------------|
| UCSD Ped1    | 14,000 | Single| Spatial & Temporal | 238×158 | biker, cart, etc                   |
| UCSD Ped2    | 4,560  | Single| Spatial & Temporal | 360×240 | biker, cart, etc                   |
| UMN Lawn     | 1,450  | Single| Temporal      | 320×240 | escape panic                       |
| UMN Indoor   | 4,415  | Single| Temporal      | 320×240 | escape panic                       |
| UMN Plaza    | 2,145  | Single| Temporal      | 320×240 | escape panic                       |
| CUHK Avenue  | 30,652 | Single| Spatial & Temporal | 640×360 | loitering, running, throwing objects |
| Subway Entrance | 72,401 | Single| Temporal      | 512×384 | avoiding payment, wrong direction   |
| Subway Exit  | 136,524| Single| Temporal      | 512×384 | avoiding payment, wrong direction   |
| Shanghai Tech| 317,398| Multi | Spatial & Temporal | 856×480 | chasing, brawling, sudden motion, etc |
| UCF-Crime    | ~13.8M | Multi | Video-level & Temporal | 320×240 | assault, burglary, robbery, etc     |
| Street Scene | 203,257| Single| Spatial & Temporal | 1280×720| jaywalking, person exits car, etc   |

3 Existing Benchmark Datasets

This section discusses in detail the publicly available datasets for the task of anomaly detection. There are a few papers which have created their own datasets but most of the works have tried to at least use one benchmark dataset in order to evaluate the performance of their proposed approaches with respect to previously published works. A summary presenting a high-level view of all of the different datasets included in this subsection can be seen in Table 2. Note that the dataset links are added as footnotes for reference.

3.1 The UCSD Pedestrian Dataset

The UCSD Pedestrian dataset was created by Mahadevan et al. (2010) for the purpose of evaluating their approach on anomaly detection. The dataset contains videos overlooking pedestrian walkways taken by a stationary camera at 10 frames per second that is mounted at an elevation. In this dataset, anomalous events are either due to non-pedestrian entities in walkways or anomalous pedestrian motion. Some anomalous examples include bikers, skaters, cats, and the like. The dataset has two (2) subsets where each subset corresponds to a particular scene. The first scene includes people walking to and from the camera’s angle while the second has people walking parallel to the camera plane. An example of the anomalies can be seen in Fig. 3.

The first subset called Peds1 contains 34 training clips and 36 testing clips having a resolution of 234 × 159. Meanwhile, the second subset called Peds2 contains 16 clips for training and 14 clips for testing having a resolution of 360 × 240. In general, there are

1 http://www.svcl.ucsd.edu/projects/anomaly/dataset.html
around 3,400 frames with anomalies present while the normal frames are around 5,500. Both subsets have a frame-level ground truth and a pixel-level ground truth.

3.2 The UMN Dataset

The UMN dataset\textsuperscript{2} has a total of 11 clips containing three (3) different scenes, specifically, a lawn scene, and indoor scene, and a plaza scene (Hu et al. 2016). These video clips were captured at 30 frames per second using a stationary camera that has no significant illumination changes. The resolution of the captured video clips is at 320 × 240. With respect to the number of frames, all in all there are 7,740 frames where 1,450, 4,415, and 2,145 belong to lawn, indoor, and plaza scenes, respectively.

In this dataset, the particular anomaly that happens is when the people run to escape or when they panic. The sequences generally start with normal behavior where an escape panic behavior ensues. Sample frames from the dataset are shown in Fig. 4.

3.3 The CUHK Avenue Dataset

Along with their proposed approach, Lu et al.\textsuperscript{3} also created a dataset called the CUHK Avenue dataset containing 16 videos for training and 21 videos for testing which includes 15,328 training frames and 15,324 testing frames with a resolution of 640 × 360. Furthermore, the dataset contains 47 different anomalies which include loitering, running, and throwing objects.

\textsuperscript{2} http://mha.cs.umn.edu
\textsuperscript{3} http://www.cse.cuhk.edu.hk/leojia/projects/detectabnormal/dataset.html
However, compared to the other datasets which have stationary cameras, the avenue dataset may have differences in camera angle and position. In addition, each of the videos is around 1 to 2 minutes long. Some example anomalies are shown in Fig. 5, where there is a running man on the left-hand side of the figure and the other image contains an anomalous action where paper is scattered around the area.

3.4 The Subway Dataset

The Subway Dataset contains two types of videos namely the "exit gate" and "entrance gate" videos. All in all, the videos are around two (2) hours long with a resolution of 512 × 384.

The exit gate video has 136,524 frames while the entrance gate video has 72,401 frames. In both scenarios, abnormality may include avoiding payment or walking in the wrong direction as the crowd. Comparing it to other datasets, the anomalies present in this dataset are relatively low.

3.5 The ShanghaiTech Campus Dataset

The ShanghaiTech Campus dataset was proposed due to the lack of scene diversity from pre-existing benchmark datasets. Compared to previous datasets, the ShanghaiTech dataset has a larger number of videos having 330 training videos and 107 testing videos.

\[^4\] http://vision.eecs.yorku.ca/research/anomalous-behaviour-data/. This link only contains the Subway Exit

\[^5\] https://svip-lab.github.io/dataset/campus_dataset.html
videos which consists of 13 different scenes and a large amount of varying anomaly types. The resolution of the videos in this dataset is at $856 \times 480$.

An example is shown in Fig. 7 where the left image is the normal image with students walking while the right image contains the anomaly where there is a biker. Furthermore, there are also anomalies which are cause by sudden motion such as chasing and brawling. These types of anomalies are not included in datasets such was UCSD Pedestrian, CUHK Avenue, UMN Dataset, and Subway Dataset.

3.6 The UCF-Crime Dataset

Due to the previous datasets being relatively small in size, the UCF-Crime Dataset\(^6\) was created by Sultani et al. (2018). This dataset contains 13 real-world anomalies namely accidents, burglary, explosion, fighting, robbery, shooting, stealing, shoplifting, and vandalism. Compared with previous datasets which were manually collected, this dataset was taken from Youtube\(^7\) and LiveLeak\(^8\) using relevant text queries. These text queries are not limited to English, other languages (using Google Translate) were also used for searching. Overall, there are 950 untrimmed real-world surveillance videos and 950 normal videos garnering a total of 1,900 videos in the dataset. Note that the entire dataset has around 128 hours worth of data having a resolution of $240 \times 320$.

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\(^6\) https://webpages.uncc.edu/cchen62/dataset.html
\(^7\) www.youtube.com
\(^8\) www.liveleak.com
The dataset is already divided into training and test sets for uniformity. The training set consists of 810 anomalous videos while having 800 normal videos while the testing set has 150 normal and 140 anomalous videos. Despite being split into different datasets, all 13 anomalies are present in both sets lying at various locations in the video.

3.7 The Street Scene Dataset

One of the recently published datasets, the Street Scene dataset (Ramachandra and Jones 2020) was created to solve the existing problems that the older datasets were facing which is to have more realistic anomalies and to have a greater variety with respect to the types of anomalies that are present. In Street Scene, there are 46 training video sequences and 35 testing sequences. These videos are taken from a stationary USB camera which views a two-lane street that has pedestrian sidewalks and bike lanes.

![Street Scene](image)

Example normal and anomaly in the Street Scene dataset are shown in Fig. 9. The left-hand side of the figure shows a person jaywalking which is an anomaly in the dataset while the right figure shows a normal scene. There are a total of 17 different anomaly types in the dataset namely jaywalking, biker outside lane, loitering, dog on sidewalk, car outside lane, biker on sidewalk, pedestrian reverses direction, and so on.

4 Evaluation Metrics

This section briefly discusses the mostly used evaluation metrics by the papers that have been presented in this paper. Most of the works have followed the metrics introduced by Li et al. (2014) where there are two (2) different criteria. The first one is a frame-level criterion where a frame is considered anomalous if at least one of its pixels are tagged as anomalous. To evaluate using the frame-level criterion, the temporal labels are used to determine metrics true positives and false positives. The second one is a pixel-level criterion where if at least 40% of the anomalous pixels are detected, the frame is considered to be anomalous. For both criterion, the area under the curve (AUC) of the receiver operating characteristic curve (ROC) is computed to measure the final performance of the models. Given a classification model having different thresholds, the receiver operating characteristic curve (ROC) illustrates the performance of the model. The true positive rate and false positive rates defined in Equations 5 and 6 are the parameters of the said curve (Bradley 1997).

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9 http://www.merl.com/demos/video-anomaly-detection
True Positive Rate = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (5)

\text{False Positive Rate} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}} \quad (6)

Basically, the ROC is a plot such that the true positive rate is on the y-axis and the false positive rate is on the x-axis. The values for each point in the plot is taken from different classification thresholds. The area under curve (AUC) of the ROC is used as a measure to determine how good the model is performing. A higher value for the AUC of the ROC signifies that the model is performing well. The strengths of this metric include threshold-invariance and scale-invariance. It is scale-invariant because it does not look at the absolute values of the predictions and looks at how well the predictions are ranked. Meanwhile, it is also threshold-invariant since it measures the performance without considering the threshold chosen for classification. However, its strengths are also its weaknesses such as the scale-invariance of the metric might not be suited if well-calibrated probabilities are desired. Moreover, it is not suited for optimizing on metrics such as false positives in specific use cases since it expresses them as an aggregated value. Additionally, an equal error rate (EER) is computed alongside the receiver operating characteristic curve. The equal error rate computes for the percentage of misclassified frames when the false positive rate is equal to the miss rate. More specifically, it is when the False Positive Rate = 1 – True Positive Rate for the frame-level criterion while it is 1 – EER for the pixel-level criterion (Li et al. 2014).

There are problems in both of these metrics as mentioned in the work of Ramachandra and Jones (2020). They have pointed out that in the frame-level criterion, an algorithm could still be considered correct even if the anomalous pixel doesn’t necessarily overlap with the spatial region as to where the event is happening. Additionally, the pixel-level criterion does not take into account predictions that do not overlap with the ground truth. This prompted Ramachandra and Jones (2020) to propose new evaluation metrics alongside their recently published dataset. They have proposed to use track-based detection criterion and region-based detection criterion which they claim is similar to object tracking and object detection metrics. The track-based detection criterion measures the false positive regions per frame against the track-based detection rate (TBDR) which is defined in Equations 7 and 8.

\[
\text{TBDR} = \frac{\text{number of anomalous tracks detected}}{\text{total number of anomalous tracks}} \quad (7)
\]

\[
\text{FPR} = \frac{\text{total false positive regions}}{\text{total frames}} \quad (8)
\]

Meanwhile, the region-based detection criterion measures the false positive regions per frame against the region-based detection rate (RBDR) across all testing frames. Correctly detected anomalous regions in frames are identified similar to the track-based detection criterion. The definition of RBDR is shown in Equation 9.

\[
\text{RBDR} = \frac{\text{number of anomalous regions detected}}{\text{total number of anomalous regions}} \quad (9)
\]

Note that anomalous tracks are correctly identified if the ground truth has an intersection over union (IoU) above a threshold \(\alpha\) with the detections. Similarly, anomalous regions in the frame is considered correctly identified if the ground truth has an IoU of above a threshold \(\beta\) with the corresponding detected regions.
5 Discussion

Based on the different methodologies discussed in this paper, it is evident that anomaly detection is indeed a hard task. Several deep learning methods ranging from simple architectures to complex unified approaches have been proposed by different researchers. By categorizing the different approaches together into groups such as reconstruction error, future frame prediction, using classifiers, and scoring, a paradigm has been introduced on how to view anomaly detection approaches. Moreover, the variety of the type of approaches present also goes to show that researchers have been exploring different ways and thinking out of the box to determine anomalous events mainly because of its difficulty.

One common theme from all of the papers is that most of them still are careful about taking into account several aspects of human action such as appearance and motion. Representations may differ such as the work of Lin et al. (2019) which uses social force maps while Xu et al. (2020) uses optical flows but the main idea remains the same. This points the research community to a direction that appearance and motion play a big part in detecting anomalies. More so, that even in deep learning approaches (which is supposed to automatically learn discriminative features), researchers still make use of these features or concepts to guide the network and make it look properly at these specific variables.

Recent papers have started to think of creating end-to-end deep learning solutions and unified architectures rather than making use of separate components in a traditional pipeline. This is important as well because end-to-end deep learning solutions are easily deployable in real-life, making the research more accessible and more usable than it is now. However, end-to-end deep learning solutions require a lot of data which might be a problem for older datasets such as the UCSD Pedestrian or UMN Dataset but large scale datasets have been proposed by Sultani et al. (2018); Ramachandra and Jones (2020); Liu et al. (2018) to help solve this problem. Yet, an important issue to also consider as well is that video data is very laborious to annotate and collect which one of the main reasons why there haven’t been as much large scale datasets published yet despite having tons of data publicly available in video sharing sites. This stresses the importance of making use of unsupervised or weakly-supervised approaches in tackling this problem.

With regards to evaluation, as presented by Ramachandra and Jones (2020), the current evaluation metrics using the frame-level criterion and pixel-level criterion might not be representative of the performance of the model due to the reasons stated in their work. Hence, there might be a need to have more robust evaluation metrics which would be more effective irrespective of the type of new datasets that might be published in the future. Future evaluation metrics must consider providing better ways to assess spatial aspects of future methodologies since it is important to know which part of the frames cause the anomalies. This in turn, allows faster and better inference to what is happening should the approaches be deployed in real life.

Looking from a different perspective, results have become better over time because methods by various researchers, have successfully managed to incorporate spatial and temporal information to their models, thereby achieving excellent results. Yet, for real-life anomalous events, it is more than spatial and temporal information, there also needs to be context added to make the models more robust. As seen from the different definitions of different authors, the very definition of what an anomaly is also vary from one context to another. One possible way to achieve this is to slowly pivot the research area towards larger datasets and datasets captured from real-life videos and real-life scenarios. Furthermore, borrowing concepts such as attention or transformers from different fields might also be helpful to achieve this goal.
6 Conclusions

This paper has provided an overview of the recent advances in anomaly detection for videos specifically using deep learning techniques. Four types of categories of current approaches have been introduced with respect to the final step in identifying anomalies such as using reconstruction error, predicting future frames, using classification, or using scoring. These categories show the diversity of the approaches and it also is a testament to the difficulty of the problem as it forces researchers and practitioners alike to think out of the box to find better solutions to the problem.

In addition, this paper has also presented the different commonly used datasets along with important details such as the video resolution and example anomalies found within the respective datasets. Over time, it can be seen that the datasets are gradually increasing in size and are also becoming closer to real-life scenarios. However, there is still an issue of manually annotating these videos. Approaches that leverage weakly-supervised or unsupervised learning should be explored more in the hopes that it might also be able to automatically annotate videos once they learn from a small sample.

Future areas of research might include adding context since most of the works have been successful in modelling both motion and appearance, studying the recently published large-scale datasets, creating end-to-end deep learning frameworks, and focusing more on approaches that require little to no supervision.

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